Modified Ant Colony Optimization with updating Pheromone by Leader and Re-initialization Pheromone for Travelling Salesman Problem

Chiabwoot Ratanavilisagul
Faculty of Applied Science, Department of Computer and Information Science, King Mongkut's University of Technology North Bangkok (KMUTNB)
Bangkok, Thailand
chaibwoot@gmail.com, chaibwoot@hotmail.com

Bundit Pasaya
Faculty of Engineering, Department of Computer Engineering, King Mongkut's Institute of Technology Ladkrabang (KMITL)
Bangkok, Thailand
kpbundit@kmitl.ac.th, bunditpp@hotmail.com

***Abstract*— Ant Colony Optimization (ACO) algorithm is a stochastic algorithm. It is used for solving combinational optimization problem. The ant colony walks along density of pheromone from ant's nest to feeding sources. It leads to create shortest path from ant's nest to feeding sources. Normally, ACO encounters the problem of trapping in local optimum. To improve solutions, 2-Opt algorithm is applied with ACO. However, 2-Opt algorithm cannot solve trapping in local optimum of ACO and cannot improve searching performance of ACO. This paper proposed improving ACO algorithm by the results from searching of 2-Opt algorithm are applied with pheromone of ants. Moreover, when ant colony occur trapping in local optimum, the pheromone of ants is re-initialized to solve trapping in local optimum problem. The proposed technique is tested on twenty-three maps from the Traveling Salesman Problem Library (TSPLIB) and gives more satisfied search results in comparison with ACOs.**

Keywords*— *ant colony optimization, 2-Opt algorithm, travelling salesman problem, optimization, re-initialization

I. Introduction

The traveling salesman problem (TSP) is a combinatorial optimization problem and a NP-complete problem. It is a well-known problem for comparison of algorithm performance. Reference [1] proposed Ant Colony Optimization algorithm (ACO) in 1991. It is motivated by the foraging behavior of ant colony [2], [3], [4]. ACO has been a well-known used for solving optimization problems [5] such as job scheduling problem, traveling salesman problem (TSP), network routing and vehicle routing problem etc. ACO tries to search for shortest paths from ant's nest to feeding sources. Each ant walks along density of pheromone and releases pheromone among walking. This behavior causes the density of pheromone in short paths that are very high. On the other hand, the density of pheromone in long paths are very low [6], [7].

The benefits of ACO, it can search for the good solution rapidly and high performance for solving TSP [5], [8], [9], [10], [11]. On the other hand, cons of ACO, it encounters trapping in the local optimum problem [5], [8], [9], [12].

To overcome cons of ACO, many researchers proposed many techniques add to ACO process such as 2-Opt [13], particles swarm optimization (PSO) [22], 3-Opt [14], [22]. The experiment results of these papers showed that these techniques can get better solutions than the standard ACO.

Reference [13] proposed the 2-Opt algorithm applied with ACO at the end of each cycle to increase the quality of the solutions. This technique is called that ACO-2OPT. Reference [14] proposed colony is divided into two colonies or multiple colonies. Then these colonies run parallel. This algorithm selects multiple colonies because a single colony easily happens to trapping in the local optimum [6], [15]. Each colony searches for solution and exchanges the best solution between that colony and another colony. If a colony happens to trapping in the local optimum, another colony helps that colony to jump out trapping in the local optimum. Thus, PACO-3OPT obtains better solution. This technique is called that a parallel cooperative hybrid algorithm based on ant colony optimization (PACO-3OPT). From the experiment results, the quality solutions of PACO-3OPT are better than the quality solutions of compared algorithms.

In case a single colony or ACO-2OPT, ACO easily happens to trapping in the local optimum or the premature stagnation of the searching [6], [15]. This algorithm has not process for handling on trapping in the local optimum. Moreover, the 2-Opt can improve solution from searching ACO, but it cannot help searching of ACO or improve searching of ACO.

