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Design of type-2 Fuzzy Logic Systems Based on Improved Ant Colony Optimization

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Abstract: An Improved Ant Colony Optimization (IACO) is proposed to design A2-C1 type fuzzy logic system (FLS) in the paper. The design includes parameters adjustment and rules selection, and the performance of the intelligent fuzzy system, which can be improved by choosing the most optimal parameters and reducing the redundant rules. In order to verify the feasibility of the proposed algorithm, the intelligence fuzzy logic systems based on the algorithms are applied to predict the Mackey-Glass chaos time series. The simulations show that both the IACO and ACO have better tracking performances. The results compared with classical algorithm BP (back-propagation design) shows the tracking performance of IACO is more precise, the result compared with ACO shows that either the training result or the testing result, the tracking performance of IACO is better, and IACO has a faster convergence rate than ACO, the results compared with the Intelligent type-1 fuzzy logic systems show that both the A2-C1 type FLS based on IACO and ACO have better tracking performance than type-1 fuzzy logic system.

Keywords: Ant colony optimization, A2-C1 type fuzzy logic system, improved ant colony optimization, neural network.

1. INTRODUCTION

Nowadays, fuzzy logic system is applied into a variety of fields. Professor L. A. Zadeh proposed the conception of fuzzy set first time [1], from that time on, fuzzy logic system attracts a large number of scholars to research. Although, fuzzy logic systems have some advantages, but there are several shortcomings, the main shortcomings are that it is too difficult to obtain the optimal parameters and rule explosion. Recent years, it has been a research hot spot that adopting intelligent algorithms to design of fuzzy logic system, respectively. Lian *et al*. optimized the radial basis function neural network based on QPSO, and the result was better than BP algorithm and least square method [2]. Zhai *et al*. combined the QPSO with the non single point interval type-2 fuzzy logic system and used to design of image noise filter, the result was better than traditional non fuzzy methods [3]. Yazdi combined GA with fuzzy logic system, and it was applied to the optimization of off center braced frame system, compared with the structure optimized only by GA, the effect was more remarkable [4]. Juang *et al*. combined ant colony optimization with fuzzy cluster to design fuzzy logic system, and used for nonlinear plant tracking control, compared with PSO and GA, the results were more better [5]. In addition, Juang also adopted cooperative continuous ant colony optimization to design fuzzy logic system, and used for water bath temperature control system, compared with QPSO and GA, the results were more precise [6]. Oscar Castillo *et al*. adopted ACO and PSO to design fuzzy logic controller for robotic autonomous systems, compared with GA, it can get a better result [7].

Ant colony optimization was proposed by Italy scholar Dorigo, which is a new bionic evolutionary algorithm [8]. Ant colony optimization was used to solve optimal combination problem. Juang *et al*. used ACO to adjust the parameters of fuzzy logic system, and successfully used for the control of the ball and beam balance system, compared with other traditional methods, the performances were more precise, but the authors assigned an ant colony system to each parameter, therefore, the process was too complex for those fuzzy logic system with much parameters to adjusted [9]. Castillo *et al*. combined several ant colony optimization including ant colony system, ant colony system based on ranking, elite ant colony system and the max-min ant colony system to optimize the membership functions of fuzzy logic system, perform rule selection and parameters adjustment, and achieved better results, but increase the complexity of the algorithm and it need too much time [10]. Olivas *et al*. combined ant

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colony algorithm with interval type-2fuzzy logic system, used the interval type-2 fuzzy logic system to adjust the parameters in ant colony optimization, successfully applied to the TSP problem and the fuzzy controller of mobile robot and achieved ideal results, but there was no rule selection and parameters adjustment of the fuzzy logic system [11]. At present, the application of ant colony optimization in fuzzy logic system is mainly focused on the type-1 fuzzy logic system, and the control problem of less rules and input values. The research of type-2 fuzzy logic system is less and less. In this paper, the ACO are used to design type-2 fuzzy logic system, and used into predict problem with more input and more rules. Although ACO has some advantages such as, positive feedback, multiple objective cooperative performance, strong robustness and parallelism, but as a randomly search algorithm it also has a disadvantage of contradiction between expanding the search scope and increasing the efficiency, aiming at improving the disadvantage. Although ACO has robustness, parallelism, positive feedback, but there is also a conflict between expanding the search space and increasing the efficiency of the algorithm, to overcome the shortcoming, an improved ant colony optimization (IACO) with global pheromone update is proposed, which is based on ant colony optimization, and applied to design the A2-C1 type interval TSK fuzzy logic system in this paper, used the designed intelligent fuzzy logical system to forecast Mackey-Glass chaos time series.

