Paper 31

by The Jin Ai

Application of Particle Swarm Optimization for the Capacitated Team Orienteering Problem

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Abstract. The capacitated team orienteering problem (CTOP) is one of important transportation problem that can be faced by any organization. In this problem, there are several location or being called vertex. Each vertex has specific score, which will be collected if the vertex is visited by any transportation vehicle. The transportation time between two vertices are defined. There are time and capacity constraints of transportation vehicles, indicates by T and Q, respectively. The CTOP objective is to find the path of several transportation vehicles visiting some selected vertices in order to maximize total collected score with the constraint of T and Q. Various algorithms, such as branch and price, variable neighborhood search, and bi-level filter and fan, have been proposed for solving the CTOP, while the particle swarm optimization (PSO) has been applied to solve similar problems of CTOP such as team orienteering problem (TOP) and team orienteering problem with time windows (TOPTW). This paper tries to apply the PSO for solving the CTOP. The computational results show that the proposed PSO algorithm is able to obtain 47 best known solutions of 130 benchmark problems.

Keywords: Capacitated Team Orienteering Problem, Particle Swarm Optimization, Solution Representation, Computational Method, Metaheuristics

1. INTRODUCTION

The capacitated team orienteering problem (CTOP) is a problem for determining several paths of transportation vehicle in order to maximize total collected profit by visiting some customer through the paths with some restrictions. As defined in earlier research, i.e. Archetti et al. (2009), the CTOP can be formally defined as follow. Let us consider a set of visiting points $V = \{1, 2, \ldots, n\}$ represent potential customers, plus a depot indexed by 0. Let $G=(V,E)$ be an undirected graph where G is the set of vertices and E is the set of edge. m identical vehicles of capacity Q are stationed at the depot. A non-negative demand d_i and a non-negative profit p_i is associated with each customer i, whereas $p_0 = d_0 = 0$. A symmetric travel time t_{ij} is associated with each edge $(i, j) \in E$. Each vehicle starts and ends its tour at the depot (vertex 0), and can visit any subset of customers with a total demand that does not exceed the capacity Q. The profit of each customer can be collected by one vehicle at most. A subset of the potential customers available has to be selected, in order to maximize the total collected profit while satisfying, for each vehicle, a time limit T on the tour duration and the capacity constraint Q.

This problem is one of important transportation problem that can be faced by any organization besides the orienteering problem (OP), team orienteering problem (TOP), traveling salesman problem (TSP), and vehicle routing problem (VRP). All of these problems are concerned with the transportation of vehicle(s) to visit some customers. Regarding to the customers to be visited, the TSP and VRP are required all customers to be visited, while the OP, TOP, and CTOP are not need this requirement. Regarding to the number of vehicles, the OP and TSP are problems with single vehicle, while the TOP, CTOP, and VRP are problems with more than one vehicles. Regarding to the capacity of vehicle(s), the OP, TSP, and TOP are not including vehicle capacity as constraint, while the CTOP and VRP include vehicles capacity as their constraints. More detail reviews of these problems can be found in Guttin and Punnen (2002), Golden et al. (2008), and Vansteenwegen et al. (2011).

Similar with TOP, the CTOP is also an NP-hard problem, hence some exact and heuristics approaches had been proposed in the past for solving the CTOP. For solving the CTOP, Archetti et al. (2009) proposed an exact method, which is branch-and-price method, and three metaheuristics, which are variable neighborhood search, and two variations of tabu search: tabu feasible and tabu admissible. Tarantilis et al. (2013) proposed a heuristics called bi-level filter and fan method for solving the CTOP. They proposed slow and fast version of the method, based on the number of iterations used in the method.

