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Neural Network Based on Improved Parallel Bat Algorithm and Its Application

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Abstract. *The artificial neural network is a research hotspot emerging in the field of artificial intelligence. Back Propagation (BP) neural network plays an important role in neural network. The network has the disadvantages of slow convergence of learning algorithms and easy falling into a local minimum. In this paper, a parallel bat algorithm with a new communication strategy is proposed, which is used to optimize the weights and thresholds of the BP neural network and establish the improved PBA-BP model. It was applied to optimize the parameters of the PID controller. Finally, we verified the effectiveness of the proposed method through the simulations.*

Keywords: BP Neural Network; Parallel Bat Algorithm; Communication Strategy; Parameter Optimization; PID control.

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1. **Introduction.** Artificial neural network has become an active interdisciplinary direction in the field of artificial intelligence [1, 2]. The research of Back Propagation neural network has been very mature and it is not competent in practical applications due to their limitations and deficiencies. Therefore, optimizing neural network models have become a research highlight in domestic and foreign research. The current research results are mainly divided into two parts.

In terms of network structure, many researchers have done theoretical research on the number of hidden layers. Jain et al. [3] pointed out that the neural network which has two hidden layers could solve any form of classification problem. Furthermore, Kim and Calise [4] proved that a three-layer network can realize the mapping of continuous functions on a uniformly approximated compact set. Hecht-Nielsen [5] proved that the number of hidden layer nodes is not fixed. If the number becomes larger, the mapping realized by three-layer network can also approximate the square-integrable function on the compact set according to the L2 norm. Another study has shown in [6] that there is an optimal value for amount of hidden layer nodes and often depends on the complexity of a given training task.

In terms of weight training algorithms, the main work includes the Newton method, conjugate gradient method, etc. The improvement of these algorithms is carried out by applying mathematical optimization theories. Besides, many scholars have also proposed some other improvement methods. Wang and Lin [7] proposed a second-order learning algorithm of the matrix based on Block Hessian. This method accelerates the convergence rate of the network and overcomes the shortcomings of the algorithm's complexity and the need for a large amount of memory. Yu and Chen [8] proposed the BP algorithm with optimal learning parameters, and the three BP algorithms proposed in the literature [9] can effectively avoid some of the shortcomings of the standard BP algorithm. Some scholars combine neural networks with novel intelligent algorithms and propose hybrid new algorithms. There are lots of useful intelligent algorithms include Bat Algorithm (BA) [10, 11], Ant Colony Optimization (ACO) [12, 13], Genetic Algorithm (GA) [14, 15], Artificial immune algorithm [16], Particle Swarm Optimization (PSO) [17, 18], Cat Swarm Optimization (CSO) [19, 20], Fish Migration Optimization (FMO) [21, 22], QUasi-Affine TRansformation Evolutionary (QUATRE) algorithm [23, 24] and Monkey King Evolution (MKE) [25, 26] etc. In the meantime, the algorithm of neural network is combined with wavelet theory, fuzzy mathematics, and chaos theory to propose fuzzy neural networks [27], Wavelet neural networks [28], Chaotic neural networks [29], Cellular neural networks [30] and other network models.

Bat algorithm has the disadvantages of slow convergence speed, low convergence accuracy, ease to fall into a local minimum, and other shortcomings, which severely limits the application field of BA. Aiming at the shortcomings, we proposed a parallel bat algorithm. Specifically, the communication strategy between groups is constructed. This algorithm is combined with BP neural network to find the best solution of weight. The effectiveness and superiority for the method are proved through PID optimization parameters.

The rest of the paper is organized as follows: Section 2 describes the model and concept of BP neural network. The formation process of the original bat algorithm is described; Section 3 presents the improved parallel bat algorithm; Section 4 introduces the model of PBA to optimize BP neural network; Section 5 shows the experiments and analyzes the results. Section 6 draws the conclusions.

2. **Related work.** This section briefly introduces the model and theory of BP neural network. The original bat algorithm is also described.

2.1. **BP neural network theory.** Biological neuron is the basic unit of brain, which is a nerve cell composed of a large number of dendrites and axons as the main body of the cell. The cell body is equivalent to the elementary processor. The dendrites are equivalent to the input terminal, which can receive afferent nerve impulses from all directions. The axons are equivalent to the output terminal, which is used to send out nerve impulses. Neurons are in contact with each other through synapses [31]. Synapses determine the strength and properties of connections between neurons, which are equivalent to connection weights.

BP neural network is a kind of multilayer feedforward neural network which is trained by error back propagation algorithm [32]. It is a very effective learning method that can be used in many fields. It is a kind of supervised learning network include an input layer, an output layer and at least one hidden layer. It differs from other types of networks in that it introduces the principle of error back propagation. The learning method of the network has changed from the original forward and one-way propagation to a combination of forwarding and backward propagation [33]. The key step is to use gradient search technology to continuously modify the weights and thresholds between network neurons so as to the error is continuously reduced along the negative gradient direction to obtain the actual output value with the smallest error from the expected output.

