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PSO Optimal Control of Model-free Adaptive Control for PVC Polymerization Process

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Abstract: Polyvinyl chloride (PVC) polymerizing process is a typical complicated industrial process with the characteristics of large inertia, big time delay and nonlinearity. Firstly, for the general nonlinear and discrete time system, a design scheme of model-free adaptive (MFA) controller is given. Then, particle swarm optimization (PSO) algorithm is applied to optimizing and setting the key parameters for controller tuning. After that, the MFA controller is used to control the system of polymerizing temperature. Finally, simulation results are given to show that the MAC strategy based on PSO obtains a good controlling performance index.

Keywords: Polyvinyl chloride (PVC), polymerization temperature, model-free adaptive control, particle swarm optimization (PSO) algorithm.

1 Introduction

Polyvinyl chloride is one of the five thermoplastic synthetic resins, widely used in all fields such as industry, agriculture, construction public utilities etc.[1] The temperature of polymerizing reaction is the most important controlled parameter in the production process. At present, the automatic control of temperature at the bottom of the polymerizer still givens priority to PID control[2], and the application of some advanced controlling technology has also achieved good controlling effect. In 1995, a design scheme of fuzzy logic and artificial neural network feedback control was developed in a batch polymerizing reactor temperature control system, to improve the stability of the system[3]. In 2003, on the basis of the conventional PID control of the polymerization kettle and in view of Laguerre function identification and predictive control, an indirect adaptive predictive control strategy was proposed, so as to shorten the producting cycle of the polymerizer and improve the equipment′s production capacity[4]. Using HOLLiASMACS system as the platform in 2007, the controlling scheme that combines the fuzzy algorithm and cascade PID algorithm was applied to the polyvinyl chloride (PVC) production facility in Benxi Otiental Chlor Alkali Co. Ltd., achieving good controlling effect[5]. In 2011, aimed at the controlling difficulty of the polymerizer for large-scale temperature and multivariables, the control strategy of predictive functional with double mode was adopted, which shortened the process time, eliminated the interference and achieved the purpose of improving and stabilizing product quality[6]. In 2013, aiming at the real-time fault diagnosis and optimized monitoring requirements of the large-scale key polymerization equipment of PVC production process, a real-time fault diagnosis strategy is proposed based on rough sets theory with the improved discernibility matrix and BP neural networks, and the proposed strategy greatly increased the accuracy rate and efficiency of the polymerization fault diagnosis system[7].

Model-free adaptive control is a control strategy that lets the controlled system get rid of relying any model, uses only input and output data of the controlled system to design the designer, so essentially overcomes the "unmodeled dynamics and robustness problem". In 1994, co-sponsored by the Hou and Han, the model free adaptive control (MFAC) theory, marked a major breakthrough of the model free control theory[8], whose thinking is that the controller is designed using only the controlled system I/O data and the controller does not contain any information of the mathematical model of the controlled process. In 1999, an adaptive PI control algorithm is developed for a class of SISO nonlinear discrete-time systems based on a generalized predictive control (GPC) approach, the simulation and real-time experiment are provided for real nonlinear systems which are known to be difficult to model and control[9]. In 2005, aimed at the characteristic of the large of lag time-varying nonlinear complex systems is difficult to control, the tin thickness model-free adaptive control system is proposed, the system

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is successfully put into operation and achieved good control effect[10]. In 2006, Shang Chuankou, Li Wei and others used the model-free adaptive control combined with the traditional PID control, and applied it to the main steam temperature control system, simulation results are given to show that it has achieved good control effect to overcome the time delay and large disturbance[11]. In 2009, aimed at the problem of multi-motor synchronization in multi-wire saw, the algorithm of MFAC is used in motor control scheme, and the feasibility and effectiveness of the method are proved by the prototype test method[12]. In 2011, aimed at the outlet pressure of boiler with the characteristics of typical nonlinear and coupled, a model free adaptive control method is used to maintain it at the respected values, compared with the traditional PID control algorithm, the simulation verifies the feasibility and robustness of the control system[13]. In 2016, Hu and Tang[14] proposed a model-free adaptive data-driven SMC algorithm, this new discrete-time nonlinear systems model-free control algorithm obtained better control performance through the simulations for the linear motor position and the information tracking speed, which also achieved robust and accurate traceability.

Because the polymerizing temperature possess features nonlinearity, time-varying and multi-variables, this paper proposes a model-free adaptive control algorithm based on particle swarm optimization. Firstly, this paper designs a model-free adaptive controller. Secondly, the particle swarm optimization algorithm is used to optimize key parameters of the controller. Then, the identified polymerization temperature model is optimized; finally, the simulation results are given to verify the effectiveness of the proposed control algorithm.

The rest of the paper is organized as follows. PVC polymerization process is presented in Section 2. PVC polymerization process temperature control based on model-free adaptive is presented in Section 3. Standard algorithm of PSO is presented in Section 4. Model-free adaptive control algorithm based on PSO optimization is presented in Section 5. Simulation study is made in Section 6, and compared with other methods. Finally, conclusions and some remarks are given in Section 7.

