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Research on an Improved Multi-Population Ant Colony Optimization Algorithm and its Application

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Abstract

In allusion to the shortcomings of easy falling into the local optimization and difficult obtaining Pareto optimal solutions for the original ant colony optimization algorithm in solving the complex optimization problems, multi-population, parallel mechanism, dynamic evaporation strategy and chaos theory are introduced into the original ant colony optimization algorithm in order to propose an improved multi-population ant colony optimization(MPPDCACO) algorithm in this paper. In the proposed MPPDCACO algorithm, the ant colony is divided into scout ants, search ants and worker ants in order to make the ACO algorithm as far as possible to avoid falling into local optimization and improve the local search ability of ant colony. The multi-population parallel mechanism is used to exchange the information and improve the computational effectiveness. The dynamic evaporation strategy is used to dynamically adjust the evaporation coefficient of pheromone in order to improve the global search capability of the ACO algorithm. The chaos theory is used to realize the optimization search in order to obtain the pheromone distributing in choosing path process. So the proposed MPPDCACO algorithm can prevent the local convergence caused by the misbalance of pheromone and can improve the searching ability. In order to test the optimization performance of the proposed MPPDCACO algorithm, 6 traveling salesman problems are selected from the TSPLIB in here. The experimental results show that the proposed MPPACACO algorithm takes on better global searching ability and higher convergence speed.

Keywords*: ant colony optimization, multi-population, parallel mechanism, dynamic evaporation strategy, chaos theory, traveling salesman problem*

1. Introduction

Ant colony optimization(ACO) algorithm was proposed in 1992 by Dorigo[1]. The ACO algorithm is a kind of simulated evolutionary algorithm by simulating ants. It does not rely on the specific problems of mathematical description and takes on strong global optimization ability and parallelism in essence. This algorithm is an effective method to solve the NP complete problem. It achieved very good results in solving traveling salesman problem (TSP), allocation problem, Jobshop scheduling problem [2-6].

The ACO algorithm mainly includes five basic system: Ant System(AS), Ant System with Elitist Strategy(ASWES), Rank-Based Version of Ant System(RBVAS), Ant Colony System(ACS) and Max-Min Ant System(MMAS). However, the ACO algorithm with single population exists long search time and is easy to occur the stagnation. In order to overcome these shortcomings, many scholars have put forward the improved algorithm. However, these improved algorithms are based on single population and single pheromone updating mechanism. In fact, the ant colony has organization and labor division, which are great significance to complete the complex task by ant colony. In