2.2. **Topological structure of BP neural network.** The training and learning process is a two-step process. The first step is the forward propagation process where the initial end information of the network layer is passed to the end of the network layer by layer. The second step is to reverse the error from the loss function. The end of the network layer is transmitted back to the originating end.

The error propagation direction is opposite to the forward propagation. The level of transmission is from back to front. By calculating the deviation of the connection weight of each level to the objective function, it is propagated layer by layer, the weight and threshold are made to an error by the method of gradient descent [34]. The learning process is a forward transmission of information plus a back propagation of errors. Training the sample and learning repeatedly to reduce the error. The structure diagram of Neural network is shown in Figure 1.

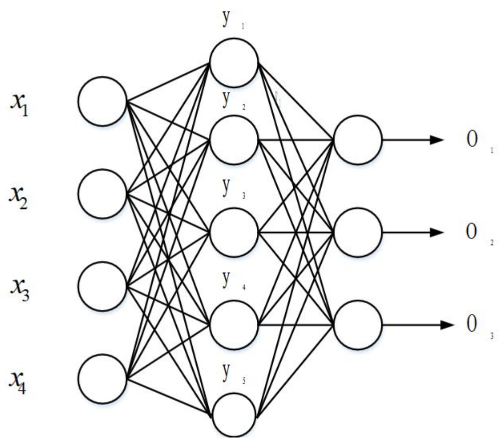

FIGURE 1. Structure Diagram of Neural Network

2.3. **BAT Algorithm.** Professor Yang proposed a new swarm intelligence algorithm called bat algorithm (BA) [35] in 2010, which has attracted great attention. The bat's motion update formula is as follows:

$$f_i = f_{min} + (f_{max} - f_{min})\beta \tag{1}$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_{best})f_i \tag{2}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{3}$$

where f is the frequency of bat flight; f_{max} and f_{min} mean the minimum and maximum values. x_i is the position of the ith bat, t is iterations now, β is a random vector, $\beta \in [0, 1]$; x_{best} means the best position of all individuals.

If $rand > r$, the optimal bat individual generates a new local solution according to the formula (4).

$$x_{new} = x_{old} + 0.01\varepsilon A^t \tag{4}$$

where ε is a random number and $\varepsilon \in [-1, 1]$. A^t means the average loudness. Generate a new solution by flying randomly. If rand $< A$ and the fitness of the bat individual is improved, the new solution is accepted. Update according to formulas (5) and (6).

$$A_i^{t+1} = \alpha A_i^t \tag{5}$$

$$r_i^{t+1} = r_i^0[1 - exp(-\gamma t)] \tag{6}$$

where α and γ are constants.

3. **The Improved parallel bat algorithm.** On the basis of original bat algorithm, we proposed a improved parallel bat algorithm (PBA) based on a new communication strategy. Parallel processing is a very critical and effective means for trend calculation [36]. The superiority of the improved algorithm is verified through test function experiments. Parallel processing is constructed by dividing the entire population into several subgroups and the several groups in the parallel structure can be created which does not know each other. When the trigger condition of communication strategy is reached, the subgroup begins to exchange information and realize cooperation.

The algorithm is processed in parallel and an appropriate communication strategy is designed. All bat individuals are divided into G subgroups and the particle population is divided into G subgroups. Each group performs BA independently and then approaches the best solution. After every R_1 iterations, the communication between the various subgroups will start. The communication strategies proposed in this paper are as follows:

$$X_{1bad}^p = X_{1bad}^p + r_1((X_{2best}^p + X_{3best}^p)/2 - X_{1bad}^p) \tag{7}$$

$$X_{1bad}^p = X_{bad} + r_2((X_{2best} + X_{3best} + X_{4best})/3 - X_{1bad}) \tag{8}$$

$$p = p^*(\frac{N_{MAX} - N}{N_{MAX}}) \tag{9}$$

where X_{1bad} means the worst particle in the first group, X_{2bad} means the best particle in the second group, and r_1 and r_2 is a random number belonging to $[0, 1]$. N is the current number of iterations. $100p\%$ represents the percentage of individuals that need to be replaced and the initial value of p is 0.1.The proposed communication strategy is specifically the first 50% iterations, the communication strategy method is used by formula (7), and the last 50% iterations communication strategy is used by formula (8) and formula (9). So the reason for separating the two strategies is that in the early optimization stage for optimization algorithm, we allow all particles to perceive the entire search space and avoid falling into a local optimal solution prematurely. Therefore, we adopted the first strategy. In the later stage of optimization, the second communication strategy is adopted to find the global optimal solution which is the ultimate goal. The information exchange between subpopulations is realized by a parallel method. The parallel BA with a communication strategy is shown in Figure 2.