In case multiple colonies or PACO-3OPT, ACO can handle trapping in the local optimum. Because, a colony happens to trapping in the local optimum, another colony can help that colony to jump out trapping in the local optimum. However, in case both colonies happen to trapping in near area or same area. In this case, its effect is similar to in case of a single colony. The chance of this case can easily occur because both colonies exchange the best solution. Each colony tries to improve its paths according to the best solution. Finally, both colonies are similar. Hence, this algorithm cannot deal with trapping in the local optima problem.

978-1-5386-4956-5/18/$31.00 ©2018 IEEE

To handle trapping in the local optima problem, this paper proposed a novel re-initialization technique apply with ACO when ant colony happens to trap in local optimum. In addition, the 2-Opt applied with ACO. The best results from searching of 2-Opt is taken to improve searching of ACO. The proposed technique can get better solutions when it is compared by standard ACO and other compared algorithms.

A set of maps in the TSPLIB [18], [19] is used to compare the standard ACO [6] by source code from [20], ACO-2OPT [13], PACO-3OPT [14], and the proposed technique. The results show that the quality of solutions of the proposed technique is better than other compared algorithms in the TSPLIB.

The rest of this paper is organized as follows. Section 2 explains TSP, the basic ACO, and the previous modified ant colony optimization algorithms. Section 3 explains the proposed PSO algorithm. Section 4 explains the case studies of TSP, the experiment setup and presents the experiment results. Section 5 concludes the paper with a brief summary.

II. Related Work

A. Travelling Salesman Problem

Traveling salesman problem (TSP) [21] is a well-known combinational discrete optimization problem and NP-hard problem. As amount of cities are increased, searching the optimal tour becomes very hard. The salesman tries to travel all cities only once and to create a closed tour of the shortest path. This problem has been used in many engineering applications such as the design of hardware devices and computer networks [25]. A complete weighted graph G = (V, A) can be used to represent a TSP. Where V is the set of n cities and A is the set of paths fully connecting all cities. Each edge (d_{ij}) is the distance between cities i and j. d_{ij} is as follows:

$$d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{1}$$

V = {1,. ., n}, A = {(i, j): i, j $\in$ V}, d(i, j) = d(j, i), Edge (i, j) $\in$ A

B. Ant colony optimization

This paper shows applying ACO with TSP. An ant (A) is the set of paths fully connecting all cities. So, an ant is a solution of TSP. The fitness function or the objective function of TSP is as follows:

$$fitness\_of\_ant = \sum_{i=1}^{n-1} d_{i,i+1} + d_{n,1} \tag{2}$$

ACO can be described shortly as follow. Initially, each edge has an initial pheromone τ_{ij} (0) between two cities. The next step is select city of ant. The first city of each ant is randomly selected, and then each ant selects next city according to probability function as follows:

$$P_{i,j}^{k} = \begin{cases} \dfrac{[\tau_{i,j}(t)]^{\alpha}[n_{i,j}]^{\beta}}{\sum_{t \in allowed}[\tau_{i,j}(t)]^{\alpha}[n_{i,j}]^{\beta}} & , j \in allowed \\ 0 & , otherwise \end{cases} \tag{3}$$

Where η_{ij} = 1/d_{ij} is the inverse of the distance, $P_{i,j}^{k}$ is the probability of ant k chooses to move from city i to city j, τ_{ij} is the pheromone, β is a parameter which determines the relative importance of pheromone versus distance (β > 0). The result from formula (3) that causes selecting edges which are shorter and have a greater amount of pheromone. After selection cities of ant has completed, the fitness of ant is calculated by (2). The fitness of each ant is used to update pheromones according to (4). This process continues until a stopping criterion is met.

$$\Delta\tau_{i,j}(t+n) = \rho\tau_{i,j} + \Delta\tau_{i,j} \tag{4}$$

$$\Delta\tau_{i,j} = \sum_{k=1}^{m} \tau_{i,j}^{k} \tag{5}$$

Where ρ is a coefficient such that (1 - ρ) represents the evaporation of trail between time t and t+n, $\tau_{i,j}^{k}$ is the amount of pheromones of the k[th] ant at its edge between t and t+n, $\Delta\tau_{ij}$ is the sum of new enhanced pheromones at this edge is degree of dissipate for pheromones, $\Delta\tau_{i,j}^{k}$ is calculated by (6), and Q is a const, L_k is fitness of ant k.

