A report about study of Partical Swarm parameter tuning for Ant Colony System

Kengo Shimizu

I. INTRODUCTION

Vehicle Routing Problem (VRP) is a combinational optimization problem of which the objective is to find the least cost route (minimum number of vehicles and total distances) under some constraints. A typical VRP can be stated as follows: Each vehicle must depart at and return to depot. Each customer is to be serviced exactly once by only one vehicle and each vehicle has a limited capacity. The customers are placed specific coordinates. The Vehicle Routing Problem with Time Windows (VRPTW) is an extension of the VRP. Each customer has time window individually: each customer is to be serviced between ready time and duetime. If the vehicle reaches a customer before ready time, this vehicle must wait until ready time. Visiting a customer after due time is treated as a infeasible solution.

The VRPTW is NP-Complete and instances with 100 customers or more are very hard to solve optimally. The VRPTW was represented as a multi-objective problem and implemented Ant Colony Optimization (ACO) to solve in previous paper. In this report, Partical Swarm Optimization (PSO) was impremented to ACO to tune particular parameters. A method to evaluate solutions was applied Pareto Ranking which use three informations which are discussed later to evaluate each other [1]. I use a direct interpretation of the VRPTW as a multi-objective problem, in which the three objective dimensions are number of vehicles, total distance (without considering waiting time) and total time (considering waiting time). My experimental results use the standard Solomon's VRPTW benchmark problem instances available at [2]. Solomon's data is clustered into six classes; C1, C2, R1, R2, RC1 and RC2.The purpose of this paper is to consider the effects of each function part of ACO and different parameters.

The rest of this paper is organized as follows. Section II presents a formal definition of the VRPTW. In Section III, gives description on procedure and each formula used in PSO and how the PSO_ACO is applied to VRPTW and Pareto Ranking is proposed and described. Numerical results are presented in Section IV. Conclusion is given in Section V.

II. VRPTW

The Vehicle Routing Problem with Time Windows (VRPTW) is an extension of the VRP. There is customer set $C = \{c_0, c_1, c_2, ..., c_n\}$ on the two-dimensional surface represented as x and y coordinates, where c_0 represents the depot and $c_i (i = 1, 2, 3, ..., n)$ represents customer i. Each vehivle has limited capacity Q and customer c_i has own demand q_i, where $q_i < Q$ and $q_0 = 0$. t_{ij} represents distnce between c_i and c_j, where $t_{ij} = t_{ji}$. Acceptable time window $[b_i, e_i]$ is assined customer i, where b_i represents ready time to ride vehicle and e_i represents the latest time to be picked up. Customer i must be picked up by e_i and the vehicle need to wait until b_i if the vehicle arrives at customer i before b_i. Moreover, customer c_i has service time s_i. When a vehicle visit customer c_i, this vehicle must wait there for it's service time. In this paper, two objecttives were picked to be minimize as follows:

- the number of vehicles
- the total distance of all vehicles.

III. PSO_ACO_VRPTW

In previous paper's this section, the principle of ACO and procedure of ACO to VRPTW was discribed and this section omits these in this report. The variables used in ACO are referred to the previous paper. Particle Swarm Optimization is originally attributed to Kennedy, Eberhart and Shi and is a robust evolutionary strategy inspired by the social behavior of animal species living in large colonies like birds, ants or fish. PSO parameter tuning were impremented to q_0 and β, which are the important parameter that create the route directly. In order to implement PSO parameter tuning to ACO, Each ant $k \in \{1, ..., m\}$ has own parameter set of q_0 and β which are determined at random within certain velue range and also has local best parameter set. Moreover, each generation has global best parameter set. The parameter set of q_0 and β is updated as follows:

$$\Delta^2 x_k = c_1 r_1 (x_{k,best} - x_k) + c_2 r_2 (x_{best} - x_k) \qquad (1)$$

where x_k represents a parameter set of ant k as a particle. c_1 and c_2 are the weight between local best particle and global best particle. r_1 and r_2 are random values. When there are some pareto optimal solutions, the parameter set which is the smallest number of vehicles in the pareto optimal solutions is picked as a best parameter set.

IV. RESULT

A. Comparison with previous studies

The values in all of tables II - **??** were studied on each of the six data sets by running 10 computer simulations. Tours and Length represent the average values of the number of vehicles and the total distance. If there were multiple pareto optimal solutions, the solution which had the smallest number of vehicle was considered. BestKnown and Precedent in TABLE