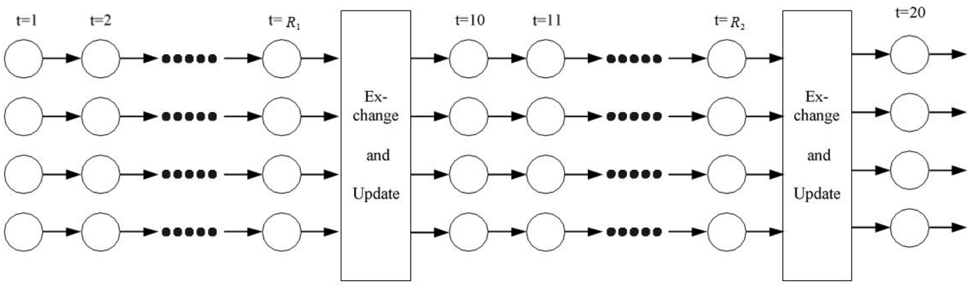

FIGURE 2. Parallel BA with a communication strategy

4. **The improved PBA-BP model and application.** The gradient descent method has the disadvantage of weak global search ability. In the problem of local minimization, it is easy to fall into local extremum. On the contrary, BA has faster convergence and better global optimization [37]. Using the improved parallel bat algorithm (PBA) and BP to train the weights and thresholds of the ANN, the global optimization of the algorithm and the local optimization of BP can be perfectly combined to make up for their shortcomings and jointly promote the improvement of the overall performance in the algorithm. We call it the improved PBA-BP model.

4.1. **The improved PBA-BP model.** Corresponding the weights and thresholds of the BP network to the position vector of each bat, the position vector of each bat corresponds to a network structure, and each component of the position vector represents a weight or threshold. The dimension is equal to the sum of the number of weights and thresholds of network [38]. We suppose that the number of nodes in each layer of the three-layer BP network are n, q, m respectively. Then the network represented by the position vector of the i-th bat is as follows:

$$\begin{aligned} X_i &= (X_{i1}, X_{i2}, ..., X_{id}) \\ &= (\omega_{11}, ..., \omega_{1q}, \omega_{n1}, ..., \omega_{nq}, W_{11}, ..., W_{1m}, W_{q1}, ..., W_{qm}, \theta_1, ..., \theta_m) \end{aligned} \tag{10}$$

where ω means the connection weight , W represents the connection weight and θ represents the threshold between the layers.

Searching for the best initial weight of BP neural network through the improved PBA is essentially to obtain a set of reference ranges for the best solution via replacing gradient descent search algorithm of the BP neural network algorithm with an optimized algorithm, and then the BP neural network re-calculates this solution. Training is performed on this basis and will overcome many shortcomings. The combination of the two can not only improve the learning effect, but also increase the computing speed and reduce the cost of learning and training.

4.2. **Application.** Using PBA-BP model for PID parameter tuning. The function of neural network in the controller is to control the output of three values of PID control parameters according to the error and error rate of change obtained by comparing the value returned by the system with the set value [39]. Aiming at the shortcomings of the BP algorithm, the improved parallel BA algorithm is used to optimize the connection weight parameters of the BP-PID controller to improve the convergence speed and learning ability of control [40]. Specific steps are as follows:

(a) Build a four-input, three-hidden-layer, three-output network structure, and use a randomly generated method to set the initial weights :

There are four input nodes :

$$\begin{cases} x(1) = e(k) - e(k-1) \\ x(2) = e(k) \\ x(3) = e(k) - 2^{*}e(k-1) + e(k-2) \\ 1 \end{cases} \tag{11}$$

Three output nodes:K_p, K_I, K_D.

(b) After the completion of the network structure, we set the learning rate, inertia coefficient, and activation function [41]. Encode the initial weights of all connected neurons in the neural network to become a real number string which is used as the particle dimension of the parallel BA algorithm.

(c) Initializing the parallel BA algorithm parameters. Set the population number, maximum iteration number, AC algebra, and initialize the particle position randomly. In the meantime, set the exchange and update formula item coefficients. Determine the objective function which is the output error:

$$J = \frac{1}{2}\sum_{k=1}^{o}(r(k) - y(k))^2 \tag{12}$$

(d) Input the calculation sample to obtain the three parameters of PID. The parameters are calculated employing incremental PID to get the output at each time. According to the target value and the output error, the fitness value of each individual was obtained.

(e) Comparing the fitness value obtained from the combination of each particle, a set of weight thresholds with the best fitness value of each particle and update the global optimal weight combination.

(f) According to the parallel BA algorithm, the particles of each weight threshold combination of each group are updated, and if the exchange algebra is reached, the communication between the groups is carried out.

(g) Detecting the condition of termination. If the conditions are met, the whole calculation process is ended. Otherwise, go back to step (d).

The PID controller is shown in Figure 3.