2 PVC polymerization process

The PVC resin is produced by suspension method production technology method. Polymerization process production device is shown in Fig. 1. Liquid vinyl chloride (VCM) in the presence of dispersants, by mixing effect dis-

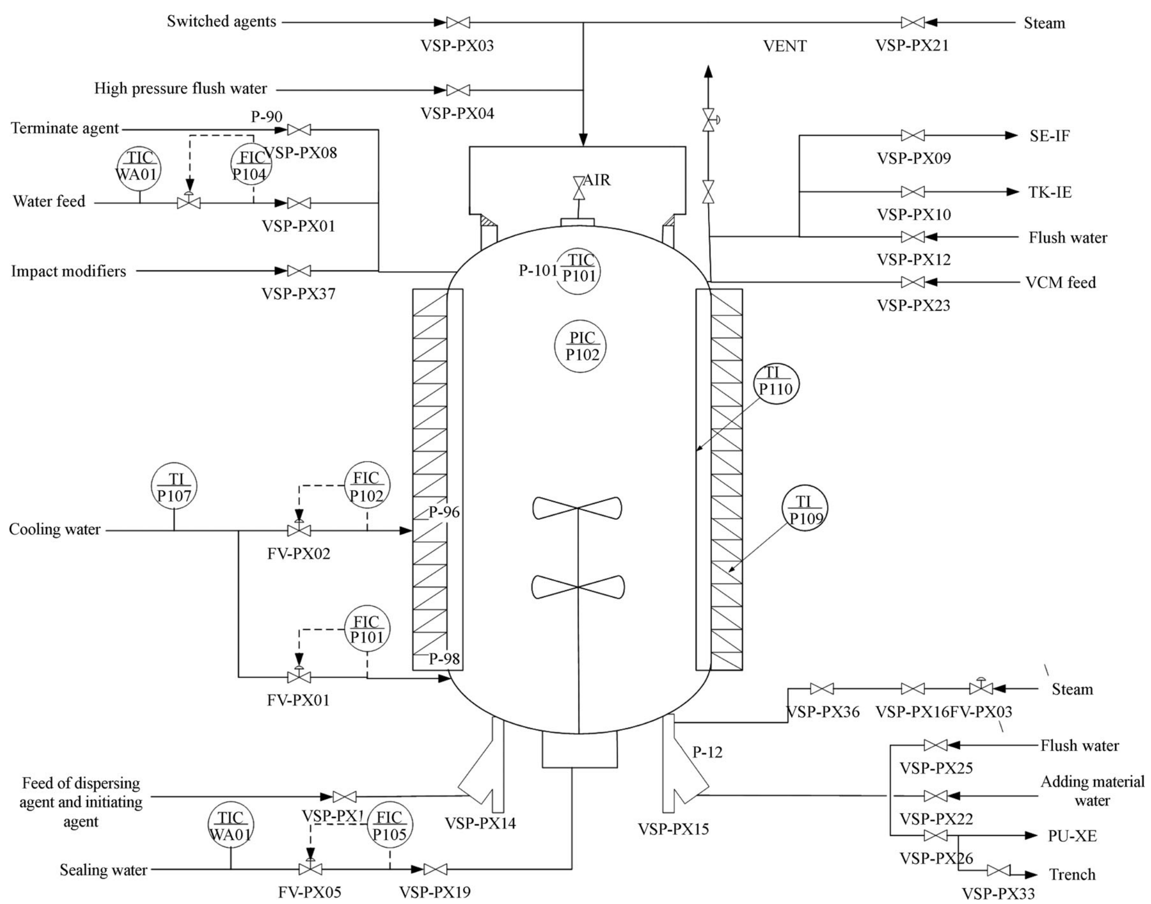

Fig. 1 Flowchart of polymerizing production process

persed droplet, suspended in water, soluble in VCM of initiator on the polymerization temperature decomposition into radicals, VCM polymerization reactions. According to the free radical polymerization mechanism of VCM suspension polymerization, including chain initiation, chain growth, chain transfer and chain termination reactions.

In the process of polyvinyl chloride (PVC) polymerization, firstly, the various raw materials and additives are added to the reaction kettle, which can be fully dispersed homogeneously by mixing blades agitation, and then the reaction is started by adding a proper proportion of the initiator. At the same time, the cooling water is injected into the external jacket of the reaction kettle and the inner baffle, whose main purpose is to remove the reaction heat. When the reaction is terminated, the termination agent is joined. At this time the conversion rate of polyvinyl chloride (VCM) is about 80−85%, and the pressure drop is 0.05 Mpa. Then the slurry is discharged through the bottom of the polymerization kettle. At last, the PVC slurry will be packaged as a product after a series of processes of being recycled, stripping, condensing, and drying. The temperature control of the whole reaction process is mainly related to the jacket cooling water, cooling water baffles, injected water and sealing water.

On the mechanism, PVC polymerization degree only lies on the temperature, so the temperature control is of great importance. The temperature deviation is controlled between ±0.2°C. At present, jacket cooling method is generally adopted to control the polymerization temperature. In this way, the initiating system is provided with a gentle polymerization rate, and the polymerization kettle is provided with good heat transfer performance. At 60°C below, the model of PVC is mainly controlled through adjusting the polymerization temperature; at 60°C above, besides the temperature, the molecular weight is controlled also through the chain transfer agent, which is the polymerization degree. The important parameters of polymerizing reaction process is shown in the notations at the last of this paper.

2.1 Chain initiation reaction

The initiator is decomposed, to primary radicals:

$$I \xrightarrow{K_d} 2R^\bullet$$

which I is initiator, $R^\bullet$ is free radicals, K_d is initiator decomposition rate constant.