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II represent the value known as the best value so far in [2] and the average values of 10 runs using MOACO_VRPTW (previous paper) method. The parameter sets were used in MOACO_VRPTW and PSO_ACO_VRPTW is shown in Table I and the number of iteration was 300. The weight parameters for PSO, c_1 and c_2, were used same value as [3]. As can be seen from TABLE II, the values of PSO_ACO_VRPTW are slightly worse than the values of MOACO_VRPTW besides benchmark C109 and C208. This is considered it is because the PSO parameters, which are q_0 and β, were not converged completely as can be seen in Figure 1 which shows the values of PSO parameters in each iteration and points are plotted on the lines every 100 iterations. The average number of vehicles was not changed among benchmark C109, C208, R211 and RC208. Figure 2 shows the convergence line of the average number of vehicles and PSO_ACO_VRPTW found the route which use less number of vehicles earlier than MOACO_VRPTW. In Figure 3, However, MOACO_VRPTW found short route earlier than PSO_ACO_VRPTW. This is considered that ants can determine route at random strongly enough to find the route which use less number of vehicles in PSO_ACO_VRPTW and it also causes PSO_ACO_VRPTW to find short route slowly. Therefor, the relation between PSO parameters and the value of solution were studied in next section IV-B.

TABLE I
PARAMETER VALUES

Parameter	MOACO_VRPTW	PSO_ACO_VRPTW
m	40	40
α	0.2	0.2
ρ	0.2	0.2
β	2.5	-
q_0	0.85	-
c_1	-	0.0002
c_2	-	0.005

TABLE II
EACH SOLUTIONS VALUE

	BestKnown		MOACO_VRPTW		PSO_ACO_VRPTW	
	Tours	Length	Tours	Length	Tours	Length
C109	10.0	828.94	10.0	897.89	10.0	890.72
C208	3.0	588.32	3.0	602.37	3.0	601.35
R112	9.0	982.14	10.2	1138.79	10.1	1146.45
R211	2.0	885.71	3.0	1042.12	3.0	1084.62
RC108	10.0	1139.82	11.0	1295.55	11.0	1313.95
RC208	3.0	828.14	3.0	1148.07	3.0	1181.04

B. *Convergence of PSO parameter set and quality of solutions*

To compare previous study with this method, calculations were done with same parameters by iteration 300 in subsection IV-A. In this subsection, calculations were done by iteration 1000 to consider relation between PSO parameter set and quality of solutions. Figure 4 shows average values of total distance with the number of iteration in x-axis. Figure 5 and 6 shows convergence of PSO parameter sets of each ant.

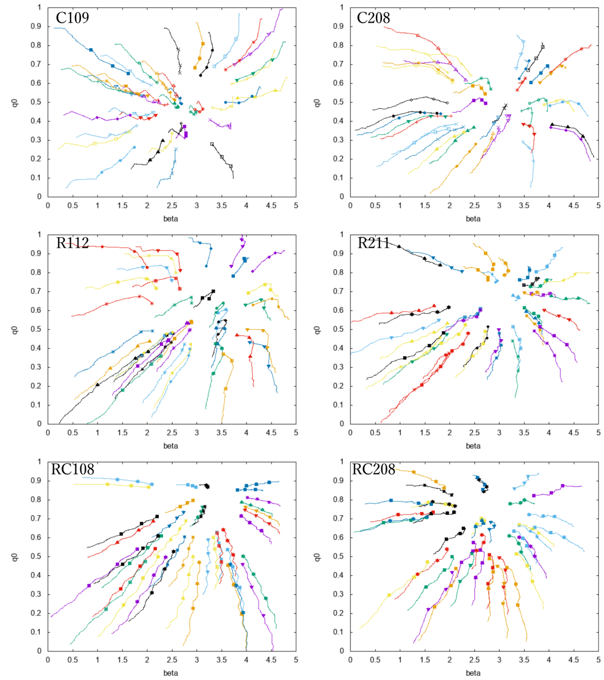

Fig. 1. convergence of PSO parameters

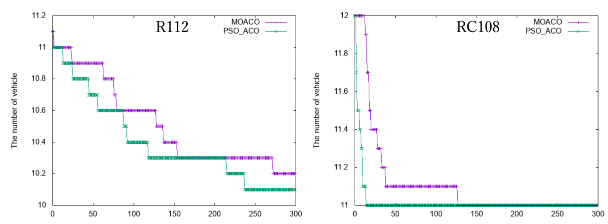

Fig. 2. convergence of the average number of vehicle

As can be seen in Figure 5, PSO parameter sets were not completely converged. On the other hand, PSO parameter sets were completely converged in Figure 6. According to Figure 4, there are barely difference in the average values of total distance between iteration 500 and 1000. It means that quality of solutions are almost converged before the PSO parameter sets are completely converged.