2. THE BASIC CONCEPTS OF IMPROVED ANT COLONY OPTIMIZATION

2.1. Ant path selection

IACO is a probabilistic method for solving complex problems as ACO, the optimal combination problems which can be solved by IACO can be represented by a graph G(N,E), here, N denotes the nodes in the graph, and E denotes the edges linking with the nodes. The difficulties of IACO are the construction of ant colony search paths and values of corresponding parameters. For rules selection, it assumes that there are r rules, and each rule has a candidates, so the total number of rules is *r–a*, those rules can be used to construct the search paths, chosen one rule from a rules by IACO, and as a part of rule-base to design fuzzy logic system. For parameters adjustment, the possible parameters are used to construct the search paths, and the optimal parameters can be obtained by IACO. Both the efficiency of parameters adjustment and rules selection are measured by the adaptive value of fuzzy logic system, the adaptive value is defined the root mean square error (RMSE) between expected values and actual output values, as follow:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_s(x^i)-y^i)^2}, \tag{1}$$

where n is the number of training data pairs or testing data pairs.

At the beginning, set all variables in IACO. Secondly, constructing the search path matrix, and the matrix must content $E(i,j)=E(j,i)$,namely, the distance from i to j is equal to the distance from j to i, on the other hand, the distance to themselves is 0,so the matrix is a symmetric matrix with the principle diagonal is 0. Eventually, ants are randomly assigned to each node, and setting up the corresponding tabu list for every ant to record the nodes visited by ant, to avoid the ant visits the same node twice in the same iteration, Tabuk denotes the tabu list of the k ant. Ants carry a certain amount of pheromone, during the process of visit the next nodes, ants will release the pheromone on the path between the visited nodes. Pheromones will evaporate over time, therefore, the shorter paths will have more pheromones, and more pheromones and more ants will attracted to select in the next iteration. The probability that ants choose the next node to be visited is

$$p_{ij^k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum\limits_{k\in Tabu_k}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}, & j \notin Tabu_k, \\ 0, & j \in Tabu_k. \end{cases} \tag{2}$$

Here, η_{ij} denotes the visibility of path (i,j) is equal to the reciprocal of length of path (i,j) , α , β denote information elicitation factor and expected heuristic factor, respectively. τ_{ij} is the number of pheromone accumulation on path (i,j),namely the pheromone trail on path (i,j).

2.2. Updating of pheromone on local paths

When ant has been completed all of nodes transfer according to (2) once. The updating of the pheromone trails on those visited paths is that:

$$\tau_{ij}(t) = \rho \times \tau_{ij}(t) + \Delta\tau_{ij}(t), \tag{3}$$

where $\Delta\tau_{ij}(t) = \sum\limits_{k=1}^{m}\Delta\tau^{k}{}_{ij}(t)$, ρ is the rate of evaporation of the pheromone trail, and 0< ρ <1, $\Delta\tau_{ij}(t) = \tau_0, \tau_0$ is the initial value of pheromone, in general it is taken the same value to indicate the same environment.

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k}, & \text{ant } k \text{ go through } (i,j), \\ 0, & \text{ant } k \text{ go through } (i,j). \end{cases}$$

Here, Q is the total number of pheromone taken by ant, L_k denotes the total length of the paths gone through by ant k in this iteration.

2.3. Updating of pheromone on global paths

When all ants visited all of the nodes, empty the tabu lists. Selected the current optimal paths based on the pheromone trails on the paths. Updating the global paths according to (4):

$$\tau_{ij}(t) = \rho \times \tau_{ij}(t) + \Delta\tau_{ij}(t). \qquad (4)$$

Here, $\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau^{k}{}_{ij}(t)$, ρ is the rate of evaporation of the pheromone trail, and 0< ρ <1.

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{1}{Ls}, & (i,j) \in \text{the optimal paths}, \\ 0, & (i,j) \notin \text{the optimal paths}, \end{cases}$$

where Ls is the total length of the current optimal paths.

The advantages of IACO as follows:

1) IACO inherits the inherent advantages of ACO, such as positive and negative feedback, parallelism, strong robustness and multiple objective coordination;
2) The updating of global pheromone trail is helpful to increase the probability of ants choosing the current optimal paths, and attracts more ants transfer to the current optimal paths. By this way, it will reduce the search scope to improve the efficiency;
3) The algorithm of updating the global pheromone trails is easy, and not as complex as the elite ant colony system and the ant colony system based on ranking. Therefore, performing the global pheromone trails update which has not affect on improving the whole efficiency of the algorithm.