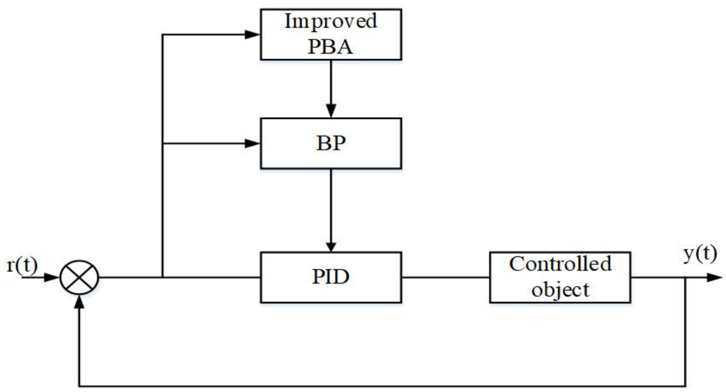

FIGURE 3. PID controller based on BP neural network optimized by PBA algorithm

5. **Experiment.** The results and comparison of the improved parallel BA , the original BA [10] and the PBA (the worst individual is replaced by the average of the other two groups) [39] are shown below. Using benchmark function to test performance of algorithms and the all benchmark functions for experiment are run 15 times on different random seeds on average. Parameter setting of parallel BA and original BA: the initial loudness $A_i^0 = 0.25$, pulse rate $r_i^0 = 0.5$, the total population size $n = 200$, the dimension of the solution space $M = 30$, the total number of iterations is 2000. Figure 4 to 9 show the comparison of the three algorithms in the test function.

The test results of the six functions are shown above. In the Rosrbrock function, the convergence speed of the improved algorithm is faster but the convergence accuracy of two algorithms is almost the same. In the Rastrigin function, the BA algorithm converges faster, but our algorithm is more excellent in convergence accuracy. In the Quadric, Griewangk, Ackley, and Spherical function, the realization of the improved algorithm is

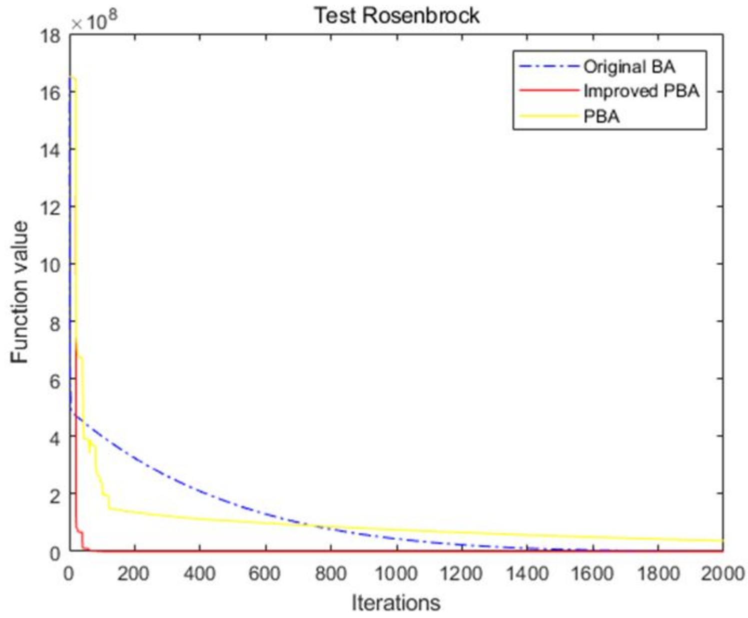

FIGURE 4. The Experimental Results of Rosrbrock Function

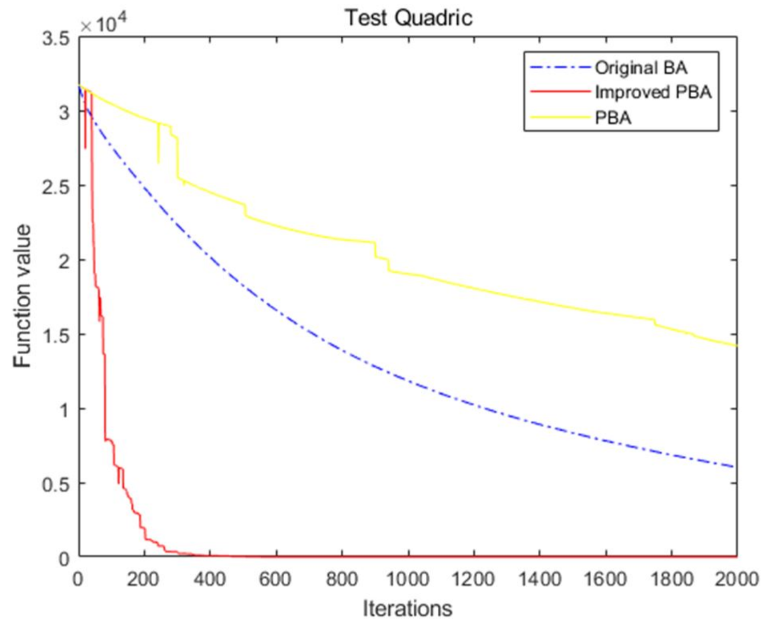

FIGURE 5. The Experimental Results of Quadric Function

great, and it is better than BA and an ordinary parallel BA in terms of convergence accuracy and convergence speed. The overall performance of algorithm is greatly improved, which proves the superiority of the algorithm.