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order to improve the speed of ACO algorithm and keep the diversity of the ant colony, the scholars have put forward a variety of improved ACO algorithms. These improved ACO algorithms can fully accelerate the convergence, which is beneficial to the parallel processing. Shen *et al.* [7] proposed a new version of an ant colony optimization (ACO) algorithm to select variables in QSAR modeling and to predict inhibiting action of some diary limidazole derivatives on cyclooxygenase(COX) enzyme. McMullen and Tarasewich [8] proposed a modified ant colony optimization technique to addresses multiple objectives associated with the general assembly line-balancing problem. Wang *et al.* [9] proposed a modified ant colony algorithm based on orientation factor in solving multi-constraint QoS routing problem. Cheng and Mao [10] proposed a modified ant algorithm, named ACS-TSPTW, based on the ACO technique to solve the TSPTW. Two local heuristics are embedded in the ACS-TSPTW algorithm to manage the time-window constraints of the problem. Guo *et al.* [11] proposed a modified ant colony algorithm to improve the precision of the traditional methods for optimal time-frequency atom search. Wang *et al.* [12] proposed an ant colony algorithm with orientation factor and applies it to multicast routing problem with the constraints of delay variation bound. Yu *et al.* [13] proposed an improved ant colony optimization (IACO), which possesses a new strategy to update the increased pheromone, called ant-weight strategy, and a mutation operation, to solve vehicle routing problem (VRP). Konstantinidis *et al.* [14] proposed a fuzzy-modified ant colony processor for image retrieval. The proposed method utilizes three different descriptors in a two-stage fuzzy ant algorithm where the query image represents the nest and the database images represent the food. Wang *et al.* [15] proposed a modified Ant Colony Algorithm (ACA) called multi-city-layer ant colony algorithm(MCLACA) to improve the computational efficiency in the stacking sequence optimization of a laminated composite plate for maximum buckling load. Yang and Zhuang [16] proposed an improved ant colony optimization algorithm(IACO) for solving mobile agent routing problem. Coelho and Bernert [17] proposed a proportional-integral-derivative (PID) controller based on a modified continuous approach of ant colony optimization combined with a differential evolution method(MACO) for synchronization of two identical discrete chaotic systems subject the different initial conditions. Zhang *et al.* [18] proposed a modified ant colony optimization algorithm to optimize the drag-energy profile and its cost function is to minimize the total heat load for the SLV reentry trajectory. Yu *et al.* [19] proposed a parallel improved ant colony optimization algorithm for solving multi-depot vehicle routing problem (MDVRP). Geng *et al.* [20] proposed a directional ant colony optimization (DACO) algorithm for solving nonlinear resource-leveling problems. The DACO algorithm introduced can efficiently improve the convergence rate and the quality of solution for real-project scheduling. Li and Yang [21] proposed a new approach of optimization and optical design for a miniature projector with two liquid lenses via integrating damped least square with the modified ant colony algorithm. Krishnaraj *et al.* [22] proposed a modified ant-colony optimisation algorithm (MACO-I and MACO-II) to solve the permutation flowshop scheduling problem. Yoo and Han [23] proposed a modified ant colony optimization (MACO) algorithm implementing a new definition of pheromone and a new cooperation mechanism between ants. Liu [24] proposed an improved ant colony algorithm of fine mining solution space in order to solve the main problems of continuous domain ant colony optimization algorithm, namely the problems of large complexity and large number of iterations. Cheng *et al.* [25] proposed an improved ant colony optimization algorithm for considering the problem of scheduling parallel batching machines with jobs of arbitrary sizes. Gao *et al.* [26] proposed an improved chaotic ant colony algorithm based on the analysis of the basic information of the river basin reservoirs and application of chaotic ant swarm algorithm. Zhu and Wang [27] proposed a modified ant colony optimization algorithm to solve the virtual network embedding (VNE) problem. Chen *et al.* [28] proposed a modified ant colony optimization (ACO) algorithm to develop an efficient tracking framework to extract the lobe fissures.

We used the method of increasing the consistency of pheromone on lobe fissure to improve the accuracy of path tracking. Mojtaba *et al.* [29] proposed a modified ant colony system to propose a metaheuristic algorithm for finding the expected shortest path. Yoo and Han [30] proposed a modified ant colony optimization (MACO) algorithm for topology optimal design of compliant mechanisms since standard ACO cannot provide an appropriate optimal topology. Pang *et al.* [31] proposed an improved ant colony optimization algorithm based on the proximity to provide a better solution to the combinatorial optimization of MTSP (multiple traveling salesman problem) problem with E-mail traffic constraints. Jiang *et al.* [32] proposed a co-evolutionary improved multi-ant colony optimization (CIMACO) algorithm for ship multi and branch pipe route design. Sharma and Grover [33] proposed a modified ant colony optimization algorithm for the problem of finding the optimal energy efficient path for the recruitment of sensor nodes for signal transmission to prolong the network lifetime.

These improved/modified ACO algorithms have better optimization performance in solving complex optimization problems. But they still exists the shortcomings of easy falling into the local optimization and difficult obtaining Pareto optimal solutions in solving the complex optimization problems. So an improved multi-population ant colony optimization(MPPDCACO) algorithm based on multi-population, parallel mechanism, dynamic evaporation strategy and chaos theory is proposed in this paper. In order to test the optimization performance of the proposed MPPDCACO algorithm, 10 traveling salesman problems are selected from the TSPLIB in here.