The ways of ending the algorithm as follows:

1) Setting the maximum number of iteration, the algorithm is end until the maximum number of iteration is reached;
2) Setting the error of the system, the algorithm is end until the error is contented;
3) Along with the performance of the iteration, the optimal paths not change again, that is to say, when the algorithm is convergent, the algorithm is end.

3. THE BASIC CONCEPTS AND FRAMEWORK OF INTERVAL TYPE-2 TSK TYPE FUZZY LOGIC SYSTEM

As the same as general type-2 fuzzy logic system, A2-C1 type interval TSK fuzzy logic system is also consisted of five parts: fuzzifier, rule-base, inference engine, type-reducer and defuzzifier. The difference is that the secondary degree of membership function of interval type-2 TSK fuzzy logic system is 1, the complexity of interval type-2 fuzzy logic system is reduced, and the consequent of A2-C1 type interval TSK fuzzy logic system is a interval set.

The fuzzifier is the mapping of an exact set of inputs into a fuzzy set, the method is divided into single point fuzzification and non single point fuzzification, the former is adopted in this paper, and the type as follow:

$$\mu_{\tilde{A}_x}(x) = 1/1, \text{ when } x = x;$$
$$\mu_{\tilde{A}_x}(x) = 1/0, \text{ when } x \neq x.$$

The rule-base is composed of a series of IF-THEN rules, for the A2-C1 type interval TSK fuzzy logic system with a multiple inputs and single output (MISO), the type of l rule is that:

$$\begin{aligned} R^l &: \text{if } x_1 \text{ is } F_1^l \text{ and } x_2 \text{ is } F_2^l \text{ and } \ldots x_n \text{ is } F_n^l, \\ &\text{then } y \text{ is } G^l, \end{aligned} \qquad (5)$$

where F_1^l, F_2^l, ..., F_n^l are antecedents, which are interval type-2 fuzzy sets, G^l is consequent, $G^l = P_0^l + P_1^l x_1 + P_2^l x_2 + \cdots + P_n^l x_n$. Here, P_0^l, P_2^l, ..., P_n^l are the parameters of the consequent, each of them is type-1 fuzzy set, $P_i^l = [c_i^k - s_i^k, c_i^k + s_i^k]$, c_i^k and s_i^k is the center and width of P_i^l, respectively.

The inference is a fuzzy set which is obtained by composing fuzzy inputs and fuzzy rules, the output of composing n-dimensional input $x = (x_1, x_2, \ldots x_n)^T \in X_1 \times X_2 \times \ldots \times X_n \equiv X$ and the l rule is that: $\tilde{B}^l = \tilde{A}_X \circ R^l$,here, $\tilde{A}_X$ is the input type-2 membership function, and "$\circ$" is fuzzy synthetics, usually adopt max-min or product arthemtic, for interval type-2 fuzzy logic system, the membership degree of $\tilde{B}^l$ is that:

$$\begin{aligned} \mu_{\tilde{B}^l} =& \mu_{\tilde{G}^l}(y) \bigcap \left\{ \left[\bigcup_{x_1 \in X_1} \mu_{\tilde{X}_1}(x_1) \bigcap \mu_{\tilde{F}_1^l}(x_1) \right] \bigcap \cdots \right. \\ & \left. \bigcap \left[\bigcup_{x_n \in X_n} \mu_{\tilde{X}_n}(x_n) \bigcap \mu_{\tilde{F}_n^l}(x_n) \right] \right\} \\ =& \mu_{\tilde{G}^l}(y) \bigcap \left\{ \left[\bigcup \mu_{\tilde{X}_1}(x_1) \bigcap \mu_{\tilde{F}_1^l}(x_1) \right] \bigcap \cdots \right. \\ & \left. \bigcap \left[\bigcup \mu_{\tilde{X}_n}(x_n) \bigcap \mu_{\tilde{F}_n^l}(x_n) \right] \right\} \\ =& \mu_{\tilde{G}^l}(y) \bigcap \left\{ \left[(1/1) \bigcap \mu_{\tilde{F}_1^l}(x_1) \right] \bigcap \cdots \right. \\ & \left. \bigcap \left[(1/1) \bigcap \mu_{\tilde{F}_n^l}(x_n) \right] \right\} \\ =& \mu_{\tilde{G}^l}(y) \bigcap \left\{ \left[\bigcap_{i=1}^{n} \mu_{\tilde{F}_i^l}(x_1) \right], \quad y \in Y. \right. \end{aligned}$$

For type-2 fuzzy logic system, the function of type-reducer is to get a type-1 fuzzy set by reducing the type-2 fuzzy set which comes from the inference. The output of center-of-sets which adopted in this paper is that:

$$y_{\cos}(x) = \frac{\sum_{i=1}^{m} c^l T_{i=1}^{n} \mu_{\tilde{F}_i^l}(x_i)}{\sum_{l=1}^{m} T_{i=1}^{n} \mu_{\tilde{F}_i^l}(x_i)},$$

where c^l is the center of the consequent of the rule l, denotes the concrete fuzzy synthesis operation.