Since PSO has been successfully applied for solving other problems that are related to CTOP, such as VRP (Ai and Kachitvichyanukul, 2009; Kuo et al., 2012; Tlili et al., 2013) and TOP (Dang et al., 2013; Ai et al., 2013), therefore, this paper tries to solve the CTOP by using a PSO algorithm. The rest of this paper is organized as follows: Section 2 describes the PSO for solving the CTOP. Section 3 presents the computational result, and the last section concludes the paper and gives suggestions for further research.

2. PROPOSED PSO ALGORITHM

Kennedy and Eberhart (1995) proposed the Particle Swarm Optimization (PSO), which is a population-based stochastic optimization technique, by mimicking the physical movement of individuals in the swarm as searching mechanism of optimal solution. In the PSO, the capability of solution searching is included in the properties of a group of particles, which are called position and velocity. A multi-dimensional-space particle position represents an alternative of problem solution. Velocity of particle is the driver of particle movement from one position to another. By moving to other position, another alternative of problem solution is evaluated.

For driving the movement of particles, PSO also imitates two important behaviors of the swarm organism, which are the cognitive behavior and the social behavior. The cognitive behavior is defined as the tendency of particle moving towards the best position ever visited by the particle, which is usually called personal best or pbest. While the social behavior is defined as the tendency of particle moving towards the best position ever visited by all particles in the swarm, which is usually called global best or gbest. The movement of particle in certain period of time is driven by three different directions that are: 1) follow its own way, 2) go towards its personal best position, and 3) go towards its global best position.

In general, the algorithm of PSO can be formally defined as follow:

1. initialization of particles, their position and initial velocity,
2. decode particles into problem solutions,
3. evaluate the quality of particles, based on their corresponding objective functions,
4. update pbest value,
5. update gbest value,
6. update velocity and position for each particle,
7. if the stopping criterion, i.e. maximum number of iteration, is reached, stop. Otherwise return to step 2.

Following this algorithm, the best problem solution is represented by the global best at the end of iteration. The details of PSO can be found in several textbooks, among others are Kennedy and Eberhart (2001) and Clerc (2006). In this research a variant of PSO called GLNPSO is used, including the computational library called ET-Lib (Nguyen et al., 2010). This algorithm, similar with other metaheuristics techniques, is actually independent from the problem being solved. In other word, this algorithm can be applied on various problem types. In the PSO methodology, we have to define specific particle representation and decoding method in order to apply PSO for solving specific problem. Particle representation is the definition on how the particle represents the problem, while decoding method is the definition on how the particle can be translated into problem solution. The following subsections define the solution representation and the decoding method for applying PSO for solving the CTOP.

2.1 Particle Representation

Based on Ai et al. (2013), particle with dimensions represents a CTOP solution with vertices, in which each particle's dimension corresponds to each vertex, i.e. dimension 1 represents vertex 1, dimension 2 represents vertex 2, and so on. Particle position is assigned to be a real number and represents a priority of vertex on the decoding method. The smaller the position of particle, the higher the priority of the corresponding vertex. Later on the decoding steps, each vertex is evaluated to be inserted into the solution paths based on its priority. Figure 1 illustrates a representation of CTOP with 7 vertices and its conversion process to priority of vertex.

dimension	1	2	3	4	5	6	7
position	0.52	2.69	1.03	0.15	1.94	3.17	1.29

sorted position	0.15	0.52	1.03	1.29	1.94	2.69	3.17
vertex no.	4	1	3	7	5	2	6
priority	1	2	3	4	5	6	7

Figure 1: Solution representation of CTOP with 7 vertices and its conversion process to priority of vertex.

2.2 Decoding Method 1

The first decoding method is a simple procedure, in which each vertex, one by one based on the priority of vertex, is evaluated to be inserted in the last sequence of each vehicle tour, starting from the first vehicle. If the insertion complies with tour duration and capacity constraints, then the vertex is placed on the sequence. Otherwise, the vertex is evaluated to be inserted to the subsequent tour. If the vertex cannot be inserted to any available tours, it implies that the vertex is decided not to be visited. Figure 2 illustrates tours construction following the first decoding method.