The mathematical model of the selected controlled object is as follows:

$$G(s) = \frac{9.2}{189s + 1} \tag{13}$$

The input of the BP nerve is the calculation formula of the sampled third-order deviation. The learning rate is set to 0.5, and the inertia coefficient is set to 0.01. The

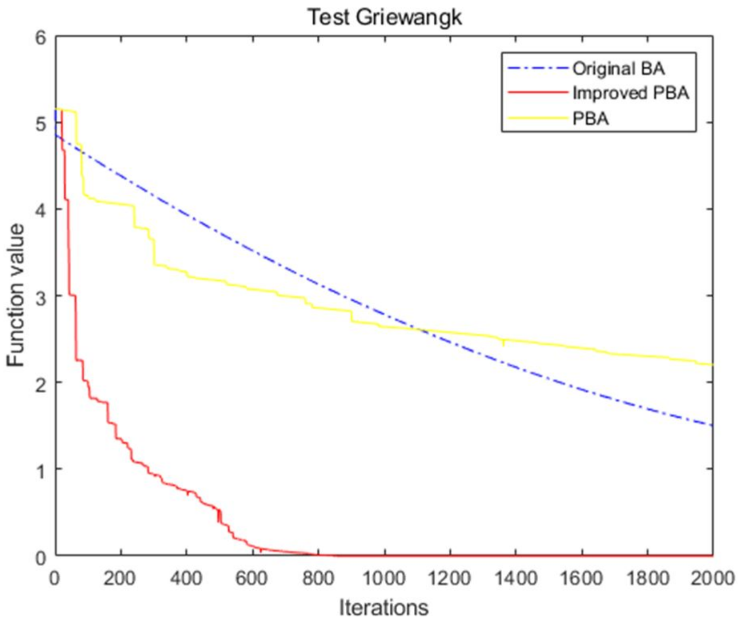

FIGURE 6. The Experimental Results of Griewangk Function

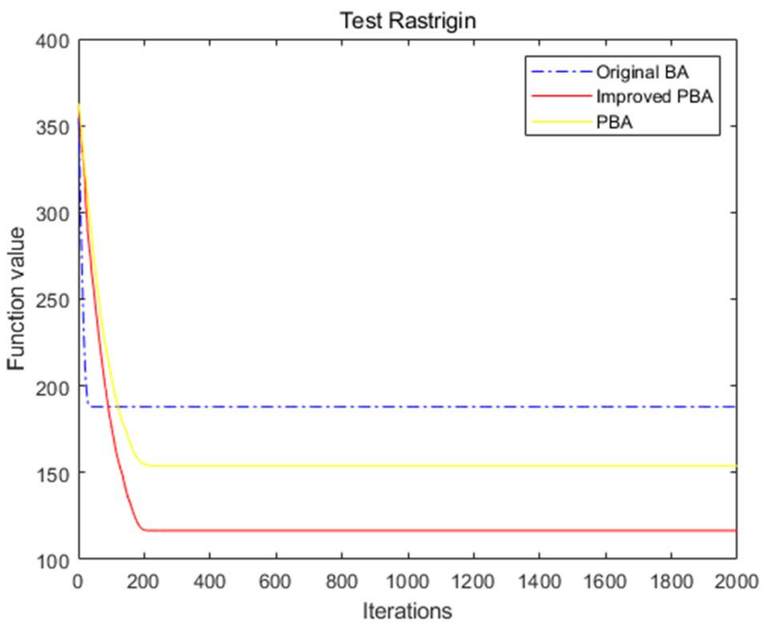

FIGURE 7. The Experimental Results of Rastrigin Function

initial value of the conventional BP network is given employing random function initialization, while the improved PBA-BP network uses the best initial weight and threshold individuals trained by the algorithm.

We can see from the Figure 10 and Figure 11 that the conventional Z-N method is slow to adjust, the response time to reach the steady-state is longer, and the control effect is poor. Compared with BP-PID and PSO-PID, the intelligent PID algorithm controller based on improved PBA-BP neural network has the advantages of faster adjustment time and smaller overshoot.

