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APPLICATION OF IMPROVED PSO AND BP HYBRID OPTIMIZATION ALGORITHM IN ELECTRICAL AUTOMATION INTELLIGENT CONTROL SYSTEM

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Abstract. A fuzzy RBF-PID control strategy based on particle swarm optimization (PSO) algorithm is proposed to solve the problem of large inertia lag in temperature control system of industrial production refuse furnace. In this control system, an improved particle swarm optimization algorithm combined with inertia weight and genetic transformation was used to optimize the initial values of membership functions of fuzzy RBF (radial basis function). Then, BP (error backpropagation) algorithm is used for fine tuning, and fuzzy reasoning and RBF learning ability are combined to adjust the PID control parameters online to achieve the optimal PID control effect. The simulation results show that the algorithm has fast tracking, small overshoot, and is not easily trapped in local minima. At the same time, its robustness and anti-interference performance are better than traditional PID control.

Key words: Improving PSO, BP hybrid optimization algorithm, Electrical automation, Intelligent control system

1. Introduction. PSO algorithm is the most popular optimization algorithm in recent years. Combining PSO algorithm with BP neural network algorithm can solve the shortage of BP neural network itself. Using particle swarm optimization algorithm instead of gradient descent in BP network can optimize the link weight of each layer of BP network, thus improve its generalization ability and learning ability, and greatly improve its convergence speed [12]. In the process of optimizing BP neural network using particle swarm optimization algorithm, the iterative method of particle swarm optimization is usually used to replace the gradient improvement in BP neural network algorithm, and PSO algorithm is used to optimize the training weight of BP neural network. The key to using PSO algorithm to solve the problems in BP neural networks is to achieve the following two points: the particle dimension value in particle swarm optimization algorithm corresponds to the number of weighted combinations in BP neural network. Using the size of each particle in PSO according to the weight of each component in BP neural network. The key to the PSO algorithm in pronunciation, based on multi- pronunciation vector and the number of weights as equal to the size of pronunciation.Replaces the motor of the particle swarm algorithm with the mean square error function in BP neural network, and uses the energy potential to research the ability of the particle swarm algorithm to reduce the mean square error of BP network.Resistance furnace is an electrical heating equipment commonly used in fields such as machinery, chemical engineering, and manufacturing.At present, the furnace temperature control system generally adopts conventional PID control, which cannot achieve good control results for objects that are difficult to establish accurate models. Therefore, it is urgent to find a fast and accurate temperature control system.With the development of science and technology, PID control and some intelligent control have been combined and applied in industrial production.For this research question.Song, W. et alThe macro and micro models were established to predict the maintenance activities of the combat troops, and the parameters were analyzed. A prediction model for equipment maintenance activities that meet the requirement of real-time mobile echelon storage was established. In the condition of meeting annual motor stock balance, an improved particle swarm optimization hybrid optimization algorithm is developed to solve the model based on the time driving consumption from the equipment allocated to the annual training program. the particle swarm optimization hybrid optimization algorithm is proposed. An example study was made on a few cars in some room [14]. In order to solve the above problems, a fuzzy RBF-PID control method based on improved PSO algorithm is adopted. This method first solves the problem of local extremum and early convergence in particle swarm optimization algorithms. By

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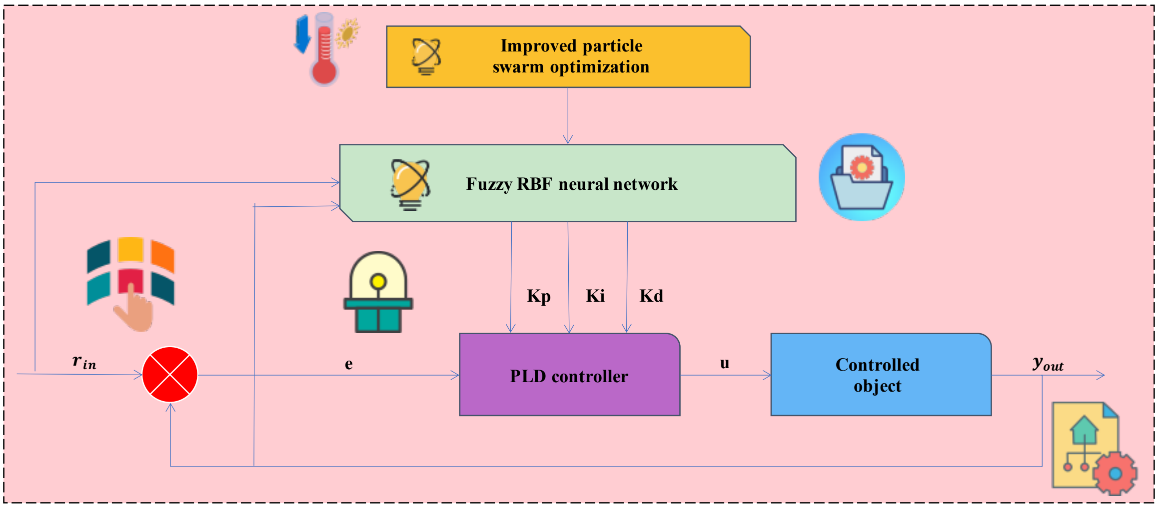