$$\Delta\tau_{i,j}^{k} = \begin{cases} \dfrac{Q}{L_k} & ,if\_the\_k^{th}\_ant\_uses\_edge(i,j)\_in\_its\_tour \\ 0,\_otherwise \end{cases} \tag{6}$$

C. The previous modified ant colony optimization algorithms

ACO-2OPT uses 2-Opt to improve the solution quality. The main concept of ACO-2OPT is can be summarized as follows: this algorithm searches for solutions by using the standard ant colony technique. After process of ant colony finished each iteration, 2-Opt are applied with ants. From the experiment results show that ACO-2OPT can improve the solution quality of ACO in solving TSP.

PACO-3OPT uses multiple colonies to solve trapping in local optimum. Moreover, this algorithm uses the 3-Opt algorithm to improve the solution quality. The main concept of PACO-3OPT is can be summarized as follows: Population is separated into two colonies. Each colony searches for solutions by using the standard ant colony technique. After process of ant colony finished each iteration and the number of iteration is divided by the defined round that equal zero, the migration process executed. The migration process, 3-Opt are applied with both colonies to improve solution and finds the local best tours. Each local best tour is compared to find the global best tours. Then, each colony replaces a randomly selected tour with global best. This algorithm can solve trapping in local optimum. If a colony happens to trapping in the local optimum, the other colony can help that colony jump out trapping in the local optimum. From the experiment results show that PACO-3OPT is better performance in solving TSP than the previous modified ACO algorithms.

However, the weak point of ACO-2OPT is problem of trapping in the local optimum because ACO-2OPT has not method for handle this problem. The weak point of PACO-3OPT, both colonies can happen to trapping in the local optimum problem. It can easily occur because both colonies share the global best tours. Both colonies attempt to change themselves according to the global best tours. So, it can easily trap into the same local optimum and cannot improve solution in long run. Moreover, the 2-OPT and the 3-OPT of both techniques cannot improve the performance of ACO searching.

III. Modified Ant Colony Optimization with updating Pheromone by Leader and Re-initialization Pheromone

For process of ACO, the pheromone is determinant for creating tours of an ant or a solution. When pheromone happen trapping in local optimum, the pheromone of ACO creates tours which are the same as the previous tour or near the previous tours. So, the tours of all ants follow the same path and construct the same solution over and over again, that no better solutions can be found anymore [6], [23]. So, changing pheromone affects to search for solution and can jump out local optimum. To handle this problem, this paper proposed re-initialize or reset some part of pheromone when all ants happen to trapping in local optimum. When pheromones occur changing, it creates the new tours and can jump out local optimum. Normally, the re-initialize should be used when colony trap or trend to trap in local optimum [16], [17] to distribute ant colony to search for other areas. The easy techniques to indicate the trapping state of the ant colony is to monitor the unchanged number of the best consecutive solution. Thereby, this paper proposed the re-initialize period (RP) considered from the unchanged number of consecutive solution.

As previously mentioned, 2-OPT can improve solution from ACO but it cannot enhance searching performance of ACO. If the pheromone is updated from good solution, it can create better solutions. The tours pass the 2-Opt process. It is good tours because it is improved. It should bring to update pheromone of ACO in order that ACO creates better solutions. On the other hand, ACO should select the best tours in order that this tour passes the 2-Opt process. The best ant which is selected is called that leader. The results from searching both ACO and 2-Opt can enhance searching performance concurrently. Hence, this paper proposed the leader passes the 2-Opt process. Then the result from 2-Opt is used to update pheromone only. This process continues until a stopping criterion is met. Both leader technique and Re-initialization technique are the proposed technique in this research. The proposed technique is called Modified Ant Colony Optimization with updating Pheromone by Leader and Re-initialization Pheromone (MACO-LR). Pseudo code of MACO-LR is shown below:

```
Initialize edges (i, j) and pheromone (τij)
While termination condition ≠ true do
   Reset Leader
   For each number of ants
     Random the start city
     For until cites in list of an ant is full
          Choose the next city with probability according to formula (3)
          The chose city is not repeat city in list of this ant
          Insert chose city into list of this ant
     End For
     Evaluate fitness of each ant
     If fitness of each ant is better than fitness of solution
          Update fitness of solution = fitness of this ant
     End If
     If fitness of each ant is better than fitness of Leader
          Leader = this ant
     End If
   End For
   Apply 2-Opt algorithm with Leader
   Update pheromone by Leader which is passed 2-Opt according to formula (4)
   Apply Evaporation
   Times of Leader consecutive unchanged ++
   If the times of Leader consecutive unchanged >= re- initialization period (RP)
     For the number of re-initialization (NR)
          Random edges (i, j) which is not repeat random previous edges (i≠ j)
          Pheromone (τij) = initial pheromone
     End for
     Set the times of Leader consecutive unchanged to 0
   End If
End While
```

