International Journal of Hybrid Information Technology
Vol.9, No.4 (2016), pp. 223-234
http://dx.doi.org/10.14257/ijhit.2016.9.4.20

Research on an Improved Ant Colony Optimization Algorithm and its Application

Ping Duan, Yong AI

Department of Information Engineering, Hubei Urban Construction Vocational and Technological College, Wuhan 430205 China

Abstract

In order to improve the global solving ability and convergence speed, avoid falling into local optimal solution, the basic ant colony optimization (ACO) algorithm is improved to propose an efficient and intelligent ant colony optimization (IMVPACO)algorithm. In the IMVPACO algorithm, the updating rules and adaptive adjustment strategy of pheromones are modify in order to better reflect the quality of the solution based on the increment of pheromone. The dynamic evaporation factor strategy is used to achieve the better balance between the solving efficiency and solving quality, and effectively avoid falling into local optimum for quickening the convergence speed. The movement rules of the ants are modify to make it adaptable for large-scale problem solving, optimize the path and improve search efficiency. A boundary symmetric mutation strategy is used to obtain the symmetric mutation for iteration results, which not only strengthens the mutation efficiency, but also improves the mutation quality. Finally, the proposed IMVPACO algorithm is applied in solving the traveling salesman problem. The simulation experiments show that the proposed IMVPACO algorithm can obtain very good results in finding optimal solution. And It takes on better global search ability and convergence performance than other traditional methods.

Keywords: *Ant colony optimization; adaptive adjustment pheromone; dynamic evaporation factor; movement rule; boundary symmetric mutation strategy; traveling salesman problem*

1. Introduction

Since international academic journal of Nature published the review of ant colony optimization(ACO) algorithm in 2000, the ACO algorithm with simulating nature ant is regarded an effective means for solving combinatorial optimization problems, and it gradually becomes the hot spot in the field of the intelligent optimization algorithms[1-3]. Because the ACO algorithm has the positive feedback mechanism, distributed computing, greedy search characteristics and robustness, parallel processing and so on, it has been widely applied in combinatorial optimization problems. And it has achieved good effect in traveling salesman problem(TSP)[4], quadratic assignment problem(QAP)[5], job-shop scheduling problem[6] and so on.

Although the ACO algorithm takes on strong discovery ability and better solution ability, strong robustness, easy realizing on computer and so on, there are also some shortcomings, such as longer search time, slow convergence speed, easy stagnation and so on. Aiming at the shortage of the algorithm, many researchers have proposed some improved ACO algorithms. Leng et al.[7] proposed an improved ant colony optimization (ACO) algorithm based on the dynamic pheromone updating and initial weighted directional diagram in in cell scheduling of the flexible manufacturing process for considering the instrument constraint, manufacturing cost and time. Yang and Lai[8] proposed a new ant colony algorithm to deal with p//T (p//T-ACO). The theoretical analysis and comparative experiments demonstrate that p//T-ACO has much better

ISSN: 1738-9968 IJHIT

performance and can be used to solve practical large scale problems efficiently. Mao and Zhao[9] proposed an adaptive max-min ant colony optimization to construct energy-aware inter-cluster routing between cluster heads and base station (BS), which balances the energy consumption of cluster heads and alleviates the hot spots problem that occurs in multi-hop WSN routing protocol to a large extent. Ugur and Aydin[10] proposed an extra data structure that we called best tours graph feeding the pheromone trail information for ACO algorithms. Algorithms are tested on Traveling Salesman Problem using TSPLIB. Our experiments and comparisons show that the method improves the performance of almost all original ACO algorithms. Xu et al.[11)] used chaotic map to enhance the ACO algorithm. The hybrid algorithm is validated for VRP problem and the experimental results demonstrate its efficiency and precision to obtain global optimal solution. Xue et al.[12] proposed a PIACO algorithm for the cloud PDTs scheduling. Li et al.[13] proposed an improved ACO) algorithm based on the meta-information to construct a dynamic scheduling model for project group management. Walid et al.[14] proposed a new hybrid method (PSO-ACO) based on combining particle swarm optimization (PSO) and ant colony optimization (ACO) algorithms for solving the traveling salesman problem (TSP). Shen and Chen[15] proposed a improved ant colony optimization (ACO) based dynamic routing and wavelength assignment (RWA) algorithm. Theoretical analysis shows that the improved ACO based RWA algorithm can effectively achieve load balancing in optical network. Escario et al.[16] proposed an ant colony extended (ACE) . Two specific features of ACE are: the division of tasks between two kinds of ants, namely patrollers and foragers, and the implementation of a regulation policy to control the number of each kind of ant during the searching process. Li and Jin[17] proposed a novel ant colony optimization algorithm (called GACO) based on Compute Unified Device Architecture (CUDA) enabled GPU. Zhang et al.[18] proposed a optimized algorithms, denoted as PMACO algorithms, which can enhance the amount of pheromone in the critical paths and promote the exploitation of the optimal solution. Experimental results in synthetic and real networks show that the PMACO algorithms are more efficient and robust than the traditional ACO algorithms, which are adaptable to solve the TSP with single or multiple objectives.