2.3 Decoding Method 2

The second decoding method requires more effort than the first one. Instead of evaluating insertion in the last sequence of each tour, this method is evaluating all possible sequence in each existing tour for inserting vertex, one by one based on the priority of vertex. At last, the vertex is being inserted into a sequence in certain tour that satisfies tour duration and vehicle capacity constraints and provides the smallest additional time. Additional time is defined as the difference between the tour duration before and after a vertex is inserted to the tour. Figure 3 illustrates tours construction following the second decoding method.

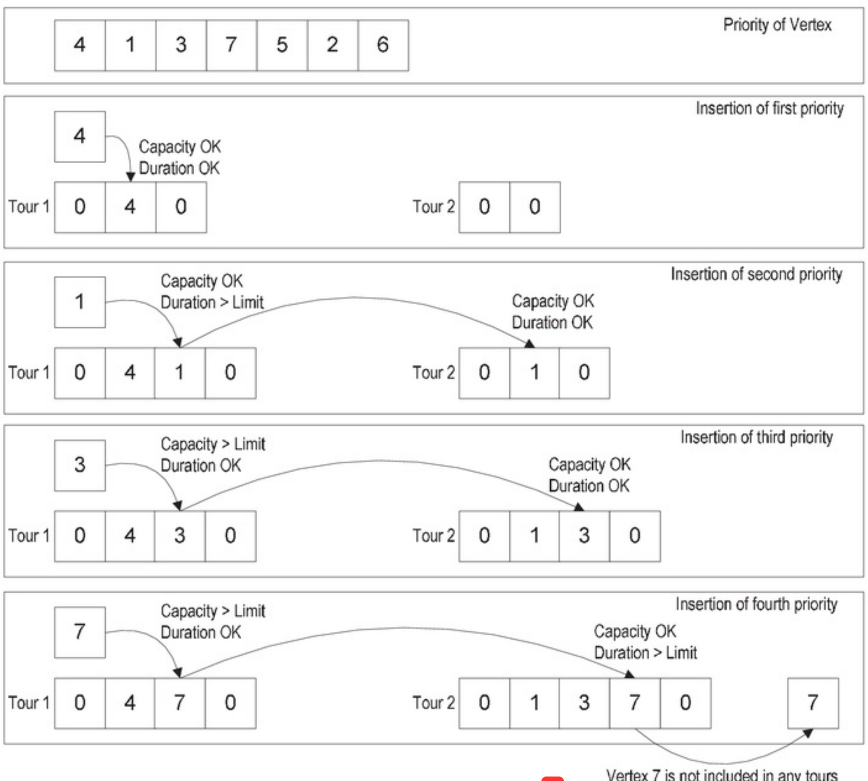

Figure 2: Illustration of tours construction in decoding method 1

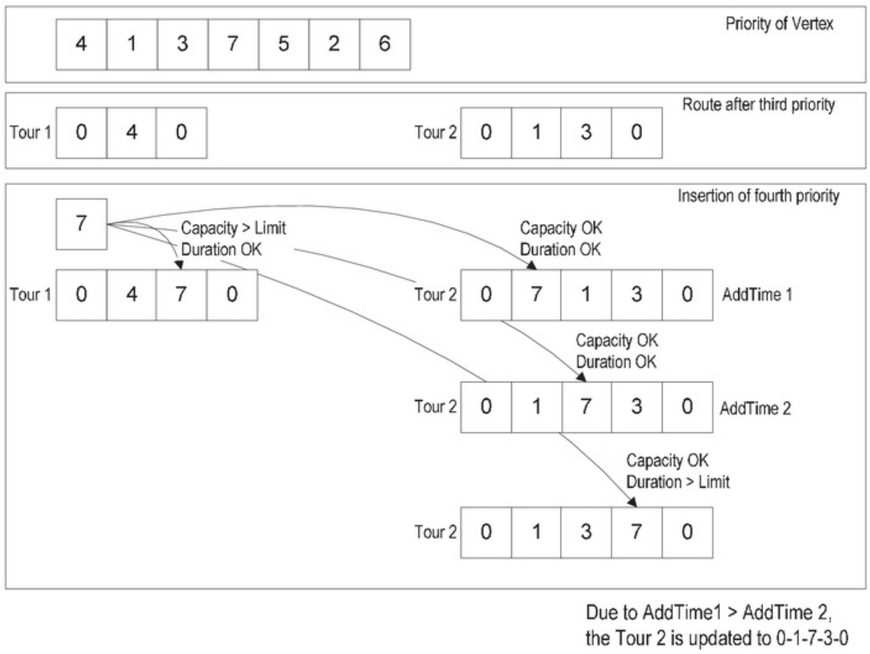

Figure 3: Illustration of tours construction in decoding method 2

3. COMPUTATIONAL EXPERIMENTS

The proposed PSO algorithm for CTOP is implemented using C# language assisted with a PSO computational library called ET-Lib (Nguyen et al., 2010). The ET-Lib uses a PSO variant called GLNPSO that has three different social behavior terms called global best, local best, and nearest neighbor best with its corresponding acceleration constant (c_g, c_l, and c_n), i.e. the movement of particle in this variant is following these equations:

$$\omega_{lh}(\tau+1)=w(\tau)\omega_{lh}(\tau)+c_p u\left(\psi_{lh}-\theta_{lh}(\tau)\right)+c_g u\left(\psi_{gh}-\theta_{lh}(\tau)\right)+c_l u\left(\psi^L_{lh}-\theta_{lh}(\tau)\right)+c_n u\left(\psi^N_{lh}-\theta_{lh}(\tau)\right) \tag{1}$$

$$\theta_{lh}(\tau+1)=\theta_{lh}(\tau)+\omega_{lh}(\tau+1) \tag{2}$$

where τ is iteration index, l is particle index, h is dimension index, u is uniform random number in interval [0,1], $w(\tau)$ is inertia weight in the iteration τ, ω_{lh} is velocity of particle l at the dimension h in the iteration τ, θ_{lh} is position of particle l at the dimension h in the iteration τ, ψ_{lh} is personal best position (pbest) of particle l at the dimension h, ψ_{gh} is global best position (gbest) at the dimension h, ψ^L_{lh} is local best position of particle l at the dimension h, and ψ^N_{lh} is nearest neighbor best position of particle l at the dimension h.