The primary radicals with monomer addition monomer free radical is

$$R^\bullet + M \xrightarrow{K_i} RM^\bullet$$

which M is Vinyl chloride monomer, $RM^\bullet$ is monomer radical, K_i is chain radical.

$$\frac{\mathrm{d}[R^\bullet]}{\mathrm{d}t} = 2K_d[I]. \tag{1}$$

Due to the rate of monomer free radical formation is much greater than the initiator decomposition rateand because of the influence of the side reactions, the free radicals cannot be completely used to induce VCM. So

$$R_i = 2fK_d[I]. \tag{2}$$

In the formula, I, M, $R^\bullet$ $RM^\bullet$ represent the initiator, VCM, primary radical and monomer free radical respectively, R_i represents the initiation rate, $f \leq 1$ is the coefficient. [ ], the subscript d and i respectively denote concentration, decomposition and trigger.

2.2 Chain growth reaction and chain termination reaction

$$RM^\bullet \underset{K_{p1}}{\overset{+M}{\rightarrow}} RM_1^\bullet \underset{K_{p2}}{\overset{+M}{\rightarrow}} RM_2^\bullet \underset{K_{p3}}{\overset{+M}{\rightarrow}} \cdots RM_n^\bullet$$

$$K_{p1} = K_{p2} = K_{p3} = \cdots = K_p.$$

With M instead of all the $RM^\bullet$, $RM_1^\bullet$, $RM_2^\bullet$, $\cdots$, $RM_n^\bullet$. There is

$$R_p = -\left[\frac{\mathrm{d}\,[M]}{\mathrm{d}t}\right]_p = K_p\,[M]\,[M^\bullet]\,. \tag{3}$$

In the formula, R is chain growth rate (namely the total rate of polymerization), and K_p is chain growth rate constant.

When the free radical molecules up to a certain length to happen chain termination reactions. Chain termination reaction is respectively divided into the coupling termination and disproportionation termination, expressed as follows:

$$M_x^\bullet + M_y^\bullet \xrightarrow{K_{tc}} M_{X+Y}.$$

Coupled termination: the degree of polymerization is the sum of two chain radicals on the number of monomer units. The generated macromolecular as initiator residues on both ends.

$$R_{tc} = 2K_{tc}\,[M^\bullet]^2 \tag{4}$$

$$M_x^\bullet + M_y^\bullet \xrightarrow{K_{tc}} M_X + M_Y.$$

Disproportionation termination: the degree of polymerization is the original chain radicals contained in the number of monomer units, each contains a initiator residues end groups (one is saturated end group, the other one is unsaturated end group).

$$R_{td} = 2K_{td}\,[M^\bullet]^2\,. \tag{5}$$

The way of termination reaction depends on the structure of the monomer and polymerization temperature. Termination of the total rate is

$$R_t = \frac{\mathrm{d}\,[M^\bullet]}{\mathrm{d}t} = 2K_t\,[M^\bullet]^2\,. \tag{6}$$

In the formula, p, t, t_c, t_d respectively represent the chain growth, termination, coupling termination and disproportionation termination.

2.3 Chain transfer reaction

In polymerization of VCM, macromolecular free radical can capture a chlorine atom or atomic hydrogen and termination from monomer, fluxing agent, initiator or macromolecules, loss of atoms in molecules will become free radical, continues to grow a new chain reaction.

When the VCM polymerization, macromolecular chain transfer to monomer free radical and significantly became the primitive response to determine the molecular weight of PVC resin.

The primary control variables of the polymerization process variables are the polymerizer temperature, pressure, jacket water flow baffle flow of water injected into the water flow, the seal water flow, the jacket outlet temperature, the shutter outlet temperature, etc. Among them, the polymerization temperature is a very important parameter, which determines the molecular weight of PVC, which corresponds to the different types of PVC products. The polymerization reaction is intermittent operation of the exothermic reaction, the use of large-scale polymerizer and higher response speed can increase its productivity, it is advantageous from economic considerations. However, the large-scale polymerizer, poor heat transfer, uneven mixing and the reaction speed is fast, resulting in that the temperature control becomes very difficult. So we should control the polymerization kettle temperature in order to reduce the production costs and improve PVC product quality.

2.4 Relationship between polymerizing temperature and conversing rate

The factors influencing conversion velocity are initiator concentration, reaction temperature and polymerize degree. Polymerization velocity is given by the following equation.

$$R_c = K_p[M]\left(\frac{R_i}{2K_t}\right)^{\frac{1}{2}} \tag{7}$$

where R_i is initiator velocity, K_p is a constant of chain increasing velocity, R_c is chain increasing ratio (polymerization velocity), K_t is the termination velocity constant, and $[M]$ is the monomer concentration. That is to say the polymerization reaction ratio is proportional to the square of initiator velocity.

$$K_p = A\mathrm{e}^{-\frac{E}{RT}} \tag{8}$$

where K_p is the polymerization velocity constant, E is the activation energy, R is the air constant, and T is the absolute temperature.

It can be seen from (7) that the reaction velocity has relationship with initiator concentration and reaction temperature of constant kind. From (8), when T increases, K becomes larger so that the polymerization velocity becomes larger too. Substitute (8) into (7) to get

$$R_c = A\mathrm{e}^{-\frac{E}{RT}}[M]\left(\frac{R_i}{2K_t}\right)^{\frac{1}{2}} \tag{9}$$

where R_c is chain growth rate (polymerizing rate).