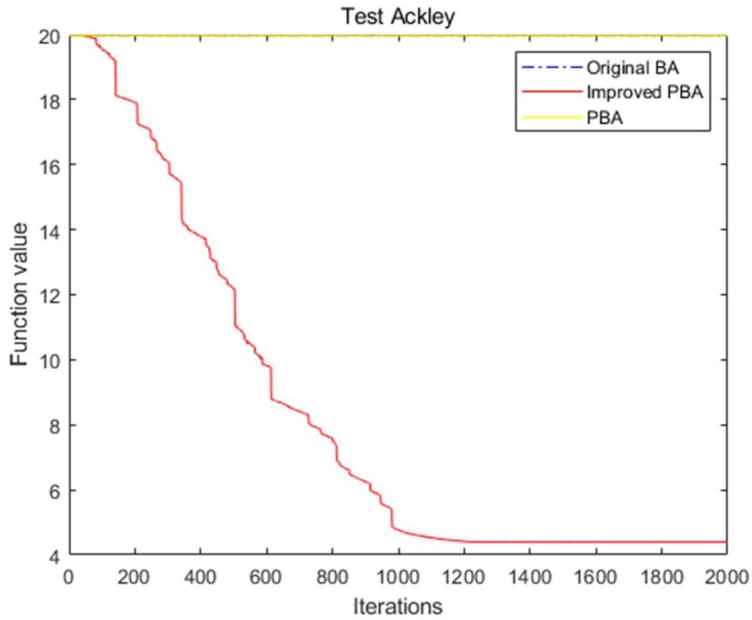

FIGURE 8. The Experimental Results of Ackley Function

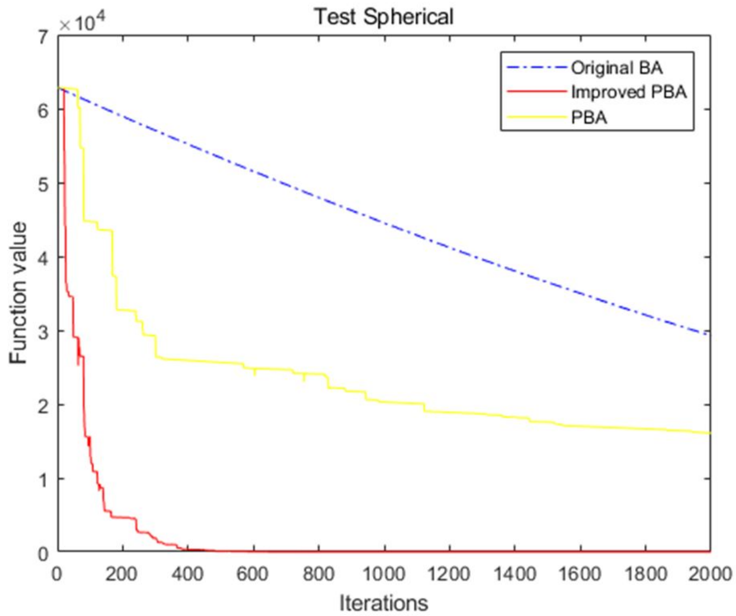

FIGURE 9. The Experimental Results of Spherical Function

The disadvantage of BP neural network is that the convergence speed is not fast enough. It tends to converge to the local extremum and is not stable enough. Through the improved PBA algorithm to optimize the controller learning of the BP neural network, the initial weights and thresholds with better control performance can be obtained. We can find that the optimized controller has better control performance by observing the response curve.

6. **Conclusions.** In order to solve the BP neural network's slow learning speed and tends to converge to the local extremum, we proposed an improved parallel bat algorithm to optimize the neural network. Therefore, the overall performance of the algorithm has

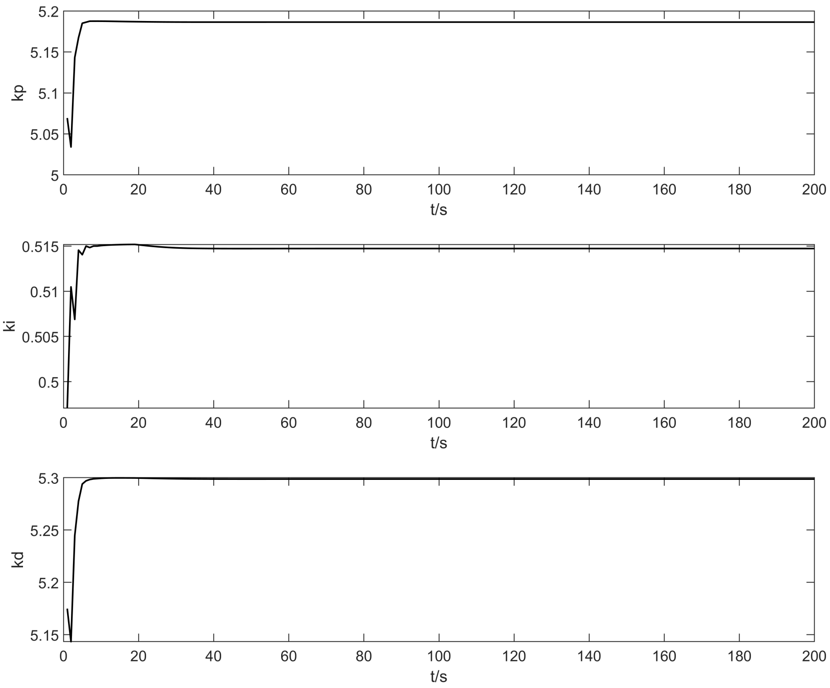

FIGURE 10. PBA-BP-PID Parameter tuning curve

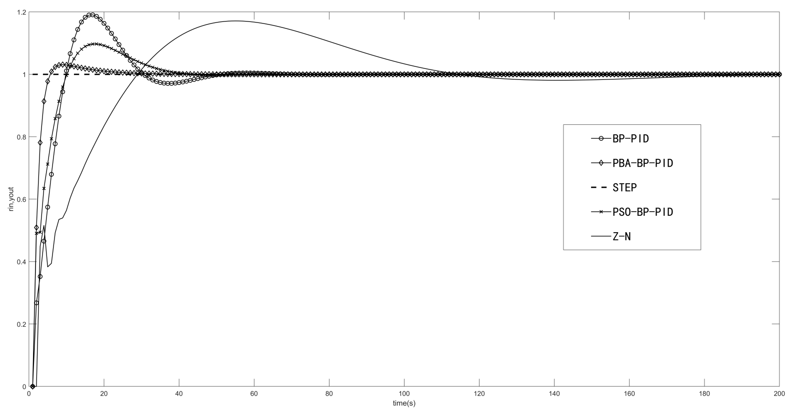

FIGURE 11. Step response curve

been greatly improved. The BP neural network algorithm based on improved parallel Bat Algorithm is used to tune the PID parameters, which improves the control performance of PID controller. The feasibility and superiority of the method are verified through experiments.