2. Ant Colony Optimization Algorithm

The ACO algorithm is a branch of newly developed form of artificial intelligence, called swarm intelligence. It is a metaheuristic inspired by the behaviour of real ants in finding the shortest path to food sources. When the ants move, they will leave the chemical pheromone trail on the path. Then the ants will tend to select the paths marked by the strongest pheromone. The ACO algorithm is an essential system based on agents that simulates the natural behaviors of the cooperation and adaptation among these ants. The ACO algorithm consists of a number of iterations for constructing solution. A number of ants construct complete solutions by heuristic information and the collected experiences in each iteration. The collected experiences are represented by using the pheromone trail. Pheromone can be deposited on the components and/or the connections used in a solution depending on the problem.

In the ACO algorithm, the ACO simulates the optimization of ant foraging behaviors. The ACO procedure is illustrated in Figure 1.

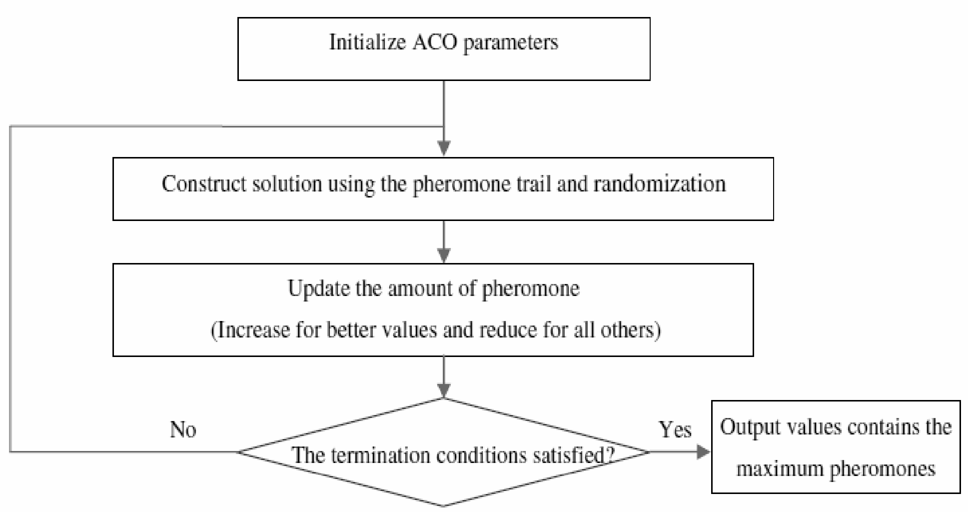

Figure 1. Searching Procedure of ACO Algorithm

In the ACO algorithm, a list of nodes are defined. This list is called **Tabu*k***, which includes all the nodes which have been visited by the k^{th} ant until the current state except for all depots. Assume that there are n cities, m ants and the initial pheromone on each path is set to a very small positive constant s_0. Each ant randomly starts at one city and visits the other cities according to the transition rule. After the ants complete their routes, the system evaluates the length of routes. Then, the system uses the pheromone update rule to update the pheromone. The procedure is to update the pheromone repeatedly.

(1) Transition rule

While the k^{th} ant is at city r, the next city s is selected from the unvisited cities set J_r^k according to the following equation:

$$s = \arg\max_{u \in J_r^k} [\tau_i(r,u) \cdot \eta(r,u)^{\beta}] \ \ if\, q \le q_0 (Exploitation) \tag{1}$$

Or visit the next city s with the probability $p_k(r,s)$,

$$p_k(r,s) = \begin{cases} \dfrac{\tau(r,s) \cdot \eta(r,s)^{\beta}}{\sum_{u \in J_r^k} \tau(r,u) \cdot \eta(r,u)^{\beta}} & if\ \ s \in J_r^k \\ 0 & otherwise \end{cases} \quad if\, q > q_0 (BiasExploitation) \tag{2}$$

where $p_k(r,s)$ is the transition probability from city r to city s for the k^{th} ant in the i^{th} group, $\tau(r,u)$ is the pheromone level between city r and city u in the i^{th} group, $\eta(r,u)$ is the heuristic information, which is defined as the inverse of the distance from city r to city u, J_r^k is the set of cities that remain to be traveled by the k^{th} ant in the i^{th} group, the parameter β controls the relative importance of the pheromone versus the heuristic information, q is a random constant deciding the k^{th} ant in the i^{th} group to choose the normal exploitation way or the biased exploitation way and q_0 is a constant between 0 and 1.