In this paper, an efficient and intelligent ant colony optimization(IMVPACO) algorithm is proposed to improve the global solving ability and convergence speed and avoid falling into local optimal solution in the basic ant colony optimization (ACO) algorithm. The traveling salesman problem is used to test the effectiveness of the IMVPACO algorithm.

2. Basic Ant Colony Optimization Algorithm

Ant colony optimization (ACO) algorithm was proposed by Marco Dorigo[19]. The ACO algorithm is a metaheuristic inspired by the behavior of real ants in their search for the shortest path to food sources. Ants tend to choose the paths marked by the strongest pheromone concentration. The ACO algorithm is an essential system based on agents that simulates the natural behavior of ants, including the mechanisms of cooperation and adaptation. The ACO algorithm simulates the techniques employed by real ants to rapidly establish the shortest route from a food source to their nest and vice versa without the use of visual information. The ACO algorithm consists of a number of cycles (iterations) of solution construction. In each iteration, a number of ants construct complete solutions by using heuristic information and the collected experiences of previous groups of ants. These collected experiences are represented by the pheromone trail which is deposited on the constituent elements of a solution. Pheromone can be deposited on the components and/or the connections used in a solution depending on the problem. The flow chart of the ACO algorithm is illustrated in Fig. 1.

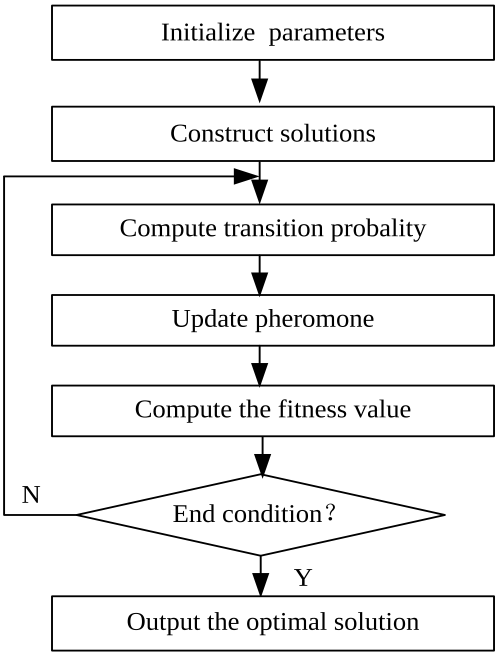

Figure 1. The Flow Chart of the ACO Algorithm

Each ant randomly starts at a city and visits the other cities according to the transition rule. The learning procedure is to update the pheromone information repeatedly.

(1) The transition rule

In the route, the k^{th} ant starts from city r, the next city s is selected among the unvisited cities memorized in J_r^k :

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

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

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

(2) The pheromone update rule

In order to improve the solution, the pheromone trails must be updated. Trail updating includes local updating and global updating. The local trail updating formula is given by:

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

In the formula (6), ρ ($0 < \rho < 1$) is the pheromone trial evaporating rate. $\Delta\tau_k(r,s)$ is the amount of pheromone trail added 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 parameter, L_k is the distance of the sequence π_k toured by ant in Δt.