It is known from (9) that the polymerizing rate of VCM (conversion rate) is the function of temperature. The polymerization degree decreases with an increase in temperature. Therefore, polymerization degree only has a relationship with temperature for the VCM polymerization reaction[15].

3 PVC polymerization process temperature control based on model-free adaptive

3.1 Mechanism modeling of polymerizer temperature

PVC polymerizing process is a typically batch exothermic reaction process. According to the heat balance principle, the total calories instantaneously released in polymerizing reaction is equal to the heat amount removed by jacket water and baffle plate water, the absorbed heat by injection water and sealing water, and the heat making the polymerizer temperature change. Thus the following equations are obtained.

$$\Delta H_R M_0 R_C = Q_j + Q_b + Q_i + Q_s + Q_f \tag{10}$$

where

$$Q_j = C_w u_j\left(T_j - T_{j0}\right) \tag{11}$$

$$Q_b = C_w u_b\left(T_b - T_{b0}\right) \tag{12}$$

$$Q_i = C_w u_i\left(T - T_{i0}\right) \tag{13}$$

$$Q_s = C_w u_s\left(T - T_{s0}\right) \tag{14}$$

$$Q_f = C_v m_v T + C_p m_p T + C_w \rho_v V T. \tag{15}$$

The outlet temperature of the baffle plate water and jacket water is defined as follows:

$$T_j = \frac{T + \alpha_j T_{j0}}{1+\alpha_j}, \quad \alpha_j = \frac{C_W u_j}{K_j A_j} \tag{16}$$

$$T_b = \frac{T + \alpha_b T_{b0}}{1+\alpha_b}, \quad \alpha_b = \frac{C_W u_b}{K_b A_b} \tag{17}$$

Based on the (10)–(17), the differential equation of the polymerizer temperature is deduced as follows:

$$\begin{aligned}\dot{T} = {} & \frac{\Delta H_R m_O \dot{R}_C - C_W u_j\left(T - T_{j0}\frac{T_{j0}}{1} + \alpha_j\right)}{m_0\left(C_v\left(1-R_C\right) + C_P R_C + C_w\rho_w\left(\frac{R_C(\rho_P-\rho_v)}{\rho_P\rho_v}\right)\right)} - \\ & \frac{C_W u_b\left(T - \frac{T_{b0}}{1} + \alpha_b\right)}{m_0\left(C_v\left(1-R_C\right) + C_P R_C + C_w\rho_w\left(\frac{R_C(\rho_P-\rho_v)}{\rho_P\rho_v}\right)\right)} - \\ & \frac{C_W\left(\frac{m_0\rho_w(\rho_P-\rho_v)}{\rho_P\rho_v}\right)\dot{R}_C\left(T - T_{i0}\right)}{m_0\left(C_v\left(1-R_C\right) + C_P R_C + C_w\rho_w\left(\frac{R_C(\rho_P-\rho_v)}{\rho_P\rho_v}\right)\right)}.\end{aligned} \tag{18}$$

On the other hand, it is known from (9) that the polymerizing rate of VCM (conversion rate) is the nonlinear function of temperature, while the temperature is an important factor affecting PVC production quality. To make sure the quality of PVC production, the polymerizer temperature has to be controlled to a certain constant value. So the model-free adaptive model is set up based on the conversion rate of VCM.

3.2 SISO discrete-time nonlinear system

A general nonlinear discrete-time system can be expressed as

$$y(k+1) = f[Y_k^{k-n}, u(k), U_{k-1}^{k-m}, k] \tag{19}$$

where

$$Y_k^{k-n} = \{y(k), y(k-1), \cdots, y(k-n)\}$$
$$U_{k-1}^{k-m} = \{u(k-1), u(k-2), \cdots, u(k-m)\}$$

and $f(\cdot)$ is an arbitrary nonlinear function, $y(k)$ is output, $u(k)$ is input, n and m are the system unknown orders. For the nonlinear system (19), the hypotheses are as follows:

Assumption 1. The output and input of system (19) are observable and controllable. $y^*(k+1)$ is a desired output for a bounded feasible control input signal $u^*(k)$, that is, when the system is driven by the control input signal, the output of the system is equal to the desired output.

Assumption 2. The controlled input of current system $u(k)$ is a continuous partial derivative.

Assumption 3. System (19) satisfies the generalized Lipschitz theorem. That is for any k and $\Delta u(k) \neq 0$

$$|\Delta y(k+1)| \leq b|\Delta u(k)|$$
$$\Delta y(k+1) = y(k+1) - y(k)$$

where $\Delta u(k) = u(k) - u(k-1)$, and b is a constant.

Lemma 1. For nonlinear system (19), if it meets the Assumptions 1–3, then when $u(k) \neq u(k-1)$, that is $\Delta u(k) \neq 0$. There must be a pseudo partial derivative $\phi(k)$ meet $|\phi(k)| \leq b$. The dynamic linear model of nonlinear system (20) can be expressed as

$$\Delta y(k+1) = \phi(k)\Delta u(k). \tag{20}$$

3.3 Model-free adaptive controller

The SISO systems (19) can be written into the dynamic linear form of (20):

$$\Delta y(k+1) = \phi(k)\Delta u(k).$$

1) The design of control law algorithm

Considering the control input criterion function:

$$J(u(k)) = |y^*(k+1) - y(k+1)|^2 + \lambda|u(k) - u(k-1)|^2$$

where $y^*(k+1)$ is the tracking signal, λ is a positive weighting factor.