(2) Pheromone update rule

In order to improve future solutions, the pheromone trails of the ants must be updated to reflect the ants' performance and the quality of the solutions found. An ant deposits pheromone trails on the arcs it traveled to update the pheromone trails. Trail updating includes local updating of trails after individual solutions have been generated and global updating of the best solution route after a predetermined number of solutions m has been accomplished. This is done with the following local trail updating equation:

$$\tau(r,u) = (1-\rho)\tau\ (r,s) + \sum_{k=1}^{m} \Delta\tau_k(r,s) \tag{3}$$

In which ρ ($0 < \rho < 1$) is a parameter that controls the speed of evaporation(The pheromone trails evaporation coefficient). $\Delta\tau_k(r,s)$ is the adding pheromone to the edge (r,s) by ant k between time t and $t+\Delta t$ in the tour. It is given by:

$$\Delta\tau_k(r,s) = \begin{cases} \dfrac{Q}{L_k} & (r,s) \in \pi_k \\ 0 & otherwise \end{cases} \tag{4}$$

Where Q is a constant, L_k is the distance of the sequence π_k toured by ant in Δt.

This updating rule indicate that the pheromone increments only relate to the current search of the ant colony, which means that history experience is ignored and the valuable solutions have not been reinforced enough. This process is repeated for a predetermined number of iterations and the best solution from all of the iterations is presented as an output of the ACO and should represent a good approximation of the optimal solution for the problem.

3. An Improved Multi-Population Ant Colony Optimization Algorithm

Because the ant colony optimization algorithm exists falling into local optimal solution and stagnation phenomenon, the ACO algorithm can not solve the global optimal solution. If there are many ants to choose the same path, the pheromone will suddenly be increased on the path, which to cause the stagnation. So multi-population, parallel mechanism, dynamic evaporation strategy and chaos theory are used to improve the ACO algorithm in order to propose an improved multi-population ant colony optimization(MPPDCACO) algorithm in this paper. In the proposed MPPDCACO algorithm, the ant colony is divided into scout ants, search ants and worker ants in order to make the ACO algorithm as far as possible to avoid falling into local optimization and improve the local search ability of ant colony. The multi-population parallel mechanism is used to exchange the information and improve the computational effectiveness. The dynamic evaporation strategy is used to dynamically adjust the evaporation coefficient of pheromone in order to improve the global search capability of the ACO algorithm. The chaos theory is used to realize the optimization search in order to obtain the pheromone distributing in choosing path process.

3.1. Multi-population

The ants in the ACO algorithm are divided into scout ants, search ants and worker ants. The search ants are used to find the optimal solution. The scout ants are used to find the other optimal solution except for the found quality path by the search ants in order to avoid to fall into local optimal solution and stagnation phenomenon. And the worker ants are the core in the ACO algorithm. The worker ants are used to execute analyzing and summarizing the optimal solution and adjust the initial pheromone distribution. The scout ants and search ants transmit all found path information to the worker ants in order to search for the optimal solution from the found path information. And the solution is coordinated and weighted in order to adjust the information. The information exchange mechanism in the ACO algorithm with multi-population is shown in Figure 2.