3. Improved Ant Volony Optimization (IMVPACO) Algorithm

3.1. Dynamic Movement Rules of Ants

Stagnation phenomenon is the basic reason to cause the shortcomings of ACO algorithm. On the basis of combining the deterministic selection and random selection, the dynamical movement probability rule is proposed to be beneficial to the selection strategy of global search in the search. The pheromone on the path is changing in the evolutionary process. And the pheromone on the visited path is strengthened, and the visited path increases the selected possibility of the next iteration. And some better solutions could be gradually forgotten in the initial stage, because the less ants pass the path. This will influence the global search capability of the algorithm. If the seldom passed path is appropriately considered in the movement strategy, it will beneficial to the global search of the solution space, which can effectively overcome the deficiency of the basic ACO algorithm. To visit the next city s with the probability $p_{ij}^{k}(t)$:

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{\tau_{ij}(t)^{\alpha}\times\eta_{ij}(t)^{\beta}\times x_{ij}(t)}{\sum\limits_{k\in allowed_k}\tau_{ik}(t)^{\alpha}\times\eta_{ik}(t)^{\beta}\times x(t)} & if\ \ j\in allowed_k\\ 0 & otherwise\end{cases} \tag{5}$$

$$x_{ij}=\frac{m\times T_c}{m\times T_c+\delta\times Q_c(i,j)\times\eta(i,j)/\eta_{\max}} \tag{6}$$

where m is the number of ants, T_c is the number of current iterations, $\eta_{\max}$ is the maximum value of heuristic function $\eta(i,j)$. $Q_c(i,j)$ is the total number of ants by passing path (i,j) from the beginning of the first iteration. The x_{ij} takes into account the parameters of Q_c and η at the same time. When the iteration tends to the suboptimal solution, although the pheromone on the suboptimal solution continuously enhanced, the number of ants Q_c continuously increased, and the value of x_{ij} decreased. When the path is selected, this strategy could depress the excessive increasing of pheromone to lead to premature convergence, and is conducive to global search of the algorithm .

3.2. Improved Updating Rules of Pheromone

In order not to submerge the heuristic factor by the residual pheromone information, the residual pheromone is updated after each search. The pheromone updating method with elitist strategy of ACO algorithm is described as follow:

$$\tau_{ij}(t+1)=\rho\tau_{ij}(t)+\Delta\tau_{ij}+\Delta\tau_{ij}^{*} \tag{7}$$

$$\Delta\tau_{ij}^{*}=\sum_{k=1}^{m}\Delta\tau_{ij}^{k} \tag{9}$$

$$\Delta\tau_{ij}^{k} = \begin{cases} Q/L_K, \textit{passed path}(i,j)\textit{ by ant } k \textit{ in this iteration} \\ 0, \textit{other} \end{cases} \tag{10}$$

$$\Delta\tau^{*} = \begin{cases} \delta Q/L^{*}, \textit{the edge}(i,j)\textit{ is one of the found optimal solutions} \\ 0, \textit{other} \end{cases} \tag{11}$$

3.3. Adaptive Adjustment Strategy of Pheromone

The traditional ACO algorithm mainly uses a fixed amount of pheromone to update the pheromone. This strategy ignores the distribution characteristics of solution and is prone to stagnation and slow convergence phenomenon, it is easy to fall into local optimum for causing premature phenomena. In this paper, adaptive adjustment strategy of pheromone is introduced to make relatively uniform pheromone distribution, which can effectively solve the contradiction between expanding search and finding optimal solution, in order to find the local optimal solution.

The real variable function $Q(t)$ is selected to replace the constant of pheromone intensity Q in the adjusting pheromone $\Delta\tau_{ij}^{k} = Q/L_K$.

$$\Delta\tau_{ij}^{k}(t) = Q(t)/L_K \tag{12}$$

$$Q(t) = \begin{cases} Q_1 & t \le T_1 \\ Q_2 & T_1 < t \le T_2 \\ Q_3 & T_2 < t \le T_3 \end{cases} \tag{13}$$

The real variable function $Q(t)$ is used to replace the constant term Q in order to continue to maintain the exploration and exploitation balance point between the random search of ant and the evocation function of path information under the pheromone evaporation or increasing in the random search process. If the obtained optimal solution does not change in a period of time, it shows that the search falls into an extreme point. Then the enforcement mechanism is adopted to decrease the amount of increasing information in order to escape from local minimal value. In the initial stage of the search process, in order to avoid falling into local optimal solution, the amount of the optimal path and worst path are reduced, the positive feedback in the ACO algorithm need be appropriately restrained by adding a small amount of negative feedback pheromone in the search process in order to reduce the difference of pheromone on the corresponding path with the local optimal solution and the worst solution and expand the scope of the search.