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REFERENCES

[1] J. Y. Zhao, J. Gong, S. T. Ma, Z. M. Lu, S. C. Chu, J. F. Roddick, Finger vein recognition scheme based on convolutional neural network using curvature gray image, *Journal of Network Intelligence*, vol. 4, no. 3, pp. 114-123, 2019.

[2] Z. M. Chan, C. Y. Lau, K. F. Thang, Visual speech recognition of lips images using convolutional neural network in VGG-M model, *Journal of Information Hiding and Multimedia Signal Processing*, vol. 11, no. 3, pp. 116-125, 2020.

[3] A. K. Jain, J. Mao, K. M, Mohiuddin, Artificial neural networks: a tutorial, *Computer*, vol. 29, no. 3, pp. 31-44, 2015.

[4] B. S. Kim, A. J. Calise, Nonlinear flight control using neural networks, *Journal of Guidance, Control and Dynamics*, vol. 20, no. 1, pp. 26-33, 2012.

[5] R. Hecht-Nielsen, Theory of the backpropagation neural network, in *Neural networks for perception*, Academic Press, pp. 65-93, 1992.

[6] M. J. Niedwiecki, M. Cioe K, A. Gacza, A new look at the statistical identification of nonstationary systems, *Automatica*, vol. 118, pp. 109037, 2020.

[7] Y. J. Wang, C. T. Lin, A second-order learning algorithm for multilayer networks based on block hessian matrix, *Neural Networks*, vol. 11, no. 9, pp. 1607-1622, 1998.

[8] X. H. Yu, G. A. Chen, Efficient backpropagation learning using optimal learning rate and momentum, *Neural Networks*, vol. 10, no. 3, pp. 517-527, 1997.

[9] Y. H. Zweiri, J. F. Whidborne, L. D. Seneviratne, A three-term backpropagation algorithm, *Neurocomputing*, vol. 50, no. 1, pp. 305-318, 2003.

[10] X. S. Yang, A new metaheuristic bat-inspired algorithm, *Nature Inspired Cooperative Strategies for Optimization*, vol. 284, pp. 65-74, 2010.

[11] T. T. Nguyen, J. S. Pan, T. K. Dao, A Compact Bat Algorithm for Unequal Clustering in Wireless Sensor Networks, *Applied Sciences*, vol. 9, no. 10, 1973, 2019.

[12] M. Dorigo, Optimization, learning and natural algorithms, *Ph. D. Thesis, Politecnico di Milano*, 1992.

[13] S. C. Chu, J. F. Roddick, C. J. Su, J. S. Pan, Constrained ant colony optimization for data clustering, in *10th Pacific Rim International Conference on Artificial Intelligence*, pp. 534-543, 2004.

[14] J. Wang, B. W. Pan, Q. R. Wang, Q. Ding, A chaotic key expansion algorithm based on genetic algorithm, *Journal of Information Hiding and Multimedia Signal Processing*, vol. 10, no. 2, pp. 289-299, 2019.

[15] T. T. Nguyen, Y. Qiao, J. S. Pan, T. K. Dao, T. T. T. Nguyen, C. J. Weng, An improvement of embedding efficiency for watermarking based on genetic algorithm, *Journal of Information Hiding and Multimedia Signal Processing*, vol. 11, no. 2, pp. 79-89, 2020.

[16] M. J. Li, A. Luo, T. S. Tong, Artificial immune algorithm and its application researc, *Control Theory and Application*, vol. 21, no. 2, pp. 153-156, 2004.

[17] J. Kennedy, R. C. Eberhart, Particle swarm optimization, in *Proc. of ICNN'95-international conference on neural networks*, pp. 1942-1948, 1995.

[18] J. F. Chang, S. C. Chu, J. F. Roddick, J. S. Pan, A parallel particle swarm optimization algorithm with communication strategies, *Journal of Information Science and Engineering*, vol. 21, no. 4, pp. 809-818, 2005.

[19] S. C. Chu, P. W. Tsai, J. S. Pan, Cat swarm optimization, in *9th Pacific Rim International Conference on Artificial Intelligence*, pp. 854-858, 2006.

[20] L. Kong, J. S. Pan, P. W. Tsai, S. Vaclav, J. H. Ho, A Balanced Power Consumption Algorithm Based on Enhanced Parallel Cat Swarm Optimization for Wireless Sensor Network, *International Journal of Distributed Sensor Networks*, vol. 11, pp. 1-10, 2015.