Defuzzifier is to translate the type-1 fuzzy set coming from the type-reducer to precise output.

4. THE DESIGN OF A2-C1 TYPE INTERVAL TSK FUZZY LOGIC SYSTEM BASED ON IACO

4.1. The basic structure of fuzzy neural network

Integrate A2-C1 type interval TSK fuzzy logic system into neural network. Design of fuzzy neural network system with five layers and assuming there are m rules, and the construction of each layer as follows:

The first layer: input layer, the input variables are X:

$$X = (x_1, x_2, \cdots, x_n)^T.$$

The second layer: membership function layer, Gauss type membership function is adopted, and the membership degree of each node as follows:

$$\tilde{\mu}_{\tilde{F}_i^l}(x_i) = [\underline{\mu}_{\tilde{F}_i^l}, \overline{\mu}_{\tilde{F}_i^l}],\ i = 1,2,\cdots,n,\ l = 1,2,\cdots,m.$$

Here, $\underline{\mu}_{\tilde{F}_i^l}(x_i) = \exp\left\{-\frac{1}{2}\left(\frac{x_i - \underline{m}_{\tilde{F}_i^l}}{\underline{\sigma}_{\tilde{F}_i^l}}\right)^2\right\}$ and $\overline{\mu}_{\tilde{F}_i^l}(x_i) = \exp\left\{-\frac{1}{2}\left(\frac{x_i - \overline{m}_{\tilde{F}_i^l}}{\overline{\sigma}_{\tilde{F}_i^l}}\right)^2\right\}$.

The third layer: rule firing layer, the firing strength of rule l is: $F^k = [\underline{F}^k, \overline{F}^k]$

Here, $\underline{F}^l = \prod_{i=1}^{n} \underline{\mu}_{\tilde{F}_i^l}(x_i)$, $\overline{F}^l = \prod_{i=1}^{n} \overline{\mu}_{\tilde{F}_i^l}(x_i)$.

The fourth layer: weight layer, the weight of the rule l is: $\underline{f}^k = \frac{\underline{F}^k}{\sum_{k=1}^{M} \underline{F}^k}, \overline{f}^k = \frac{\overline{F}^k}{\sum_{k=1}^{M} \overline{F}^k}$

The fifth layer: output layer, the output of the system is:

$$y = \frac{\underline{y} + \overline{y}}{2}.$$

Here, $y = \sum_{l=1}^{M} f^l G^l$, $G^l = P_0^l + P_1^l x_1 + \cdots + P_n^l x_n$.

4.2. The parameters adjustment of A2-C1 type interval TSK fuzzy logic system based on IACO

IACO, as an improved method of ACO, is also can be use to solve optimal combination problem, the output of fuzzy logic system can been regarded as a combination of some parameters, through selecting the optimal parameters can optimize the system. The total number of the parameters need to adjust are calculated firstly, it means the number of nodes in *G(N,E)* are obtained. Secondly, regarding the possible parameters as the paths of IACO, and the search paths matrix is constructed according to the characteristics of the IACO. Finally, iteration to get the current optimal parameters, and integrate into A2-C1 type interval TSK fuzzy logic system, output the result until content the condition of the ending algorithm. The objective function is defined as the root mean square error of (1).

The steps of adjusting the parameters of interval type-2 TSK fuzzy logic system based on IACO:

Step 1: Calculating the number of parameters to be adjusted, regarding the possible parameters as the paths of IACO to construct the search matrix according to the characteristics of IACO.

Step 2: Defining all parameters in IACO, assigning ants to each node randomly, and establishing the corresponding tabu for each ant to record the visited nodes, and avoid ant visiting the same nodes repeatedly in the same iteration.

Step 3: Calculated the next node to visit according to (2) when k ant accomplished visiting all of the node one time, the RMSE of the system constructed by the parameters which selected by k ant is calculated according to (1), defining the L_k in (3) is the RMSE, and update pheromone trails on local paths according to (3).

