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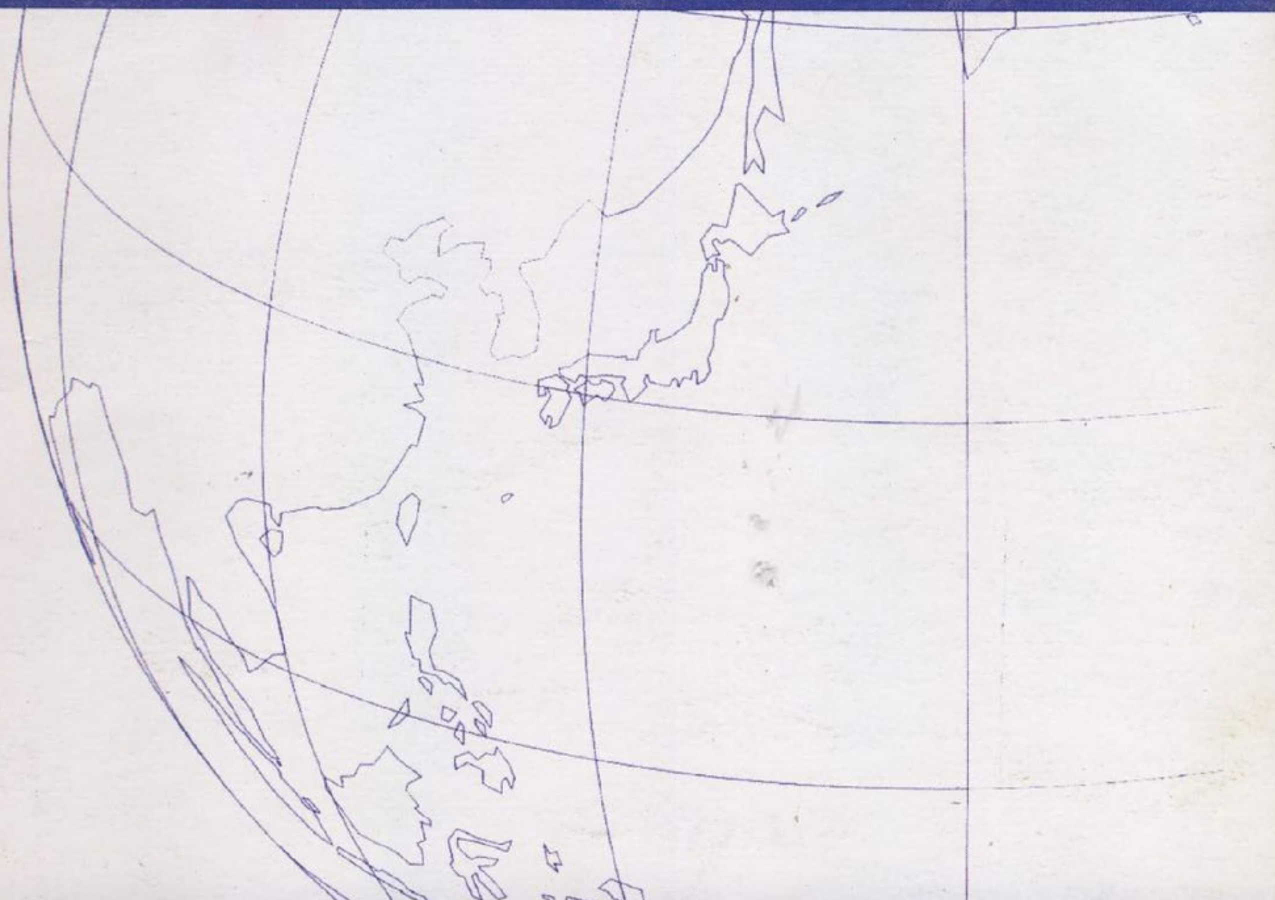

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CONTENTS

A Particle Swarm Optimization for the Heterogeneous Fleet Vehicle Routing Problem

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Abstract

This paper presents an application of particle swarm optimization (PSO) for solving the heterogeneous fleet vehicle routing problem (HVRP). HVRP is a vehicle routing problem (VRP) variant that takes different types of vehicle into consideration. Based on the number of vehicles in each type, there are two types of HVRP in the literature: the vehicle fleet mix problem (VFM) that deals with unlimited number of vehicles and the fixed fleet version of HVRP that deals with fixed number of vehicles. This paper focus only on the latter since normally the number available vehicle is known in advance in the actual operations. A PSO algorithm, solution representations and decoding methods that have been successfully applied to the basic variant of VRP are re-utilized as the basic solution technique. In order to acquire the nature of heterogeneous type of vehicles into the technique, a special preprocessing method is incorporated to the vehicle list, so that a vehicle with lower relative routing cost is given higher priority over the bigger one. The proposed algorithm is tested using benchmark data set and the computational result shows that the proposed method is competitive with other published results for solving HVRP.