[21] J. S. Pan, P. W. Tsai, Y. B. Liao, Fish migration optimization based on the fishy biology, in *2010 Fourth International Conference on Genetic and Evolutionary Computing*, pp. 783-386, 2010.

[22] S. C. Chu, Z. G. Du, J. S. Pan, Discrete fish migration optimization for traveling salesman problem, *Data Science and Pattern Recognition*, vol. 4, no. 2, pp. 1-18, 2020.

[23] Z. Y. Meng, J. S. Pan, QUasi-Affine transformation evolution with external archive (QUATRE-EAR): an enhanced structure for differential evolution, *Knowledge-Based Systems*, vol. 155, pp. 35-53, 2018.

[24] J. S. Pan, Z. Y. Meng, H. R. Xu, X. Q. Li. QUasi-Affine transformation evolution (QUATRE) algorithm: A new simple and accurate structure for global optimization, in *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*, pp. 657-667, 2016.

[25] J. S. Pan, Z. Y. Meng, S. C. Chu, H. R. Xu, Monkey king evolution: an enhanced ebb-tide-fish algorithm for global optimization and its application in vehicle navigation under wireless sensor network environment, *Telecommunication Systems*, vol. 65, no. 3, pp. 351-364, 2017.

[26] Z. Y. Meng, J. S. Pan, Monkey king evolution: A new memetic evolutionary algorithm and its application in vehicle fuel consumption optimization, *Knowledge-Based Systems*, vol. 97, pp. 144-157, 2016.

[27] C. M. Xu, L. J. Er, J. K. Liu, Dynamic fuzzy neural network and its fast self-adjusting learning algorithm, *Control and Decision*, vol. 20, no. 2, pp. 226-229, 2005.

[28] M. Huang, X. K. Fang, J. H. Huang, G. S. Sheng, Optimization of Wavelet Neural Networks with Hybrid Genetic Algorithm Based on Multi-encoding, *Journal of System Simulation*, vol. 16, no. 9, pp. 2080-2082, 2004.

[29] X. F. Li, L. H Zou, Chaos bp hybrid learning algorithm of feedforward neural network, *Control and Decision*, vol. 19, no. 4, pp. 462-464, 2004.

[30] L. O. Chua, L. Yang, Celluar neural networks: Thoery, *IEEE Trancsactions on Circuits and Systems*, vol. 35, no. 10, pp. 1257-1272, 1988.

[31] T. T. Nguyen, J. S. Pan, J. C. W. Lin, T. K. Dao, T. X. H. Nguyen, An optimal node coverage in wireless sensor network based on whale optimization algorithm, *Data Science and Pattern Recognition*, vol. 2, no. 2, pp. 11-21, 2018.

[32] S. K. Yu, Z. F. Diao, A dynamic all parameters adaptive BP neural networks model and its application on oil reservoir prediction, *Applied Mathematics and Computation*, vol. 195, no. 1, pp. 66-75, 2008.

[33] B. H. M. Sadeghi, A BP-neural network predictor model for plastic injection molding process, *Journal of Materials Processing Technology*, vol. 103, no. 3, pp. 411-416, 2000.

[34] X. W. Li, S. J. Cho, S. T. Kim, Combined use of BP neural network and computational integral imaging reconstruction for optical multiple-image security, *Optics Communications*, vol. 315, pp. 147-158, 2014.

[35] P. W. Tsai, J. S. Pan, S. M. Chen, B. Y. Liao, Enhanced parallel cat swarm optimization based on the Taguchi method, *Expert Systems with Applications*, vol. 39, no. 7, pp. 6309-6319, 2012.

[36] F. Hutter, H. H. Hoos, K. L. Brown, Parallel algorithm configuration, in *International Conference on Learning and Intelligent Optimization*, pp. 55-70, 2012.

[37] C. M. Wu, S. R. Fu, T. T. Li, Research of the WSN routing based on artificial bee colony algorithm, *Journal of Information Hiding and Multimedia Signal Processing*, vol. 8, no. 1, pp. 120-126, 2017.

[38] J. S. Pan, X. P. Wang, S. C. Chu, T. T. Nguyen, A multi-group grasshopper optimisation algorithm for application in capacitated vehicle routing problem, *Data Science and Pattern Recognition*, vol. 4, no. 1, pp. 41-56, 2020.

[39] C. F. TsaiT. K. Dao, W. J. YangT. T. Nguyen, T. S. Pan, Parallelized Bat Algorithm with a Communication Strategy, in *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*, pp. 87-95, 2014.

[40] J. S. Pan, J. W. Zhuang, H. Luo, S. C. Chu, Multi-group flower pollination algorithm based on novel communication strategies, *Journal of Internet Technology*, vol. 22, no. 2, pp. 257-269, 2021.

[41] F. Q. Zhang, T. Y. Wu, Y. Wang, R. Xiong, G. Y. Ding, P. Mei, L. Y. Liu, Application of quantum genetic optimization of LVQ neural network in smart city traffic network prediction, *IEEE Access*, vol. 8, pp. 104555-104564, 2020.