Step 4: When all ants visited all of the nodes one time, the current optimal paths are obtained, that is to say the current optimal parameters can be obtained, the RMSE of the fuzzy logic system constructed by the current optimal parameters is calculated according to (1), defining the Ls in (4) is the RMSE, and update the pheromone trails on global paths according to (4).

Step 5: Emptying the tabus, adding one on the epoch of iteration, and ending the algorithm according to one of the above 3 methods.

Step 6: Output the results.

4.3. The parameters adjustment of A2-C1 type interval TSK fuzzy logic system based on IACO

When obtained the optimal parameters by IACO, that is to say, the number of the rules is certain. But not every rule is contribute to improve the efficiency of the system, on the contrary ,the low efficiency rules not only have negative effect on the efficiency of the fuzzy logic system, but also will increase the complexity of the fuzzy logic system, therefore, it is necessary to perform rule-select through some mechanism. In this paper, IACO is adopted. Regard the RMSE of the A2-C1 type interval TSK fuzzy logic system which consists of each single rule as the search paths of IACO. Because of we adopt product reasoning during the process of construction of the fuzzy logic system, therefore, the total length of the paths is that product the length of each path selected by ant, not sum them up.

The steps of rules selection of interval type-2 TSK fuzzy logic system based on IACO:

Step 1: Defining all of the variables in IACO, calculating the RMSE of each rule according to (1) as the search paths of IACO, and constructing the search matrix according to the characteristics of IACO.

Step 2: Assigning ants to each node randomly, and establishing the corresponding tabu for every ant to record the nodes visited by the ant.

Step 3: Selecting the next node to visit based on (2), when ant has accomplished a transfer, updating the local pheromone trails according to (3), in (3) the L_k is equal to the product of each length of path visited by ant k.

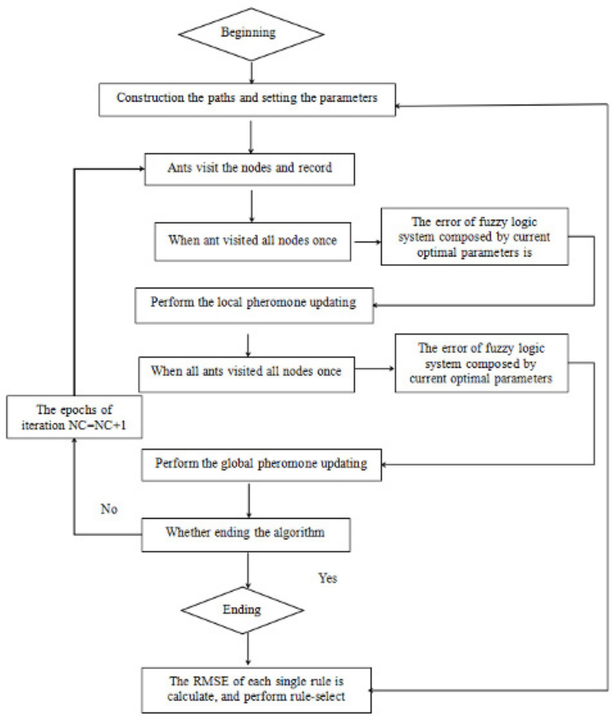

Fig. 1. The flow chart of design of fuzzy logic system based on IACO.

Step 4: When all ants visited all of the nodes, the current optimal paths are found based on the pheromone trails on the paths, and the length of the current optimal paths is calculated.

Step 5: Updating the global pheromone trails according to (4), here, *Ls* is equal to the product of the current optimal paths.

Step 6: Emptying the tabus, epochs of iteration add one, the next iteration is conducted.

Step 7: Output the optimal paths, that is to say, the optimal rules are obtained, and regard those rules as the rule-base to design the A2-C1 type interval TSK fuzzy logic system.

Step 8: Ending the algorithm until the end condition is contended.

The flow chart of design of fuzzy logic system based on IACO is in Fig. 1.

5. APPLICATION EXAMPLES

In order to verify the feasibility and superiority of proposed method for design of A2-C1 type interval TSK fuzzy logic system, the method is used to forecast the Mackey-Glass chaos time series, the form of the Mackey-Glass as (6).

$$\frac{ds(t)}{dt} = \frac{0.2s(t-\tau)}{1+s^{10}(t-\tau)} - 0.1s(t) \tag{6}$$

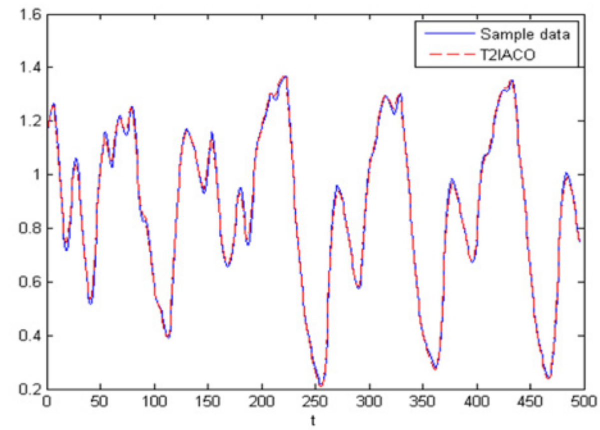

Fig. 2. The training result of T2IACO.