3.4. Dynamic Evaporation Factor Strategy

The evaporation factor of pheromone ρ in the basic ACO algorithm is a constant. The ρ value directly relates to the global search ability and convergence speed of the ACO algorithm. For large-scale problems, because there exists the evaporation factor of pheromone, the pheromone on the unvisited path will be reduced to close to 0. This will reduce the global searching ability of the ACO algorithm. If the pheromone is too large, the selection probability of the visited path will be large, this also will affect the global search ability of the ACO algorithm. Therefore, how to set the value of pheromone has become the key to control the pheromone releasing and evaporating. The concept of dynamic evaporation rate is proposed in this paper. The idea is to set a large value for dynamic evaporation rate ρ at the beginning of the ACO algorithm in order to enhance the global search ability. But with the operation of the ACO algorithm, the evaporation rate ρ will continue to decay ,so that the ACO algorithm can quickly converge to the optimal solution. The dynamic evaporation rate strategy in the ACO algorithm not only increases the global search capability, but also accelerates the convergence to a certain extent.

In order to better explore decay model of the evaporation rate, there are three different decay models of curve decay model, line decay model and scale decay model. The curve decay model is selected according to implementing a set of experiments. The expression of curve decay model is described as follow:

$$\rho(t) = \frac{T \times (\tau_{\max} - \tau_{\min}) \times t}{T-1} + \frac{T \times \tau_{\min} - \tau_{\max}}{T-1} \tag{14}$$

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

3.5. Boundary Symmetric Mutation Strategy

According to the statistics theory, when the number of samples tends to infinity, the distribution of the samples will meet the normal distribution or tend to the normal distribution. In solving TSP, the city coordinates are sorted according to the values of these coordinates. Although the number is very small, the distributions of the cities still have centrotaxis, and more of the cities will be relatively concentrated on the central region. The ants s are always from the boundary to the center, then from the center to the boundary at beginning of the algorithm. That's all ants comply with the trajectory model of boundary-center-boundary in the search.

Due to the perplexing paths in the center area and existing a lot of overlapping paths, the pros and cons of the paths mainly be reflected by the boundary paths. When the mutation strategy is used for the mutation of the boundary paths. This strategy can improve the mutation efficiency and obtain higher quality solutions. In this paper, when the mutation strategy is applied, the quartile idea in probability theory is used to mutate the 1/4 paths in the beginning and end of the path. According to the symmetry of boundary, boundary mutation only takes place within this boundary, and does not occur the crossover and mutation of the boundary. The experimental results show that this improved mutation strategy can significantly improve the mutation efficiency and its effectiveness.

Based on the above discussed points, an improved ant colony optimization (IMVPACO) algorithm based on combining the dynamic movement rules of ants, improved updating rules of pheromone, adaptive adjustment strategy of pheromone, dynamic evaporation factor strategy and boundary symmetric mutation strategy is proposed in this paper.

4. The Steps of the Proposed IMVPACO Algorithm

According to the idea of proposed IMVPACO algorithm , the steps of the proposed IMVPACO algorithm in solving TSP problem are given:

Step 1. Initialize parameters.

The parameters of the proposed IMVPACO algorithm are initialized. These parameters include the ant size(m), the maximum iteration times($T_{\max}$), the pheromone factor(α), heuristic factor(β), evaporation factor of pheromone(ρ), pheromone amount (Q), initial concentration of pheromone($\tau_{ij}(0)$),initial uniform probability(q_0),and so on.

Step 2. Classification of cities

These cities are divided into the center city and boundary city according to the geographic coordinate information of cities. The classified result is saved and sorted in order to prepare for the subsequent running of the IMVPACO algorithm.

Step 3. The m ants are randomly placed into n cities, and this city is added into Tabu list of the ant.

Step 4. For each ant, when Tabu table is not null, the selection probability to the next city is calculated according to the equation (5) in the dynamic movement rules of ants(Section 3.1). Then this city is added into the Tabu list, and the pheromone is locally updated.

Step 5. After the ants have completed a choice, the path length is calculated. Then the respective Tabu list is modified. Repeat **Step 4** until the completed touring of the ant. The current optimal path length is saved, and the global optimal path is updated in this iteration.

Step 6. Update the pheromone

The pheromone on the optimal path is globally updated according to the equation (7) in the improved updating rules of pheromone(Section 3.2).

Step 7. Iteration control

Set the iterative counter $t = t + 1$. If $t < T_{\max}$, return to Step 4. Otherwise, the proposed IMVPACO algorithm is terminated, and the optimal solution is output.