IV. Experiments and Results

A. Parameters Setting

Parameters are as follows for all experiments: $\rho = 0.05$, $\beta = 1$, $\alpha = 1$, $Q = 1$, as suggested by [20], $\tau_0 = (n \times L_{nn})^{-1}$ where L_{nn} is the length of list of ant that is produced by the nearest neighbor heuristic [24] and n is the number of cities. The number of experiments of each map is set as 20 runs. The maximum number of iterations is set as 2000. The number of ants is set as 100. The non-ACO parameters are as follows: For PACO-3OPT algorithm, each colony has 50 ants, the number of colonies is set as 2, and the migration interval is set as 10. For proposal algorithm, the re-initialization period (RP) = 10, the number of re-initialization (NR) is about 10 percent of the pheromone table size. This research is conducted by a personal computer of AMD FX-8320 with 3.5 GHz CPU and 8 GB RAM and Visual C++ 2010 as the programming language. All maps are used in experiment are from TSPLIB [18], [19].

B. The measures of algorithm performance

The measures of algorithm performance in the experiments are as follows: the average best fitness value (ABF) is the average of best fitness in the final iteration from all running (20 runs). ABF indicates the solution searching efficiency of an algorithm. The closer the ABF to the optimum point of a method, the better the method. SR is the success round. SD is the standard deviation. SR and SD indicate the solution searching reliability of an algorithm.

C. Experiment of proposed algorithm

From the experimental results of Table 1 show that MACO-LR can locate the optimum points of all tested maps. The quality solution of MACO-LR is better than that of ACO, ACO-2OPT, and PACO-3OPT because of its lowest ABF all tested maps. The reliability of MACO-LR is better than that of

ACO, ACO-2OPT, and PACO-3OPT because of its lowest SD all tested maps. In addition, SR of MACO-LR is better than that of ACO, ACO-2OPT, and PACO-3OPT because of its highest SR all tested maps. MACO-LR can solve trapping in the local optimum that is better than ACO, ACO-2OPT, and PACO-3OPT. So, MACO-LR can get better results than ACO, ACO-2OPT, and PACO-3OPT.

V. CONCLUSION

The 2-OPT or 3-OPT is applied with ACO to improve solution, so it get better solutions. But both algorithms cannot solve trapping in the local optimum problem. Moreover, both algorithms cannot improve searching of ACO. From these weak points, this paper proposed the results from 2-Opt update pheromone of ants to improve searching of ACO. Moreover, some parts of pheromone are re-initialized when ant colony happen to trapping in the local optimum in order to solve trapping in the local optimum problem. The proposed technique is called that MACO-LR. MACO-LR can solve trapping in local optimum problem and improve searching. So, it can get better solutions. From the experimental results show that the proposed MACO-LR outperforms ACO, ACO-2OPT, and PACO-3OPT with regard to the reliability and quality of solutions in all maps.