The 1000 data are chosen, and the former 500 data is used to design the A2-C1 type interval TSK fuzzy logic system based on IACO, and the later 500 data is used to test the system. The fuzzy logic system is MISO with for inputs and one output, taking two fuzzy sets for each antecedent, therefore, there are 16 rules in total. Integrating A2-C1 type interval TSK fuzzy logic system into neural network, and five layers fuzzy neutral network are obtained. Gauss type, single point fuzzification, product inference, center-of-sets type-reducer and center-of-sets defuzzifier are adopted in this paper.

Firstly, the updating of the parameters is performed, the number of the parameters to be adjusted is 416, therefore, we need construct a 416*416 random symmetrical matrix which contents the principle diagonal is 0. The parameter adjustment is performed firstly, when the optimal parameters are obtained, the rules are also obtained at the same time, then, the rules selection is performed, by this way, the optimal rules are obtained. The parameters of IACO are taken as follows: Information elicitation factor α=0.5, expected heuristic β=1.2, pheromone evaporation coefficient ρ=0.7, the pheromone taken by ant Q=300 and the maximum epochs of iteration is 2000.

The training result of the A2-C1 type interval TSK fuzzy logic system based on IACO (T2IACO) as Fig. 2. In this paper, we also research the A2-C1 type interval TSK fuzzy logic system based on ACO, the same parameters as IACO are taken the same values, the same structure and data pairs as A2-C1 type interval TSK fuzzy logic system based on IACO. The training result of the A2-C1 type interval TSK fuzzy logic based on ACO (T2ACO) as Fig. 3.

In order to illustrate the necessary of updating the global pheromone, we also compare the A2-C1 type interval TSK fuzzy logic system based on IACO with the A2-C1 type interval TSK fuzzy logic system based on ACO, they have the same structure, the same test data, the same parameters and the same epochs of iteration, where the epochs of iteration is 2000. Fig. 4 shows the compared

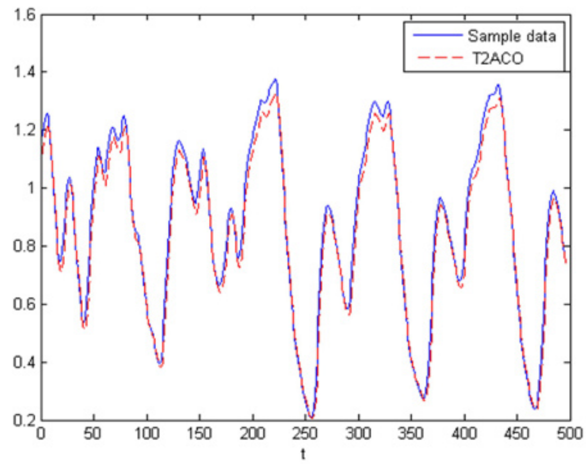

Fig. 3. The training result of T2ACO.

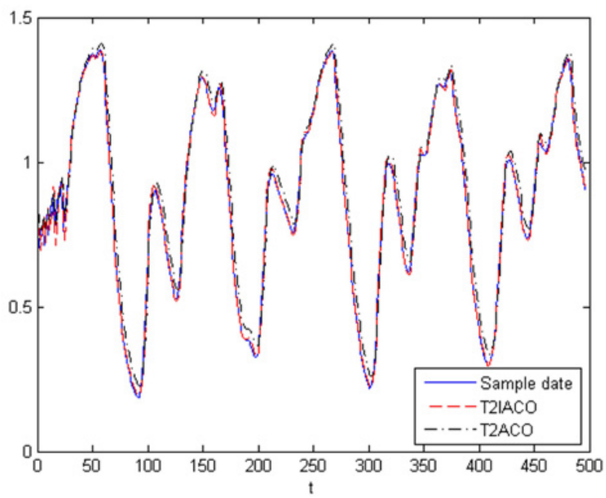

Fig. 4. The compared result with T2ACO.

result.