Fig. 2.1: Structure diagram of temperature control system

adding the modified algorithm, an improved PSO algorithm was established, and the primary importance of fuzzy RBF neural network was optimized using this strategy.Then, BP (Error Backpropagation) algorithm is used to adjust the key, center, and width of RBF neural network. Finally, combined with the power expression ability of fuzzy logic and self- learning ability of RBF neural network, PID is not adjusted online. Matlab test results show that this method has good control, adaptability, and robustness [5, 11].

2. Methods.

2.1. Resistance furnace temperature control system. The resistance furnace is a complex controlled object with large hysteresis and inertia. Due to the inconvenient modification of control parameters in traditional PID controllers and the difficulty in ensuring their control quality in terms of control accuracy, stability time, and overshoot, the author proposes to apply fuzzy RBF tuning PID control technology to the furnace temperature control system for resistance furnace temperature.The structure of its temperature control system is shown in Figure 2.1, where PSO is improved to optimize the weights of the fuzzy RBF neural network. The system's given value r_{in} and the controlled object's output y_{out} are combined with the fuzzy RBF neural network and the three parameters (K_p, K_i, K_d) of the PID controller to form a functional relationship, the controller to output u, and then combined with the controlled object output y_{out} to form a complete closed-loop control structure [8, 4].

2.2. Improving PSO and BP hybrid optimization algorithm.

(1) Hybrid optimization algorithm. In the PID control of fuzzy RBF neural network, the selection of parameters w_{ij}, c_{ij}, and b_{ij} has a significant impact on the approximation ability of the network function, the author selects a hybrid optimization algorithm that combines improved PSO and BP with inertia weight factor and genetic mutation operator to adjust its parameters. Firstly, PSO with inertia weight has been applied to international research. If an earlier result occurs, a change is made to take the command to jump out of the best locale and search for objects in other locales until a global solution is found. Then, an adaptive algorithm is designed using BP (Error Backpropagation) algorithm to get the optimal control parameters [7, 9].

(2) Improved particle swarm optimization algorithm. In order to expand particle space exploration and improve global and local searching ability, inertia weight w is introduced into the PSO model, and its velocity and position iteration method are as follows:

$$v_{id}(t+1) = wv_{id}(t) + c_1r_1\left(p_{id}(t) - x_{id}(t)\right) + c_2r_2\left(p_{gd}(t) - x_{id}(t)\right) \tag{2.1}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{2.2}$$

$$w(t)=\left\{\begin{array}{l}1 \times \frac{t}{G}+0.4,0 \leq \frac{t}{G} \leq 0.5 \\ -1 \times \frac{t}{G}+1.4,0.5 \leq \frac{t}{G} \leq 1\end{array}\right. \tag{2.3}$$

In the formula, c_1 and c_2 are learning factors, and $c_1 = c_2 = 2$; t is the number of iterations; $1 \leq i \leq m, 1 \leq d \leq N$; r_1 and r_2 take the random number between (0,1); G is the total number of iterations [10].