Put (20) into the criterion function for $u(k)$ to get the basic control law algorithms:

$$u(k) = u(k-1) + \frac{\rho_k \phi(k)}{\lambda + |\phi(k)|^2}[y^*(k+1) - y(k)]$$

where ρ_k is the step sequence with range of $(0, 2]$.

By online estimation, $\phi(k)$ can be replaced by $\hat{\phi}(k)$. We get the expression of control law algorithm.

2) Pseudo partial derivative estimation algorithm

Take into account that the symmetry similar structural system has a certain superiority[16].

Here is a symmetry similar estimation algorithm with control law.

$$J(\phi(k)) = \big(y^0(k) - y(k-1) - \phi(k)\Delta u(k-1)\big)^2 + \mu\Big(\phi(k) - \hat{\phi}(k-1)\Big)^2$$

where $y^0(k)$ is the actual output of the system, $\hat{\phi}(k-1)$ is the estimation value of $\phi(k-1)$.

Then the pseudo partial derivative estimation algorithm is:

$$\hat{\phi}(k) = \hat{\phi}(k-1) + \frac{\eta_k \Delta u(k-1)}{\mu + |\Delta u(k-1)|^2} \times \Big(\Delta y(k) - \hat{\phi}(k-1)\Delta u(k-1)\Big)$$

where μ is the weighting factor, η_k is the step sequence.

3) The design of model-free adaptive controller

Based on previously obtained control law algorithms and parameter estimation algorithm, MFAC algorithm can be written as

$$\hat{\phi}(k) = \hat{\phi}(k-1) + \tfrac{\eta_k \Delta u(k-1)}{\mu + |\Delta u(k-1)|^2} \times \Big(\Delta y(k) - \hat{\phi}(k-1)\Delta u(k-1)\Big) \tag{21}$$

$$\hat{\phi}(k) = \hat{\phi}(1), \quad \hat{\phi}(k) \leq \varepsilon or |\Delta u(k-1)| \leq \varepsilon \tag{22}$$

$$u(k) = u(k-1) + \frac{\rho_k \hat{\phi}(k)}{\lambda + |\hat{\phi}(k)|^2}[y^*(k+1) - y(k)] \tag{23}$$

where $\eta_k, \rho_k \in (0, 2)$, μ, λ are weighting factors, ε is a sufficiently small positive number, $\hat{\phi}(1)$ is the initial constant of $\hat{\phi}(k)$.

4 Standard algorithm of PSO

The PSO is a population based optimization technique, where the population is called as warm. A simple explanation of the PSOs operation is as follows. Each particle represents a possible solution to the optimization task at hand. For the remainder of this paper, reference will be made to unconstrained minimization problems. During each iteration each particle accelerates in the direction of its own personal best solution found so far, as well as in the direction of the global best position discovered sofar by any of the particles in the swarm. This means that if a particle discovers a promising new solution, all the other particles will move closer to it, exploring the region more thoroughly in the process.

Assume a D-dimensional target search space made of population formed by M particles. $S = \{X_1, X_2, \cdots, X_m\}$, where the position of i-th particle can be expressed as a D-dimensional vector $X_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$. In each iteration, the moving distance of the particle is its flight speed which can be expressed as $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$. According to certain criteria the current fitness value of the particle can be calculated, namely, the particle′s position merits. The detailed flowchart of the PSO is shown in Fig. 2.

So far, the position and velocity of i-th particle can be represented as follows: $X_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$ and $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$. Particle velocities V_i on each dimension are limited to $(V_{\min}, V_{\max})$ which controls the local and global exploration capability of a particle. And the best particle is able to search the optimal position $p_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$, the optimal position that we could search for the entire swarm is $p_g = (p_{g1}, p_{g2}, \cdots, p_{gD})$. During each iteration, the particles update the rate and position according to the following formula:

$$v_{id}^{k+1} = v_{id}^k + c_1 r_1 (p_{id}^k - x_{id}^k) + c_2 r_2 (p_{gd}^k - x_{id}^k) \tag{24}$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \tag{25}$$

where $i = 1, 2, \cdots, m$, $d = 1, 2, \cdots, D$, k is the current evolution algebra, r_1, r_2 are random numbers in [0,1], c_1, c_2 are learning factors which are known as the acceleration factor. v_{id}^k is the current speed of the particles, $c_1 r_1 (p_{id}^k - x_{id}^k)$ is the cognitive term, it represents the particles on their own learning, $c_2 r_2 (p_{gd}^k - x_{id}^k)$ is the social term, it represents the collaboration among particles. In addition, to ensure searching the efficiency can be limited, the range of speed v_{id} is $[v_{\min}, v_{\max}]$, the range of positions x_{id} is $[x_{\min}, x_{\max}]$.

Bring the inertia weight factor into (12) type to correct it, namely

$$v_{id}^{k+1} = w v_{id}^k + c_1 r_1 (p_{id}^k - x_{id}^k) + c_2 r_2 (p_{gd}^k - x_{id}^k) \tag{26}$$

where w is the inertia weighting factor. The iterative algorithm which is made of (25) and (26) is often referred to as the standard PSO algorithm[15−21].