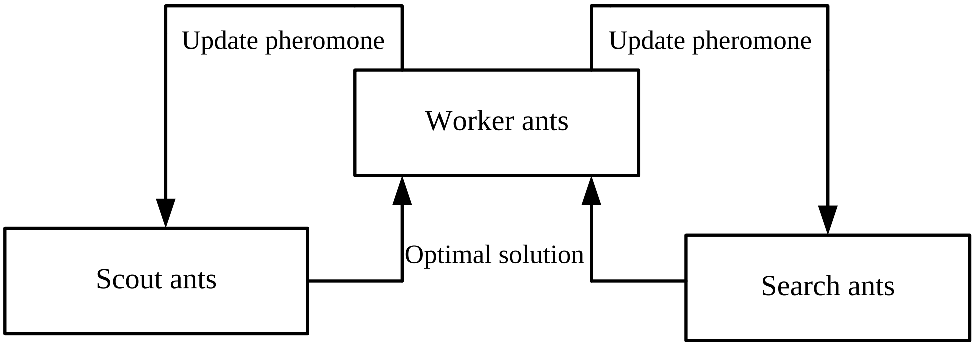

Figure 2. The Information Exchange Mechanism

3.2. Dynamic Evaporation Strategy

The evaporation coefficient of pheromone(ρ) is one constant in the basic ACO algorithm. However, the evaporation coefficient value of pheromone(ρ) directly affects the global search ability. However, if the pheromone concentration is lager, the selected probability of unvisited path will be larger. But the lager pheromone concentration will directly affect the global search ability of ACO algorithm. Therefore, a dynamic evaporation coefficient strategy of pheromone $\rho(t)$ is proposed to control the pheromone evaporation in this paper. It can not only increase the global search ability, but also accelerate the convergence speed. The dynamic evaporation coefficient strategy of pheromone is described as follow:

$$\rho(t) = \frac{T \times (\tau_{\max} - \tau_{\min}) \times t}{T-1} + \frac{T \times \tau_{\min} - \tau_{\max}}{T-1} \tag{5}$$

$$\tau(t) = (1 - \rho(t)) \times \tau(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{6}$$

where the $\tau_{\max}$ and $\tau_{\min}$ respectively are the upper pheromone and lower pheromone. t T and t respectively are the maximum number of iteration and the current iteration.

3.3. Chaos Theory

Chaos often exists in the nonlinear systems. It is a kind of characteristic which has a bounded unstable dynamic behavior and exhibits sensitive dependence on its initial conditions. Chaos optimization algorithm (COA) is a recently proposed population-based stochastic optimization algorithm. The basic procedure of COA is divided into two steps. The first, the COA searches all points in turn within changing range of variables and takes the better point as the current optimum point by using the ergodicity, regularity, initial sensitivity and topological transitivity of chaos. Then the current optimum point is regarded as the center, a tiny chaotic disturbance is imposed and the careful search is executed in order to search for the global optimum point with the higher probability. The COA has the features with easy implementation, short running time and robust mechanisms.

Generally, the main problem of COA is to generate the chaotic variables. The logistic chaotic model is used to generate the chaotic variable. The map expression of the logistic model is followed as:

$$x_{n+1} = L(\mu, x_n) = \mu x_n (1 - x_n) \qquad \mu \in [0,4], n = 0,1,2,3,\cdots \tag{7}$$

where control variable ($\mu \in [0,4]$) is the parameter of the Logistic. The studies have shown, when $x_n \in [0,1]$, the Logistic mapping work is in the chaotic state.

4. Traveling Salesmen Problem (TSP)

Traveling salesmen problem(TSP) is one which has commanded much attention of mathematicians and computer scientists specifically, because it is easy to describe and difficult to solve. The TSP can simply be stated as: a search for the shortest closed tour that visits each city once and only once. The distance between the cities is independent of the direction of traversing the arcs, that is, $d_{ij} = d_{ji}$ for every pair of nodes in symmetric TSP.

Define the variables:

$$x_{ij} = \begin{cases} 1 & \text{if } \textit{the arc}(i,j) \textit{ is in the tour} \\ 0 & \textit{otherwise} \end{cases} \tag{8}$$

Objective function:

$$z = \min \sum_{i} \sum_{j} d_{ij} x_{ij} \tag{9}$$

The constraints are written as follows:

$$\sum_{i=1}^{n} x_{ij} = 1, \ j = 1,2,3,\cdots,n \tag{10}$$

$$\sum_{j=1}^{n} x_{ij} = 1, i = 1,2,3,\cdots,n \tag{11}$$

$$x_{ij} \in \{0,1\}, i, j = 1,2,3,\cdots,n \tag{12}$$

$$\sum_{i,j \in S}^{n} x_{ij} \le |S| - 1, 2 \le |S| \le N - 2 \tag{13}$$

5. Experiment Results and Analysis

In this paper, 6 TSP from TSPLIB standard library(http://www.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95/) are selected to test the optimization performance of the proposed MPPDCACO algorithm. The distance between any two cities is computed by using the Euclidian distance. And the basic ACO algorithm and CACO algorithm are selected to compare the optimized performances with the MPPDCACO algorithm. The obtained initial values of parameters in the basic ACO algorithm, CACO algorithm, ICACO algorithm and MPPDCACO algorithm are: ants m=40, pheromone factor α=1.0, heuristic factor β=2.0, initial evaporation coefficient of pheromone $\rho(t) = 0.05$, pheromone amount Q=80, maximum iteration times $T_{\max}$=500. For each TSP, the basic ACO algorithm, CACO algorithm and MPPDCACO algorithm are run independently 25 times, and the best optimal value and average optimal value are found. The results are listed in Table 1.

Table 1. The Results for 6 TSP

No.	Instances	Cities	Optimal value	Algorithms	Found best value	Average
1	oliver30	30	423.74	ACO	421.52	446.37
				CACO	428.63	440.19
				MPPDCACO	**423.74**	436.3
2	att48	48	33522	ACO	33587	33825
				CACO	33548	33793
				MPPDCACO	**33523**	33734
3	eil51	51	426	ACO	442	478
				CACO	429	451
				MPPDCACO	**426**	440
3	pr76	76	108159	ACO	110031	110401
				CACO	109384	109676
				MPPDCACO	109217	109403
4	pr144	144	58537	ACO	58773	58930
				CACO	58683	58736

				MPPDCACO	58617	58704
				ACO	16179	16840
5	dl198	198	15780	CACO	16034	16463
				MPPDCACO	15905	16145
				ACO	62701	63051
6	d1655	1655	62128	CACO	62594	62725
				MPPDCACO	62498	62658

As can be seen from Table 1, the best value and average value of the proposed MPPDCACO algorithm are best than the basic ACO algorithm and CACO algorithm for 6 TSP instances. For oliver30 and eil51, the proposed MPPDCACO algorithm finds the best known solutions (423.74 and 426) in the experiment. For att48, pr76, dl198 and d1655, the found best values (33523, 58617, 15905 and 62498) are close to the best known values (33522, 58537, 15780 and 62128). The experimental results show that the proposed MPPACACO algorithm takes on better global searching ability.

In order to further test the performance of the proposed MPPDCACO algorithm, the best route found is shown in Figure 3, Figure 4 and Figure 5 for oliver30, eil51 and pr76 in the experiment.

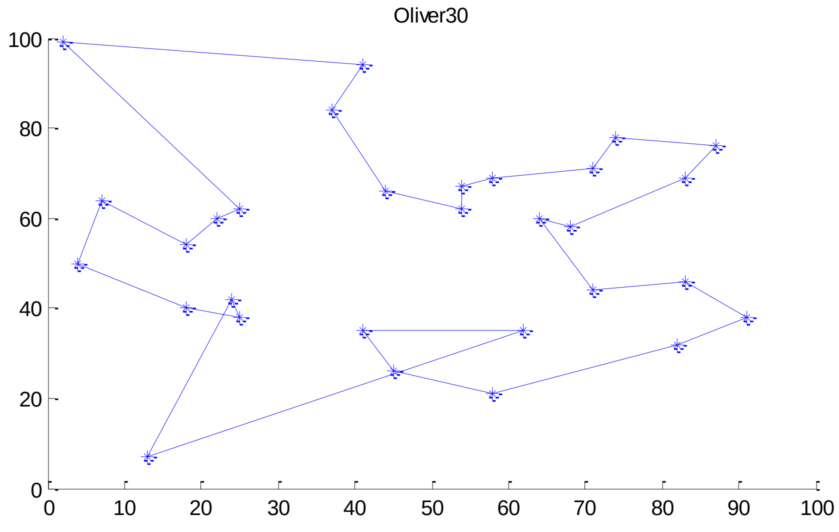

Figure 3. The Best Route Found for Oliver30 (423.74)