In general, particles update their state at the next moment based on their current position and speed. However, if the target of the particle search has already fallen into the local extreme, the particles are limited to the local space and cannot be fully optimized in the entire search space. In order to enable the particles to jump out of the local optimum and discover the global optimal position, a mutation operator is introduced to mutate the particles that have fallen into the local extreme with probability p. The formula is as follows:

$$p=\left\{\begin{array}{l}k, \sigma^2<\sigma_d, J\left(P_{\text {gbest }}\right)>J_d \\ 0\end{array}\right. \tag{2.4}$$

In the equation, k is $[0.1, 03]$ Any value between; σ^2 is the variance of population fitness; The value of σ_d^2 is generally much smaller than the maximum value of σ^2; J_d is set to the theoretical optimal value [17]. The author employs a random perturbation approach to perform mutation operations on the global extreme value (p_{gbest}), where $p_{\text{gbest},k}$ is the k-th dimensional value of p_{gbest}, η Following a normal $(0,1)$ distribution, that is:

$$p_{\text{gbest},k} = p_{\text{gbest },k}(1+0.5\eta) \tag{2.5}$$

The improved methods of PSO algorithm are as follows: ① initial total size m of particle swarm, the velocity c_1 and c_2, the number of iterations G, and velocity and position [18]. ② Select the appropriate fitness J and use ITAE (the wrong rate of time error) criterion as the fitness function for improving PSO algorithm. The calculation formula is as follows:

$$J=\int_0^{+\infty} t|e(t)| dt \tag{2.6}$$

(3). Find the fitness values of each particle, sort them according to the minimum value, and obtain the particles corresponding to the minimum value as the initial position of the global extremum. At the same time, the initial position corresponding to the particle fitness value is the initial position of the local extremum [20, 3]. ④ Calculate the inertia weight factor w according to equation (2.3), then calculate the mutation probability p according to equation (2.4), and randomly select the random number n between $(0,1)$. If $n < p$, then perform the mutation operation according to equation (2.5). ⑤ Based on models (2.1) and (2.2), the velocity and position of particles in the flame are updated. ⑥Calculate new exercise results, and then update the effectiveness of individuals and groups . When the number of iterations reaches the preset number, stop the iteration, otherwise it will turn to (2).

3. Result Analysis. The author designed the controller using a resistance furnace as the controlled object, and the transfer function of the controlled object is:

$$G(s)=\frac{K}{Ts+1} e^{-Ts}=\frac{1}{60s+1} e^{-80s} \tag{3.1}$$

This system uses the unit step signal as the input signal, utilizes practical experience and three other control parameters, and then combines the author's control system. After multiple simulation experiments, as shown in Table 3.1, the final system parameters are set as follows: Sampling time of 20 seconds, learning $\eta = 0.15$, inertia coefficient a=0.02, the initial value ranges of the center vector c_{ij} and the base width vector b_{ij} of the Gaussian function are $[-6, 6], [0.1, 3]$, respectively, the initial value range of network weight w_{ij} is $[-1, 1]$, the total number of population particles is 60, the total number of iterations is 300, and the dimension of particles is $N = 168$, which means there are a total of 168 parameters that need to be optimized [16].

Figures 3.1 and 3.2 show the simulation comparison and fitness function J optimization process without input disturbance, while Figures 3.3 and 3.4 show the simulation comparison and fitness function J optimization process with 10% disturbance added to the system at 600 seconds, from the figure, it can be seen that compared

Table 3.1: Parameter simulation experiment

Learning Rate	inertial coefficient	Base width vector	center vector	Network weight	Is it stable	overshoot	Time when e is zero
0.16	0.02	[0.1 3]	[-3 3]	[-1 1]	Yes	7.41	125.1
0.21	0.02	[0.1 3]	[-3 3]	[-1 1]	Yes	12.21	137.1
0.16	0.02	[0.1 3]	[-4 4]	[-1 1]	No	-	-
0.21	0.02	[0.1 3]	[-4 4]	[-1 1]	No	-	-
0.16	0.02	[0 4]	[-3 3]	[-1 1]	No	-	-
0.21	0.02	[0 4]	[-3 3]	[-1 1]	No	-	-
0.16	0.02	[0 4]	[-6 6]	[-1 1]	Yes	-	-
0.21	0.02	[0 4]	[-6 6]	[-1 1]	No	-	-
0.11	0.02	[0.1 3]	[-6 6]	[-1 1]	Yes	not have	300.1
0.16	0.02	[0.1 3]	[-6 6]	[-1 1]	Yes	not have	120.1
0.21	0.02	[0.1 3]	[-6 6]	[-1 1]	Yes	2.81	151.1
0.26	0.02	[0.1 3]	[-6 6]	[-1 1]	Yes	9.81	293.2