From Fig. 4, it is obvious that the T2IACO has a better tracking performance than T2ACO, and it proved that updating global pheromone do can improve the performance of algorithm. In order to illustrate IACO has a better performance than classical algorithm BP for design of fuzzy logic system. The compared result shows as Fig. 5.

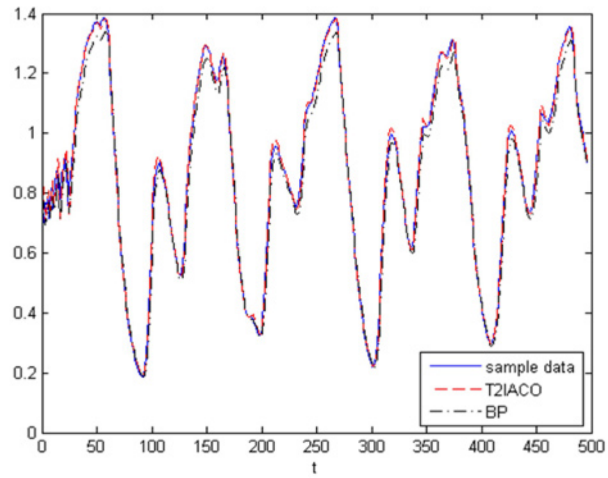

Fig. 5. The result of compared with BP.

From Fig. 5, we can see intelligence IACO has a better performance than classical tradition BP algorithm. Thereby, it is proved that IACO can overcome the shortcomings of traditional algorithms and have a high-efficiency.

In this paper, we also design type-1 TSK fuzzy logic system based on IACO (T1IACO) and ACO (T1ACO), respectively. And compared with A2-C1 type interval TSK fuzzy logic system based on IACO (T2IACO) and ACO (T2ACO), respectively. We set the same epochs of iteration 2000, and the same values for the same parameters in IACO and ACO, the same structure fuzzy logic system, that is to say, the Gauss type membership function, single point fuzzification and product inference are adopted, when design of type-1 TSK fuzzy logic system. The result of compared with T1IACO shows in Fig. 6.

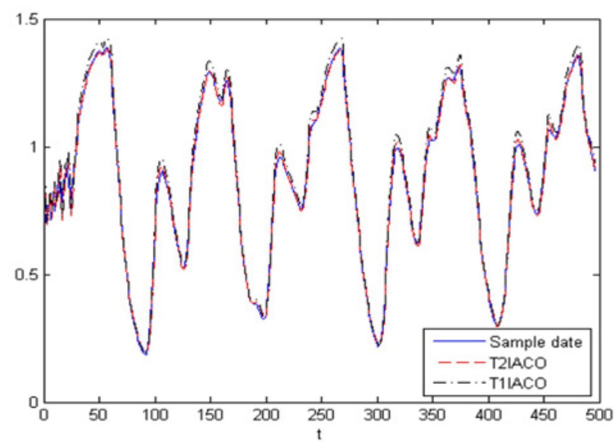

Fig. 6. The result of compared with T1IACO.

From Fig. 6, it shows that the tracking performance of T2IACO is better than T1IACO, on the one hand, it indicates that A2-C1 type interval TSK fuzzy logic system has a better performance than type-1 fuzzy logic system, for some complex problem, A2-C1 type interval TSK fuzzy logic system has more accuracy than type-1 TSK fuzzy logic system, on the other hand, it also indicates that the proposed IACO can be used to design type-1 TSK fuzzy logic system. ACO is also used to design type-1 fuzzy logic system, and the compare between A2-C1 type interval TSK fuzzy logic system based on ACO (T2ACO) and type-1 TSK fuzzy logic system based on ACO (T1ACO) is also performed in this part, the comparison of result as Fig. 7.

It obvious that the T2ACO has a better tracking perfor-

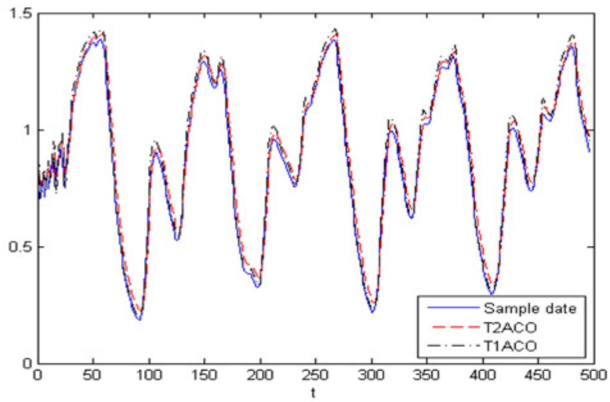

Fig. 7. The result of compared between T2ACO and T1ACO.