5. Experimental Analysis

5.1. Experiment Introduction and Parameter Set

In this paper, ten datasets of traveling salesman problem(TSP) from the TSPLIB standard library(http://www.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95/) are selected to test the performance of the proposed IMVPACO algorithm. According to the characteristics of TSPLIB standard library, the distance between any two cities is calculated by the Euclidian distance and then rounded off after the decimal point. In order to illustrate the effectiveness of the proposed IMVPACO algorithm, the standard ACO algorithm and IACO algorithm[20] are used to compare the optimized performances in here. The experiment environments are followed: Matlab2012b, the Pentium CPU 2.40GHz, 4.0GB RAM with the Windows XP operating system. For each TSP, these algorithms are run independently 30 times, and the best optimal value and average optimal value are found in this paper.

The values of parameters for the standard ACO algorithm, IACO algorithm and IMVPACO algorithm could be a complicated problem itself, the parameters' change could affect the optimum value of three algorithms. So the most reasonable initial values of these parameters for the standard ACO algorithm, IACO algorithm and IMVPACO algorithm are obtained by testing and modifying. The obtained initial values of these parameters are shown in Table 1.

Table 1. The Initial Values of Parameters for the ACO, PACO and IMVPACO Algorithms

Ants (m)	Pheromone factor(α)	Evaporation factor (ρ)	Initial concentration($\tau_{ij}(0)$)
100	1.0	0.05	1.5
Iteration ($T_{\max}$)	Heuristic factor (β)	Pheromone amount (Q)	initial uniform probability(q_0)
500	2.0	100	0.5

5.2. Experimental Results and Analysis

In the experiment, the standard ACO algorithm, IACO algorithm and IMVPACO algorithm are run on Matlab platform. Ten TSP benchmark instances with cities scale from 51 to 14051 are performed. In here, the optimal value(Best) and the number of iterations are used to illustrate the solving ability of the proposed IMVPACO algorithm. The experimental results are shown in Table 2.

Table 2. The Experimental Results in Solving TSP

Index	Instance	Optimum	ACO		IACO		IMVPACO	
			Best	Iterations	Best	Iterations	Best	Iterations
1	eil51	426	447	235	434	198	427	104
2	pe76	108159	109 986	241	109853	205	109003	186
3	rad100	7910	8056	296	7968	276	7938	267
4	pr124	59030	59794	289	59481	253	59084	194
5	kroA150	26524	26965	368	26794	350	26683	301
6	rat195	2323	2408	358	2396	330	2353	276
7	pr299	48191	48946	423	48802	389	48662	305
8	pcb442	50778	51905	418	51843	381	51457	336
9	u724	41910	43046	445	42994	405	42859	376
10	brd14051	469385	499052	479	496034	452	490432	401

As can be seen from the Table 2, for the ten TSP instances, the optimal value(Best) and the number of iterations of the proposed IMVPACO algorithm are best in this experiment. Because the four experiment values are close to the optimal solutions. For TSP instances with eil51,pr76,rad100 and rat195, the obtained best solutions 427, 108159, 7938 and 2353 are close to the best known solutions 426, 109003,7910 and 2323. In the number of iterations, the proposed IMVPACO algorithm is best than the standard ACO algorithm, IACO algorithm in solving TSP with same scale. At the same time, for larger scale instances, the experiment results show that the proposed IMVPACO algorithm in the optimal value(Best) and the number of iterations is better than the ACO algorithm and IACO algorithm.

In order to further illustrate the optimization performance of the proposed IMVPACO algorithm, two best routes found by the IMVPACO algorithm are shown in Fig.2. and Fig.3.