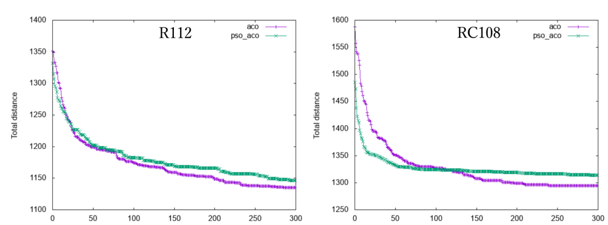

Fig. 3. convergence of the average value of total distance

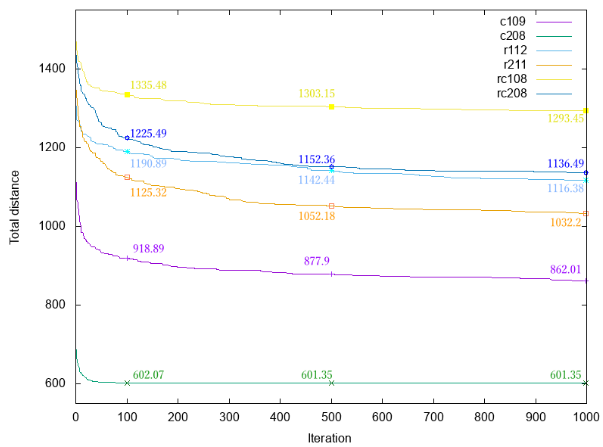

Fig. 4. convergence of the average value of total distance of each benchmark

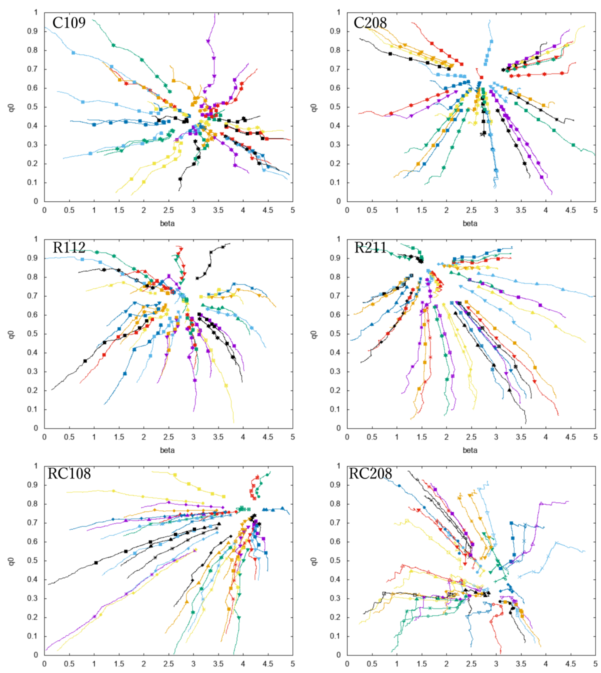

Fig. 5. convergence of PSO parameters at iteration 500

V. CONCLUSION

This report represents a multi-objective ant colony optimization approach to the vehicle routing problem with time windows with particle swarm parameter tuning. In this PSO_ACO_VRPTW, the Pareto ranking method was applied. Therefor, the pheromone trail could be able to take not only global best solution but Pareto optimal set into account. The solution quality of this method was not considered superior to previous method, MOACO. However, this method showed almost as good solution as MOACO showed without parameter tuning by a human. Moreover, it is generally agreed today that simple ACO likely ends with a local optima and this method obviously has this problem. Further study about avoiding

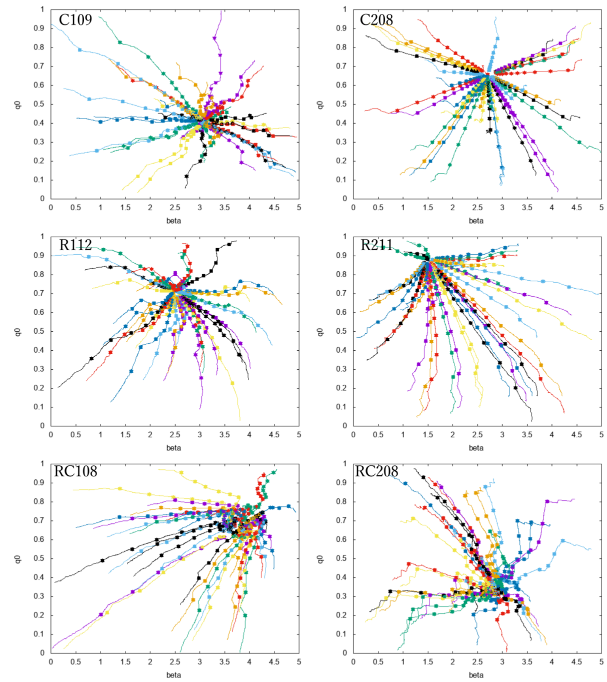

Fig. 6. convergence of PSO parameters at iteration 1000

ending with local optima is needed in order to find better solutions in this study.

REFERENCES

[1] Benjamin Baran and Matilde Schaerer, “A MULTIOBJECTIVE ANT COLONY SYSTEM FOR VEHICLE ROUTING PROBLEM WITH TIME WINDOWS,” The 21st IASTED International Multi-Conference on Applied Informatics (AI 2003), February 10-13, 2003, Innsbruck, Austria

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[3] Ryota N, Syuhei I and Hiroyuki E, “The effect of parameter tuning using Particle Swarm Optimization,” IPSJ SIG Technical Report, Vol.2015-MPS-105 No.1 2015/9/29