Table 1. The RMSE of each algorithm and running time.

	Train error	Test error	Time(h)
T2IACO	0.0243	0.0285	2.04
T2ACO	0.0294	0.0318	2.02
T2BP	0.0316	0.0325	1.06
T1IACO	0.1076	0.1254	1.45
T1ACO	0.1576	0.1674	1.38

mance than T1ACO, which indicates that ACO can also be used to design type-1 TSK fuzzy logic system, and can obtain a good result. The RMSE of each algorithm and the time of epochs of iteration is 2000 show in Table 1. Here, the epochs of iteration are taken the same value 2000, and the structures of fuzzy logic systems are also same. From Table 1, we can see that both the errors of T2IACO and T2ACO are less than the BP algorithm, which indicate that intelligent ant colony optimization and the proposed improved ant colony optimization can overcome the disadvantage of classical BP algorithm, but the BP algorithm has an advantage in the iteration time. Compared the time of T2IACO with T2ACO, the time of T2ACO is less than T2IACO, but just a little, and it indicates that performance the updating of global pheromone will not increase the complexity of ant colony optimization, but it do can improve the performance. Compared the A2-C1 type interval TSK fuzzy logic systems with the type-1 fuzzy logic systems, it indicates the more algorithm complexity, the more precise output result.

In order to further compare the performance of each algorithm, the comprehensive evaluation error sum (CEES) of each algorithm is also made in this paper, and the definition of CEES as (7):

$$CEES = \frac{1}{2}\sum_{i=1}^{n}[y^{(i)} - f(x^{(i)})]^2, \tag{7}$$

where n is the number of training data pairs or testing data pairs, and $y^{(i)}$ and $f(x^{(i)})$ is expected output and actual output, respectively. The CEES of each algorithm shows in Table 2.

Table 2. The CEES of each algorithm.

	The train of CEES	The test of CEES
T2IACO	0.1464	0.2014
T2ACO	0.2144	0.2508
T2BP	0.2476	0.2620
T1IACO	1.8731	2.0083
T1ACO	1.9842	2.2914

From Table 2, we can see the CEESs of the A2-C1 type interval TSK fuzzy logic systems are less than the type-1 TSK fuzzy logic systems, and the CEESs of the IACO is less than ACO, that is to say, the A2-C1 type interval TSK fuzzy logic systems have a better performance than type-1 TSK fuzzy logic system, and the proposed IACO has a better performance than ACO for design of fuzzy logic system, regardless of the type.

6. CONCLUSION

In this paper, an improved ant colony optimization with updating the global pheromone is proposed based on ant colony optimization, and it was used to adjust parameters and select rules, including A2-C1 type interval TSK fuzzy logic system and type-1 TSK fuzzy logic system, and the concrete methods and steps are given, and it is applied to forecast the Mackey-Glass chaos time series. The simulation results show it is feasible and high-performance, both used to design A2-C1 type interval TSK fuzzy logic system and type-1 TSK fuzzy logic system can achieve better tracking performance, the result of compares with classical BP algorithm shows intelligent IACO can overcome the shortcoming of non intelligent algorithm, and has a better tracking performance than BP algorithm. ACO is also used to design the fuzzy logic system, including A2-C1 type interval TSK fuzzy logic system and type-1 TSK fuzzy logic system, and the simulation results shows it also can achieve ideal result, the result of compare IACO with ACO shows updating the global pheromone can improve the performance, and will not increase the complexity of the algorithm. Compared A2-C1 type interval TSK fuzzy logic systems with type-1 TSK fuzzy logic systems have better tracking performance under the same condition. The ACO and IACO are used to design A2-C1 type interval TSK fuzzy logic system, which is the most complexity interval type-2 fuzzy logic system [12–15], of course, they are also can be used to design some simple fuzzy logic systems, such as type-1 fuzzy logic system, A1-C1 Type fuzzy logic system, A2-C0 Type fuzzy logic system. The IACO and ACO also can be applied to design general type-2 fuzzy logic systems [16, 17] which have more computation complexity than interval type-2 fuzzy logic systems, and they can also be used to solve multi-objective problem, however, there are still some difficult problems to be solved. In addition, the fuzzy logic systems based on ACO and IACO also can be used in control and forecasting fields [18–21].

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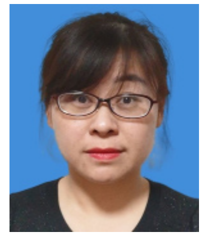

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