The computational experiments are conducted using Archetti et al. (2009) CTOP benchmark data set, which consists of three sets of problem. The first data set or called the original set, which originally taken from Christofides' VRP benchmark data set, consists of 10 problem instances. By modifying the number, capacity, and time limit of vehicles, the second data set are generated consist of 90 different problem instances. While the third data set is generated by modifying the number of vehicles only, which are 30 different problem instances are included in this data set. Therefore, 130 different problem instances are involved in the computational experiments.

A simple experimental design is applied here to select PSO parameters setting. We are varying the value of acceleration constants (c_p, c_g, c_l, and c_n) among the values of 0, 1, 2; number of particles (L) between the values of 30 and 50; and number of iteration (T) between the values 200 and 500. Using the problem case p09 in the original set to compare the statistical results in term of solution quality and computational time, we concluded that these settings are the best: c_p=1, c_g=1, c_l=1, and c_n=1, L=30, and T=500.

All the test instances are run on a computer with Intel Core 2 Duo @ 2.40 GHz CPU and 2 GB RAM. For each instance, 10 replications of the PSO algorithm runs are conducted.

An experiment is conducted to compare the performance of the Decoding Method 1 and Decoding Method 2 by applying both method for the original set. The best result of obtained from each decoding method are compared in Table 1. It is shown that the Decoding Method 2 is able to find better (higher) profit for four instances (p09, p10, p15, and p16) than Decoding Method 1. While both methods are resulting the same profit for the other instances. It is implied that the Decoding Method 2 is better than Decoding Method 1. Therefore, only the Decoding Method 2 is applied in the subsequent computational experiments.