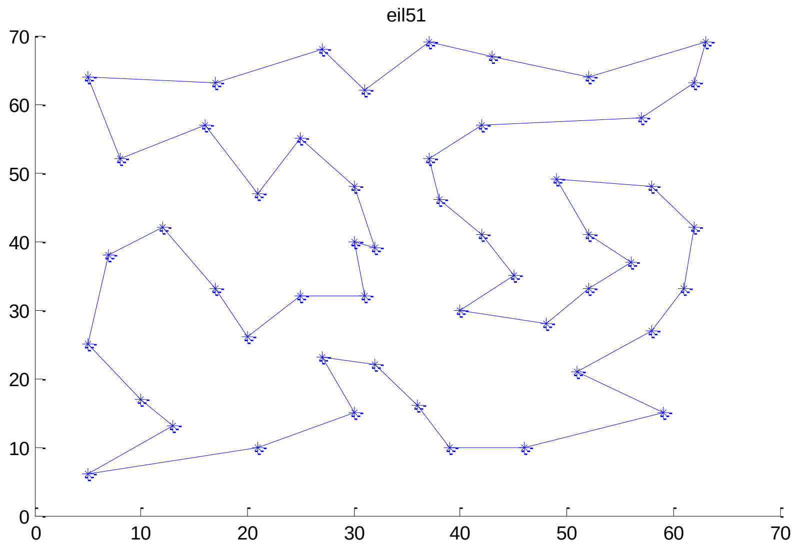

Figure 4. The Best Route Found for Eil51 (426)

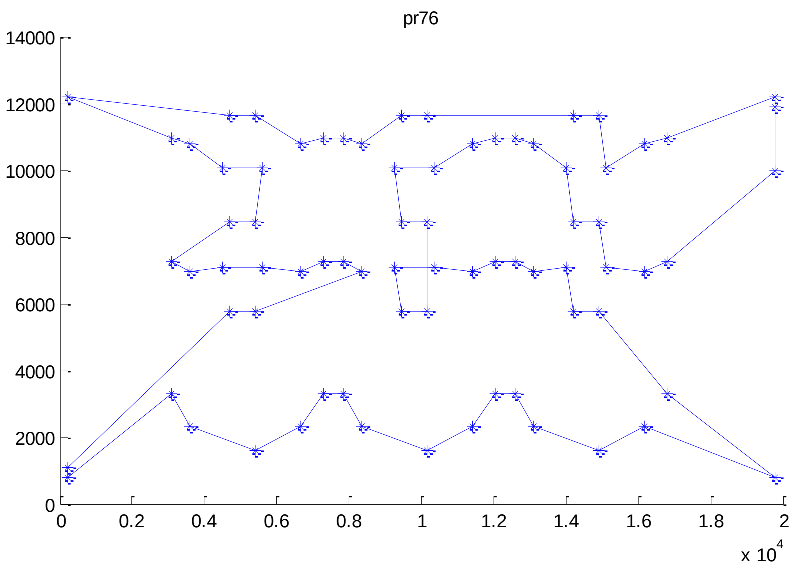

Figure 5. The Best Route Found for Pr76 (109217)

6. Conclusion

The ACO algorithm has been successfully applied in quadratic assignment problems, dynamic routing problems, scheduling problems, TSP and so on. But it exists the shortcomings of easy falling into the local optimization and difficult obtaining Pareto optimal solutions in solving the complex optimization problems. In this paper, an improved multi-population ant colony optimization(MPPDCACO) algorithm based on multi-population, parallel mechanism, dynamic evaporation strategy and chaos theory is proposed to solve TSP. The proposed MPPDCACO algorithm can prevent the local convergence caused by the misbalance of pheromone and can improve the searching ability. Finally, 6 traveling salesman problems are selected from the TSPLIB are selected in order to test the optimization performance of the proposed MPPDCACO algorithm.

The experimental results show that the proposed MPPACACO algorithm takes on better global searching ability and higher convergence speed.

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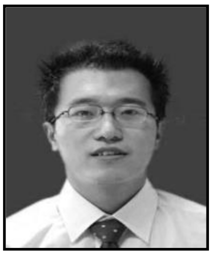

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