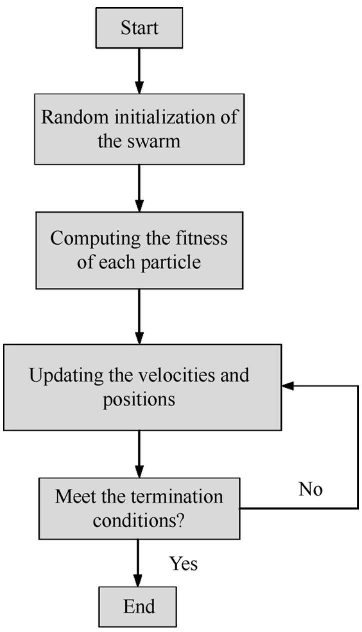

Fig. 2 Detailed flowchart of the PSO

5 Model-free adaptive control algorithm based on PSO optimization

Step 1. Initialization.

Because two parameters of model-free adaptive controller requires optimization and tuning, so the search space dimension is identified ($D = 2$), the population size is selected to ($M = 20$), maximum number of iterations is set to ($M = 20$) ($Iter = 800$). Position X_i and its speed V_i of the group is random initialized. Maximum speed is limited to $[0.01, +1]$, maximum position is limited to $[2, 100]$. w is used linear decreasing strategy. Learning factor value is 1.496 2.

Step 2. Select the fitness function.

Goal of optimization is to ensure the system output can follow a given reference trajectory in the input $u(k)$. System output can follow a given reference trajectory. So the fitness function is expressed as

$$Q = \sum_{k=0}^{\infty} \left\{ [y^*(k+1) - y(k+1)]^2 + [u(k) - u(k-1)]^2 \right\}.$$

The fitness function ensures that the system output can track the given reference trajectory, it also ensures the control energy as small as possible.

Step 3. Evaluate fitness of each particle.

According to the given fitness function by (2), the fitness value of the particle is calculated and determined.

Step 4. Update individual extreme.

For each particle, its fitness value is compared with the individual extreme. If the particle is better than the current individual extreme, then set p_i to the particle′s position and update individual extreme, otherwise leave the original value.

Step 5. Update the global extremum.

If the individual extreme of all the particles are best to the current global extremum, then set p_g as the position of the particle while update its global extremum, otherwise leave the original value.

Step 6. Update state of particles.

Using (25) and (26) to update each particle′s position and speed. If $V_i > v_{\max}$, then change as $v_{\max}$; if $V_i < v_{\min}$, change it as $V_{\min}$. So the same as limit its location update.

Step 7. To test whether meets of end condition.

If the current number of iterations reaches a pre-set maximum number $Iter$, then stop the iteration and output the optimal value, otherwise go to Step 2.

Finally, output optimal value is used to optimize key parameters of the controller.

6 Research on simulation of polymerizing process

6.1 Construct model for polymerization temperature

The polymerization process is always accompanied by volume shrinkage. The volume of organic phase in the polymerizer is

$$V = \frac{M}{\rho} \tag{27}$$

where V is the volume of the organic phase, M is the quality of the organic phase, ρ is the density of the organic phase.

During the reaction, the density of organic phase in polymerizer at any time is

$$\rho = \frac{M}{\frac{M_0(1-R)}{\rho_v} + \frac{M_0 R}{\rho_p}}. \tag{28}$$

Ignore the heat exchange between the reactor and the outside, and at the same time, ignore other heat loss in heat exchange process. Then the exothermic heat of reaction in the unit time is

$$Q = \sum_{i=1}^{n} u_i c_w (T_o - T_i). \tag{29}$$

where Q is the total quantity of heat released in unit time, u_i is the jacketed baffle flow of cooling water and injected water; c_w is the specific heat capacity of water, T_o is outlet temperature of cooling water for jacket baffle and the temperature of the reactor inside, T_i is jacket baffle inlet temperature of the cooling water and injected water.

Ignore the temperature of polymerization reaction kettle affected by conversion rate, thereby the function relationship between the heat released and the temperature inside the reactor can be expressed as

$$\frac{\mathrm{d}Q}{\mathrm{d}t} = \frac{\mathrm{d}^2T}{\mathrm{d}t^2} + c_1\frac{\mathrm{d}T}{\mathrm{d}t} + c_2T. \tag{30}$$

The removed heat by cooling water and injected water in the unit time is expressed as

$$u_i c_w (T_o - T_i) = c_w U(T - \tau) \tag{31}$$

where T is the temperature inside the kettle, $U(T-\tau)$ is the flow of the cooling water and injected water, namely the opening degree of cold water valve.

Simultaneous (30) and (31), the relationship between the temperature of the kettle and the valve opening is obtained.

$$\frac{\mathrm{d}^2T}{\mathrm{d}t^2} + c_1\frac{\mathrm{d}T}{\mathrm{d}t} + c_2T = c_w U(t-\tau). \tag{32}$$

So, the equation (32) is the model of the polymerizer temperature T.

The equation of the valve opening degree for the cooling water and the injected water in polymerizing process can be expressed as

$$y''(t) + ay'(t) = bu(t-\tau) \tag{33}$$

where $y(t)$ is reactor temperature, $u(t)$ is the valve opening degree of the cooling water and the injected water, τ is a pure time delay, a, b are constants.