TABLE I. COMPARATIVE RESULTS OF ACO, ACO-2OPT, PACO-3OPT, AND MACO-LR ON TSP

Techniques		**ACO**			**ACO-2OPT**		
Problem name	**Optimum point**	**ABF**	**SD**	**SR**	**ABF**	**SD**	**SR**
burma14	3323	3323	0.00	20	3323	0.00	20
ulysses16	6859	6859	0.00	20	6859	0.00	20
gr17	2085	2085	0.00	20	2085	0.00	20
gr21	2707	2707	0.00	20	2707	0.00	20
ulysses22	7013	7034.5	2.77	0	7013	0.00	20
fri26	937	937	0.00	20	937	0.00	20
bayg29	1610	1653	15.29	0	1612	2.45	12
bays29	2020	2063.5	17.01	0	2020.6	1.80	18
Oliver30	420	420.2	0.60	18	420	0.00	20
dantzig42	699	715.1	8.35	0	701.2	2.32	8
swiss42	1273	1318.3	14.55	0	1279.8	7.95	3
eil51	426	448.1	5.89	0	430.2	3.43	6
berlin52	7542	8015.8	75.36	0	7646.3	76.15	5
brazil58	25395	26683.4	322.28	0	26095.5	155.32	0
st70	675	736.2	9.48	0	702.4	9.73	0
pr76	108159	119485	1096.17	0	113744	824.73	0
eil76	538	589.7	10.41	0	571.7	3.63	0
rat99	1211	1395	32.78	0	1339.3	16.58	0
eil101	629	724.5	5.89	0	692.3	6.45	0
lin105	14379	16010.2	273.58	0	15061.5	170.21	0
kroA100	21282	23899.1	313.12	0	22819	366.67	0
kroB100	22141	25166.6	403.68	0	23677.9	235.09	0
kroC100	20749	23669.5	461.84	0	22200.6	323.07	0

TABLE I. (CONTINUED).

Techniques		**PACO-3OPT**			**MACO-RL**		
Problem name	**Optimum point**	**ABF**	**SD**	**SR**	**ABF**	**SD**	**SR**
burma14	3323	3323	0.00	20	3323	0.00	20
ulysses16	6859	7013	0.00	20	6859	0.00	20
gr17	2085	2085	0.00	20	2085	0.00	20
gr21	2707	2707	0.00	20	2707	0.00	20
ulysses22	7013	6859	0.00	20	7013	0.00	20
fri26	937	937	0.00	20	937	0.00	20
bayg29	1610	1610	0.00	20	1610	0.00	20
bays29	2020	2020	0.00	20	2020	0.00	20
Oliver30	420	420	0.00	20	420	0.00	20
dantzig42	699	700.5	2.29	14	699	0.00	20
swiss42	1273	1273.2	0.40	16	1273	0.00	20
eil51	426	427.6	1.43	8	426	0.00	20
berlin52	7542	7563.7	65.10	18	7542	0.00	20
brazil58	25395	25946.7	74.19	0	25395	0.00	20
st70	675	693.3	7.77	0	675	0.00	20
pr76	108159	108491	414.64	12	108159	0.00	20
eil76	538	563.1	8.32	0	538	0.00	20
rat99	1211	1217.4	4.90	0	1211	0.00	20
eil101	629	684	8.26	0	629	0.00	20
lin105	14379	14423.1	71.46	11	14379	0.00	20
kroA100	21282	21393.4	67.87	9	21282	0.00	20
kroB100	22141	22168.6	21.88	6	22141	0.00	20
kroC100	20749	20823.6	85.68	7	20749	0.00	20

REFERENCES

[1] A. Colorni, M. Dorigo, V. Maniezzo, "Distributed optimization by ant colonies," Proceedings of European Conference on Artificial Life, Paris, France, pp. 134-142, 1991.

[2] J. L. Denebourg, J. M. Pasteels, and J. C. Verhaeghe, "Probabilistic behavior in ants: A strategy of errors?," J. Theoret. Biol., vol. 105, pp. 259-271, 1983.

[3] J. L. Denebourgand S. Goss, "Collective patternsand decision-making," Ethology, Ecology & Evolution, vol. 1, pp. 295-311, 1989.

[4] S. Goss, R. Beckers, J. L. Denebourg, S. Aron and J. M. Pasteels, "How trail laying and trail following can solve foragingproblems for ant colonies," in Behavioral Mechanisms of Food Selection, R. N. Hughes Ed., NATO-AS1 Series. Berlin: Springer-Verlag, vol. 20, 1990.