Table 1: Comparison of profit obtained by each decoding method on original set

Problem Instance					**Profit**	
No.	***n***	***m***	***Q***	***T***	**DM 1**	**DM 2**
p03	101	15	200	200	1409	1409
p06	51	10	160	200	761	761
p07	76	20	140	160	1327	1327
p08	101	15	200	230	1409	1409
p09	151	10	200	200	1674	*2058*
p10	200	20	200	200	2890	*3048*
p13	121	15	200	720	1287	1287
p14	101	10	200	1040	1710	1710
p15	151	15	200	200	2035	*2129*
p16	200	15	200	200	2920	*3070*

Table 2 presents the comparison of the Decoding Method 2 results with the Branch & Price of Archetti et al. (2009) over the original set. All the profit obtained by each methods are presented under the *P* column. The BK column shows the best known solution of each corresponding instances obtained by any other methods, after Archetti et al. (2009). The CPU column shows the computational time of each method in seconds. In the Branch & Price results, the sign '–' indicates that the computational time is exceeded 3600 seconds and the algorithm is terminated at that time limit. The percentage deviation of a method (*P*) from its correspondence best known solution (P_{BKS}), which is indicated as %*D*, is calculated by following equation:

$$\%D = \frac{P_{BKS} - P}{P_{BKS}} \times 100\% \qquad (3)$$

Table 2: Comparison of profit obtained by each decoding method on original set

	BK	**Branch & Price**			**PSO with DM 2**		
No.	***P***	***P***	**CPU**	**%*D***	***P***	**CPU**	**%*D***
p03	1409	1409	41	0	1409	5.89	0
p06	761	761	2	0	761	1.84	0
p07	1327	1327	2	0	1327	3.67	0
p08	1409	1409	17	0	1409	5.23	0
p09	2064	1164	–	43.6	2058	7.96	0.29
p10	3048	1735	–	43.08	3048	13.3	0
p13	1287	1287	21	0	1287	5.98	0
p14	1710	1710	1082	0	1710	3.84	0
p15	2159	2159	1866	0	2129	9.25	1.39
p16	2968	588	–	80.19	3070	13.5	-3.44
Average	1355			16.69	1821		-0.18

It is shown in Table 2 from the %*D* column for PSO that there are one negative value, 7 zero values, and 2 positive values. Negative value of %*D* indicates that the PSO result is outperformed existing best known solution, zero value of %*D* indicates that the PSO result is similar with existing best known solution, and positive value of %*D* indicates that the PSO result is worse than existing best known solution. To have a single criteria for comparison, the average of %*D* is also calculated. Based on this criteria, we can easily conclude that the PSO with DM 2 is able to provide better result than Branch & Price method.

The results of PSO with DM 2 over three data set are summarized in Table 3. It is shown that PSO is able to solve CTOP with results that are very close to the existing best known solution, i.e. the average percentage deviation for all data set is less than 1%. The proposed PSO is also able to provide 47 among 130 solution of instances that are similar with its corresponding best known solution. In addition, the PSO is able to result one solution of instance, which is p16 in the original set, outperforming its existing best known solution.

Table 3: Summary of PSO results

Data Set	Original	Second	Third
Average %*D*	-0.18	0.60	0.73
Average CPU (s)	7.04	3.98	8.32
%*D* = 0	7	37	3
%D < 0	1	0	0

4. CONCLUDING REMARK

This paper is successfully presented that PSO is also able to solve the CTOP, especially using proposed Decoding Method 2. The computational results show that the proposed PSO algorithm is able to obtain 47 best known solutions of 130 benchmark problems and to improve 1 best known solution, while in average the percentage deviation for all data set is less than 1%.

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