On the discrete disposal of (33), select 300 groups of collected data, and use the least squares method to identify the data. Select $n_a = 2$, $n_b = 1$ and lag $n = 5$, the model parameters is obtained and the fitting result is shown in Fig. 3.

As can be seen in the simulation results, using the least squares method to identify the parameters of the controlled object, the ultimate goodness of fit runs up to 93.77%, the loss function is 0.055 06, final prediction error is 0.056 54. Therefore, the least squares parameter identification can satisfy the modeling requirement of the temperature for the polymerizing process.

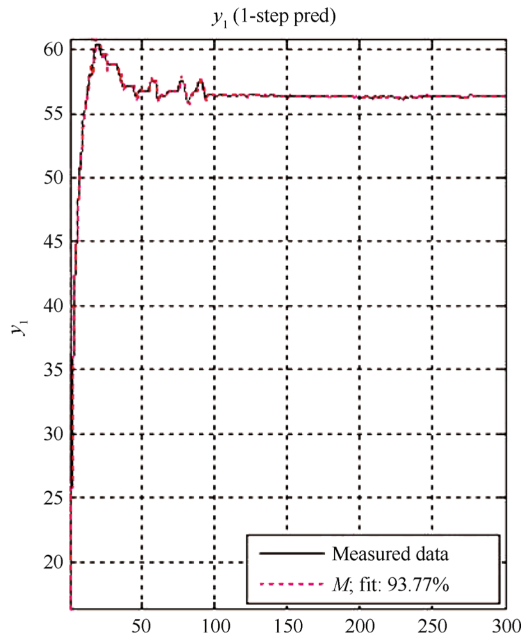

Fig. 3 Least-squares fitting results

6.2 The simulation research

Aiming at the control of the reacting temperature of polymerizing process, under the environment of MATLAB language, the MFAC method adopted in this paper is compared with the controlling effect of traditional PID. According to the actual reacting temperature required by a certain type of PVC products from a certain chemical group, the polymerization temperature in simulation is set to 56.4°C, and initial temperature of polymerization reactor is 40°C.

In view of the actually operating conditions during polymerizing process, considering two cases of normal operation and operation suffering from sudden disturbance, the output responses between MFAC and traditional PID control system are compared.

1) When the polymerization kettle run in good condition, parameters of the model-free adaptive controller are set: step sequence $\eta_k = 0.1$, $\rho_k = 0.1$, weighting factor $\mu = 1$, $\lambda = 33$. Parameters of PID controller are set: scale coefficient $K_p = 0.014$, integral coefficient $K_i = 0.006$, differential coefficient $K_d = 0.06$. It can be seen by the contrast in Fig. 4 that the output of the system can stably track the setting value. So the effectiveness of the model-free adaptive control strategy can be validated.

From Fig. 4, the model-free adaptive control method has faster response, the ability to adapt is better than other control method.

The analysis of simulation results is given in Table 1.

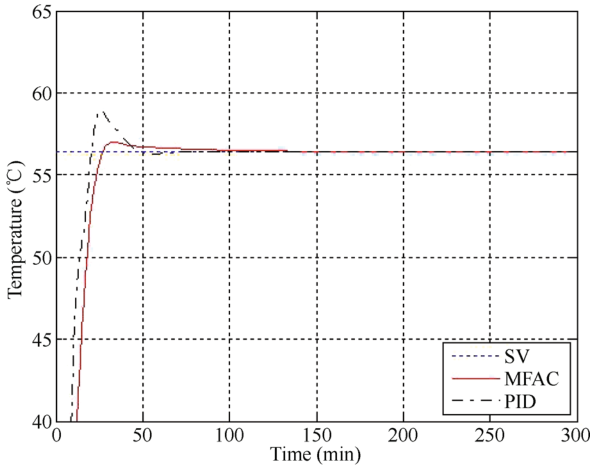

Fig. 4 Polymerizer normal operation of the kettle temperature control result

Table 1 Simulation analysis and parameters of two controller algorithms

Control algorithm	Parameter selection	Overshoot
PID	$\eta_k = 0.1, p_k = 0.1,$ $\mu = 1, \lambda = 33$	3.5%
MFAC	$k_p = 0.014,$ $k_i = 0.006,$ $k_d = 0.06$	2.5%

It can be seen from Table 1, compared with PID control algorithm, the model-free adaptive control method has the smaller overshoot, the output of the system can stably track the setting value.

2) It is supposed that polymerization kettle suffered from a sudden disturbance during operating process, for example, factors like reacting material suddenly heated unequally, which led to temperature of polymerization kettle changing in a sudden. In the 100th minute, step disturbance with amplitude of 2°C is added to the simulation, and the simulation results are shown in Fig. 5. Compared with PID control strategy, in the face of random interference, using MFAC method can be quicker to overcome the disturbance, which restores the system to the set value as soon as possible, at the same time, ensuring less bias and stronger robustness to the system.

From Fig. 5, the model-free adaptive control method can be quicker to overcome the disturbance, the ability to anti-interference is better than other control method.

The analysis of simulation results is given in Table 2.

It can be seen from Table 2, compared with PID control algorithm, the model-free adaptive control method has the smaller deviation and stronger robustness.