[5] V. Selvi, and R. Umarani, "Comparative Analysis of Ant Colony and Particle Swarm Optimization Techniques," International Journal of Computer Applications, vol. 5., pp. 1–6, August 2010.

[6] M. Dorigo, V. Maniezzo, A. Colorni, "Ant system: optimization by a colony of cooperating agents," IEEE Transactions on Systems, Man, and Cybernetics, vol. 26, pp. 693–698, pp.1-13, February 1996.

[7] M. Dorigo, L.M. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman problem," IEEE Transactions on Evolutionary Computation, vol 1, pp. 53 - 66, April 1997.

[8] Y. Zhang, Z. Pei, J. Yang, Y. Liang, "An Improved Ant Colony Optimization Algorithm Based on Route Optimization and Its Applications in Travelling Salesman Problem," IEEE, BIBE, pp. 693–698, 2007.

[9] X. Song, B. Li, and H. Yang, "Improved Ant Colony Algorithm and its Applications in TSP," Sixth International Conference on Intelligent Systems Design and Applications, october 2006.

[10] M. Dorigo and, LM. Gambardella, "Ant colony system: A cooperative learning approach to the traveling salesman problem," IEEE Transactions on Evolutionary Computation, pp. 53–66, 1997.

[11] M. Dorigo and, LM. Gambardella, "A study of some properties of ant-Q," Proceedings of the 44th International Conference on Parallel Problem Solving from Nature, Berlin: Springer-Verlag, pp. 656–665, 1996.

[12] A. Colorni and, M. Dorigo, "Heuristics from nature for hard combinatorial optimization problems," International Trans Operational Research, pp. 1–21, 1996.

[13] Jun-man K, Yi Z, "Application of an improved ant colony optimization on generalized traveling salesman problem," Energy Proc., pp. 319–325, 2012.

[14] Saban Gülcü¸ Mostafa Mahi, Ömer Kaan Baykan, Halife Kodaz, "A parallel cooperative hybrid method based on ant colony optimization and 3-Opt algorithm for solving traveling salesman problem," Soft Comput, pp. 1–17, 2016.

[15] Kolli VM, Sharvani G, "An ACO-based efficient stagnation avoidance methodology for MANETS," Proceedings of ninth international conference on wireless communication and sensor networks. Springer, pp. 125–132, 2014.

[16] C. Ratanavilisagul, "Dynamic population size and mutation round strategy assisted modified particle swarm optimization with mutation and reposition," International Electrical Engineering Congress, pp. and449–452, 2016.

[17] C. Ratanavilisagul, and B. Kruatrachue, "A modified particle swarm optimization with mutation and reposition," International Journal of Innovative Computing, Information and Control, vol. 10, pp. 2127–2142, 2014.

[18] http://www.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95

[19] http://stevedower.id.au/blog/research/oliver-30

[20] http://yarpiz.com/53/ypea103-ant-colony-optimization

[21] E. L. Lawler, J. K. Lenstra, A. H. G. Rinnooy-Kan and D. B. Shmoys Eds., "The Travelling Salesman Problem," New York: Wiley, 1985.

[22] Mahi M, Baykan ÖK, Kodaz H, "A new hybrid method based on Particle Swarm Optimization, Ant Colony Optimization and 3-Opt algorithms for Traveling Salesman Problem," Applied Soft Computing, pp. 484–490, 2015

[23] X. Yang and J. s. Wang, "Application of improved ant colony optimization algorithm on traveling salesman problem, " 2016 Chinese Control and Decision Conference (CCDC), Yinchuan, 2016, pp. 2156-2160.

[24] D. J. Rosenkrantz, R. E. Stearns, and P. M. Lewis, “An analysis of several heuristics for the traveling salesman problem,” SIAM J. Comput.,vol. 6, pp. 563–581, 1977.

G. Laporte, “The Traveling Salesman Problem – an overview of exact and approximate algorithms,” European Journal of Operational Research 59 pp. 231–247, 1992.