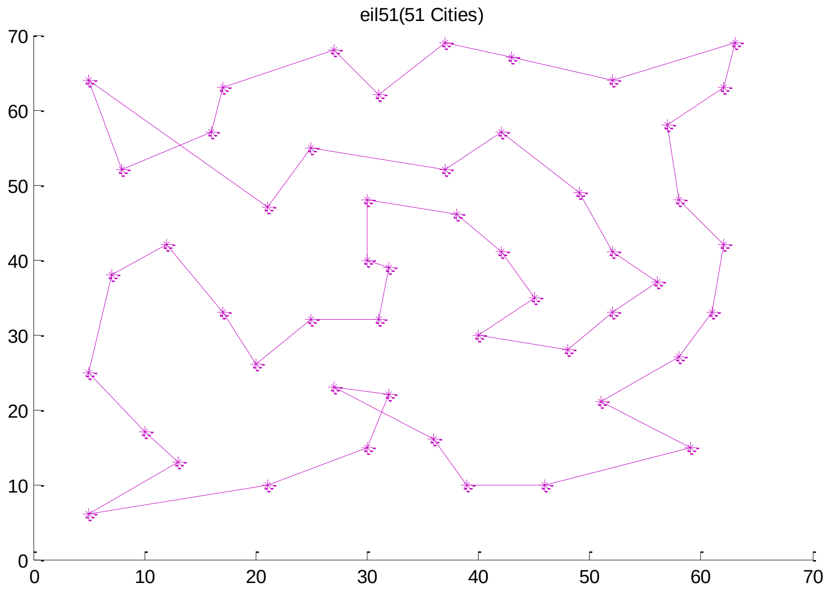

Figure 2. The Best Routes Found for eil51

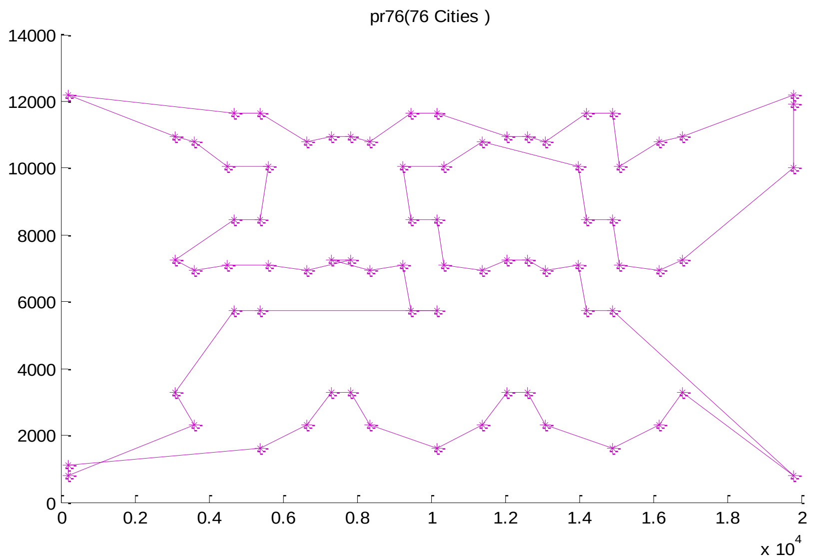

Figure 3. The Best Routes Found for pr76

6. Conclusion

The ACO algorithm is a stochastic, population-based, evolutionary search algorithm. It is an efficient and powerful optimization algorithm, which widely applied in scientific research and engineering field. This paper proposes an efficient and intelligent ant colony optimization (IMVPACO)algorithm. In the IMVPACO algorithm, In the IMVPACO algorithm, the updating rules and adaptive adjustment strategy of pheromones are modify in order to better reflect the quality of the solution based on the increment of pheromone. The dynamic evaporation factor strategy is used to achieve the better balance between the solving efficiency and solving quality, and effectively avoid falling into local optimum for quickening the convergence speed. The movement rules of the ants are modify to make it adaptable for large-scale problem solving, optimize the path and improve search efficiency. A boundary symmetric mutation strategy is used to obtain the symmetric mutation for iteration results, which not only strengthens the mutation efficiency, but also improves the mutation quality. The traveling salesman problem is used to test the effectiveness of the proposed IMVPACO algorithm. The simulation experiments show that the proposed IMVPACO algorithm can obtain very good results in finding optimal solution.