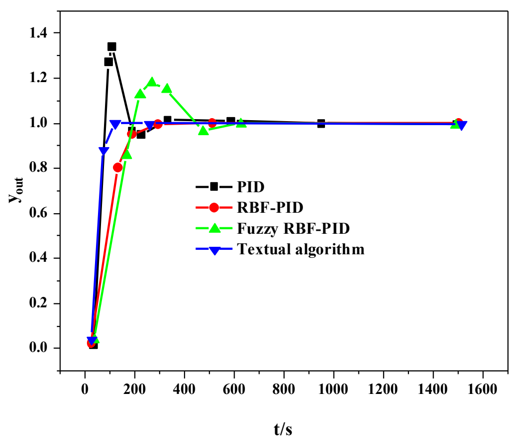

Fig. 3.1: Comparison of simulation curves

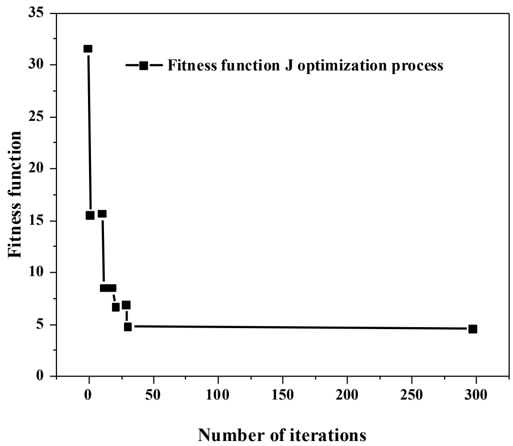

Fig. 3.2: Optimization process of fitness function J

with traditional PID controllers, RBF-PID controllers have a reduced overshoot and are prone to oscillations, making it difficult for the system to achieve rapid stability. However, adopting fuzzy RBF-PID control strategy can significantly improve system performance, but the adjustment time is long [13, 2, 6, 19, 15, 1]. In comparison, the fuzzy RBF-PID control method using improved particle swarm optimization algorithm has short response time, good anti-interference performance, and demonstrated good control accuracy.

4. Conclusion. The author proposes a fuzzy RBF-PID control strategy based on improved particle swarm optimization algorithm for resistance furnace temperature control in industrial production, which addresses the issues of large inertia and large lag of temperature control objects. This algorithm not only combines the characteristics of traditional PID controllers, but also has reasoning and self-learning abilities, overcoming the problems of traditional PID controllers being unable to adjust parameters online and having poor adaptability.At the same time, the algorithm introduces inertia weight and personnel variables to improve the searching ability of particle swarm, avoids the early capture of local extremum by particles, and uses ITAE objective function as the driving mechanism of the improved PSO algorithm. Through Matlab simulation analysis, the performance of the fuzzy RBF-PID control algorithm based on improved PSO algorithm is superior to other

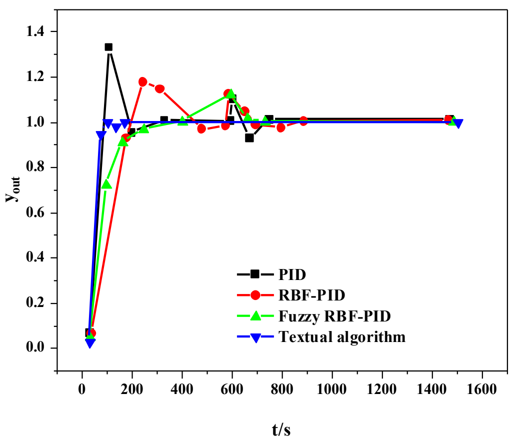

Fig. 3.3: Comparison of simulation curves with 10% disturbance added to the system

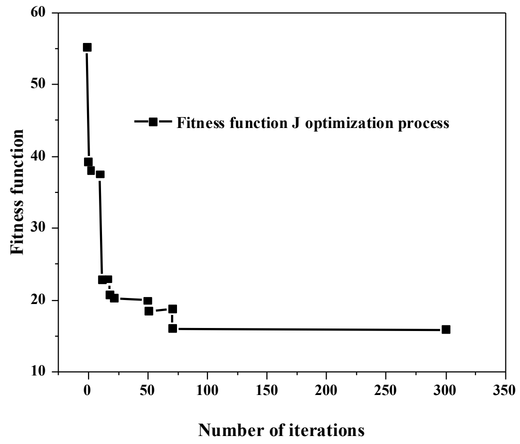

Fig. 3.4: Optimization process of fitness function J with 10% disturbance in the system

PID control algorithms, with shorter response time and better convergence.

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