Table 2 Simulation analysis and deviation of two controller algorithms

Control algorithm	Disturbance	Deviation
PID	2.0°C	1.4°C
MFAC	2.0°C	2.0°C

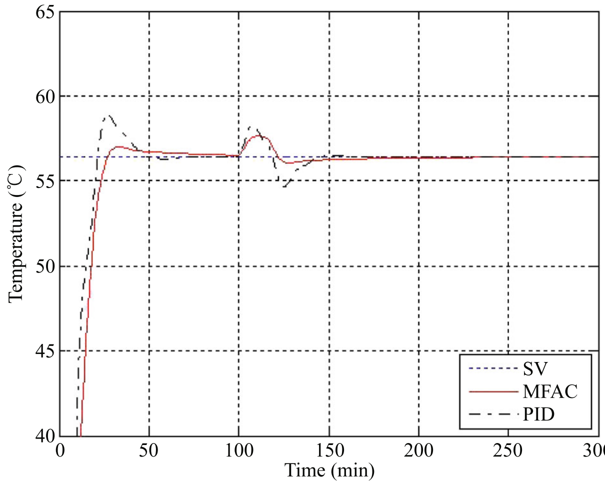

Fig. 5 Polymerization kettle temperature control results by step disturbance

3) Using PSO algorithm to optimize and tune parameters of model free adaptive controller, parameters of the model-free adaptive controller are set: step sequence $\eta_k = 0.1$, $\rho_k = 0.1$, weighting factor $\mu = 1$, $\lambda = 33$. Parameters of PID controller are set: scale coefficient $K_p = 0.014$, integral coefficient $K_i = 0.006$, differential coefficient $K_d = 0.06$, compared with the controlling effects of MFAC and PID, the simulation results are shown in Fig. 6. It can be seen from the simulation diagram, after tuning, response speed of the PSO-MFAC system is superior to the pure MFAC system, ensuring the system reach the set temperature value in a relatively short time.

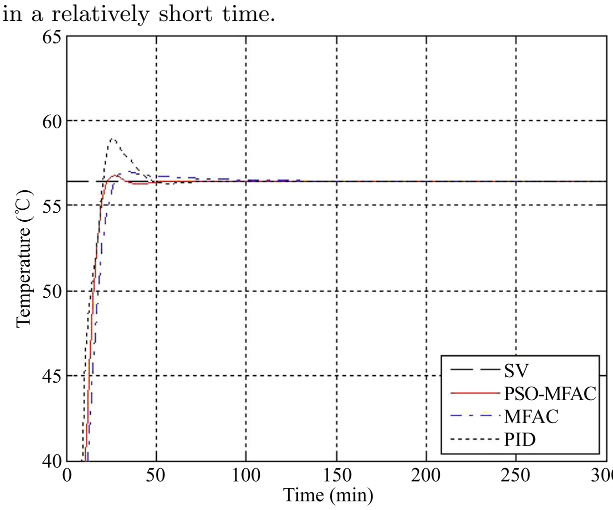

Fig. 6 PSO-MFAC, MFAC and PID temperature control curve comparison

From Fig. 6, after using PSO algorithm to optimize and tune parameters of model free adaptive controller, the method of PSO-MFAC can be faster to achieve the stable time.

The analysis of simulation results is given in Table 3.

It can be seen from Table 3, compared with the controlling effects of MFAC and PID, the overshoot of PSO-MFAC control method is the smallest, and the settling time is the shortest.

Table 3 Simulation analysis and overshoot of three controller algorithms

Control algorithm	Overshoot	Stable time
PID	3.5%	75 s
MFAC	2.5%	75 s
PSO-MFAC	2.5%	50 s

7 Conclusions

According to the theory of model-free adaptive control, a model free adaptive control algorithm for the polymerization temperature is proposed. On this basis, the particle swarm optimization algorithm is used to optimize and tune the key parameters of the controller. Using real operating data exist in the polymerizing process, the polymerization temperature model is established. This model-free adaptive control algorithm is applied to PVC polymerization, and compared the traditional PID in terms of controlling effect. The simulation shows the effectiveness of the MFAC algorithm. Moreover under the same conditions, the model-free adaptive control strategy optimized by the particle swarm can obtain better tracking effect. In future research, the model free adaptive control algorithm will be applied to the actual operation of polymerization temperature of the PVC production. In addition, this control algorithm provides an excellent reference for other complex industrial temperature control.

Notations.

ΔH_R : Reaction exothermic coefficient
M_0 : Initial quality of VCM
M_v : Residual mass of VCM
M_p : PVC quality after conversion
R_c : PVC conversion rate
Q_j : Heat removed from jacket water
Q_b : Heat removed from baffle water
Q_i : Heat removed from injected water
Q_s : Heat removed from sealing water
Q_f : Heat-changing value of reactor material
C_w : Specific heat of water
C_p : Specific heat of PVC
C_v : Specific heat of VCM
u_j : Jacket water flow
u_b : Baffle water flow
u_i : Injected water flow
u_s : Sealing water flow
V : Volume difference
T_j : Outlet temperature of jacket water
T_b : Outlet temperature of baffle water
T_{b0} : Inlet temperature of baffle water
T_{j0} : Inlet temperature of jacket water
T_{i0} : Inlet temperature of injected water
A_b : Baffle size
K_b : Heat-transferring coefficient of baffle.

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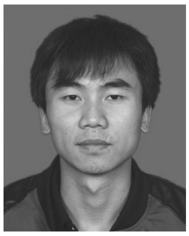

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