References

[1] M. Dorigo and G. D. Caro, "ant algorithms for discrete optimization", Artificial Life, vol. 5, no. 3, **(1999)**, pp. 137-172.
[2] T. Stutzle and H. H. Hoos, "MAX-MIN ant system", Future Generation Computer Systems, vol. 16, no. 8, **(2000)**, pp. 889-914.
[3] J. Dero and P. Siarry, "Continuous interacting ant colony algorithm based on dense hierarchy", Future Generation Computer Systems, vol. 20, no. 5, **(2004)**, pp. 841-856.
[4] M. Dorigo and L. M. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman problem", IEEE Transactions on Evolutionary Computation, vol. 1, no. 1, **(1997)**, pp. 53-66.
[5] L. M. Gambardella, E. Taillard and M. Dorigo, "Ant colonies for the quadratic assignment problem", Journal of the Operational Research Society, vol. 50, no. 1, **(1999)**, pp. 167-176.
[6] A. Colorni, M. Dorigo and V. Maniezzo, "Ant system for job-shop scheduling", Belgian Journal of Operations Research, Statisticsand Computer-Science, vol. 34, no. 1, **(1994)**, pp. 39-54.
[7] S. Leng, X. B. Wei and W. Y. Zhang, "Improved ACO scheduling algorithm based on flexible process", Transactions of Nanjing University of Aeronautics and Astronautics, vol. 23, no. 2, **(2006)**, pp. 154-160.
[8] Y. Yi, Yang and J. L. Lai, "Computation model and improved ACO algorithm for p//T", Journal of Systems Engineering and Electronics, vol. 20, no. 6, **(2009)**, pp. 1336-1343.
[9] S. Mao and C. L. Zhao, "Unequal clustering algorithm for WSN based on fuzzy logic and improved ACO", Journal of China Universities of Posts and Telecommunications, vol. 18, no. 6, **(2011)**, pp. 89-97.
[10] A. Ugur and D. Aydin, "Improving performance of ACO algorithms using crossover mechanism based on best tours graph", International Journal of Innovative Computing, Information and Control, vol. 8, no. 4, **(2012)**, pp. 2789-2802.
[11] H. L. Xu, X. Qian and L. Zhang, "Study of ACO algorithm optimization based on improved tent chaotic mapping", Journal of Information and Computational Science, vol. 9, no. 6, **(2012)**, pp. 1653-1660.
[12] S. J. Xue, J. Zhang and X. D. Xu, "An improved algorithm based on ACO for cloud service PDTs scheduling", Advances in Information Sciences and Service Sciences, vol. 4, no. 8, **(2012)**, pp. 340-348.
[13] Y. C. Li, L. P. Liu, S. J. Zhou and Z. C. Yang, "Dynamic resource scheduling in construction project group management based on improved ACO algorithm", Energy Education Science and Technology Part A: Energy Science and Research, vol. 31, no. 2, **(2013)**, pp. 1111-1116.
[14] E. Walid, E. A. Haikal, A. Ajith and A. M. Alimi, "A comparative study of the improvement of performance using a PSO modified by ACO applied to TSP.Applied Soft Computing Journal", vol. 25, no. 12, **(2014)**, pp. 234-241.
[15] J. H. Shen and J. Chen, "An improved ACO based RWA algorithm and its application in wavelength converter allocation issue of the intelligent optical networks", Journal of Computational Information Systems, vol. 10, no. 8, **(2014)**, pp. 3341-3349.
[16] J. B. Escario, J. F. Jimenez and J. M. Giron-Sierra, "Ant colony extended: Experiments on the travelling salesman problem", Expert Systems with Applications, vol. 42, no. 1, **(2015)**, pp. 390-410.
[17] F. Li and M. L. Jin, "GACO: a GPU-based high performance parallel multi-ant Colony Optimization algorithm", Journal of Information and Computational Science, vol. 11, no. 6, **(2014)**, pp. 1775-1784.
[18] Z. L. Zhang, C. Gao, Y. X. Liu and T. Qian, "A universal optimization strategy for ant colony optimization algorithms based on the Physarum-inspired mathematical model", Bioinspiration and Biomimetics, vol. 9, no. 3, **(2014)**, pp. 1-7.
[19] M. Dorigo and L. M. Gambardella, "Ant colonies for the travelling salesman problem", Biosystems, vol. 43, no. 2, **(1997)**, pp. 73-81.
[20] H. S. Paulora, T. Maria, A. Steiner and S. Scheer, "A new approach to solve the traveling salesman problem", Neurocomputing, vol. 70, no. 4, **(2006)**, pp. 1013-1021.

Authors

Ping Duan. She holds an undergraduate degree from Huazhong University of Science & Technology. Her research interests include artificial intelligence and software engineering. Currently, she is an associate professor at Hubei Urban Construction Vocational and Technological College.

Yong Ai. He holds a Doctor of Engineering from Wuhan University. His research interests include Digital city and virtual space. Currently, he is a lecturer at Hubei Urban Construction Vocational and Technological College.