Keywords: Vehicle Routing Problem, Heterogeneous Fleet, Particle Swarm Optimization, Meta-heuristics

1. Introduction

The Heterogeneous Fleet Vehicle Routing Problem (HVRP) extends the Capacitated Vehicle Routing Problem (CVRP) by relaxing condition on vehicle characteristics. While in CVRP all vehicles are identical, in HVRP the vehicles may differ from one another as they may have different capacity, cost, and other characteristics. In the literature, the HVRP is defined as follows [1]. Let $G = (V, A)$ be a graph where $V = \{v_0, v_1, \ldots, v_n\}$ is the vertex set and $A = \{(v_i, v_j) | v_i, v_j \in V, i \neq j\}$ is the arc set. Vertex v_0 represents a depot with a fleet of vehicles, while the remaining vertices correspond to customers. Each customer v_i has a non-negative demand q_i. There are several vehicle types, in which vehicle of type k is characterized by its fixed cost f_k, variable cost per distance unit g_k, and capacity Q_k. For each vehicle type k, m_k vehicles are available. With each arc (v_i, v_j), there is an associated distance d_{ij}. The HVRP consists of designing a set of vehicle routes in such way that: (1) each route starts and ends at the depot, (2) each customer is visited exactly once, (3) the total demand of a route does not exceed the capacity of the vehicle assigned to it, and (4) the total routing cost is minimized.

As defined above, the HVRP is dealing with many types of vehicles. With regard to the number of vehicle type k (m_k), there are two types of problem in the literature. The first problem deals with unlimited number of m_k, which is usually called vehicle fleet mix problem or the VFM, and the second problem deals with fixed and limited m_k, which is called the fixed fleet version of HVRP [2]. This paper only focuses on the latter, since normally the number of available vehicles is known in advance in the actual operations.

Some research works that have dealt with the HVRP mainly proposed solution methodology for solving it. Taillard [2] proposed a method for solving the HVRP called heuristic column generation (HCG), which is a hybrid technique of tabu search with linear programming. Variants of simulated annealing algorithm which are called list-based threshold accepting (LBTA) algorithm [3] and backtracking adaptive threshold accepting (BATA) algorithm [1] have been proposed for solving the HVRP. Li *et al.* [4] also proposed another variant of simulated annealing which is called record-to-record travel (HRTR) algorithm for solving the HVRP. From the computational results of those methods over the benchmark data set of Taillard [2], it can be concluded that the HRTR method is able to provide better solution quality among others.

Recently, particle swarm optimization (PSO), which is an emerging evolutionary computing method, has been successfully applied for solving the CVRP [5, 6] and the vehicle routing problem with simultaneous pickup and delivery – VRPSPD [7]. It is noted that these VRP variants only cope with identical type of vehicles. Therefore, this paper attempts to extend these algorithms to take different type of vehicles into consideration, i.e., to solve HVRP. The same PSO framework and solution representation as previously published will be used; however, an additional procedure is developed in order to deal with heterogeneous fleet of vehicles.

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The remainder of this paper is organized as follow: Section 2 describes the proposed solution methodology: the PSO algorithm and the solution representation are briefly reviewed, and the additional procedure to deal with heterogeneous fleet of vehicles is explained. Section 3 presents the computational results of the proposed method on the benchmark data set. Finally, Section 4 concludes the work presented in this paper and recommends further direction on this work.

2. The Proposed Solution Methodology

2.1 PSO Algorithm

PSO is a population based search method which imitates the physical movements of the individuals in the swarm as a searching method. In the PSO, the best solution of a specific problem is sought after by a swarm of particles that act as a searching agent. A multi-dimensional particle position is representing a problem solution and a velocity vector is representing the searching ability of the particle. Each PSO iteration step consists of the movement of every particle in the swarm from one position to the next based on the velocity. Moving from one position to another, a particle is evaluating different prospective solution of the problem. In imitating the cognitive and social behavior of the swarm, the PSO mechanism also maintains the information about the personal best position of each particle, which is defined as the position that gives the best objective function among the positions that have been visited by the particle, and the global best position, which is the best among all personal best. These personal best and global best position are used for updating particle velocity. More information on PSO mechanism, technique, and application is provided by Kennedy and Eberhart [8] and also Clerc [9].

In earlier works of Ai and Kachitvichyanukul [5–7], a PSO framework for solving VRP had been proposed based on the GLNPSO, a PSO Algorithm with multiple social learning structures [10]. This PSO version also incorporates the local best, which is the best position among several adjacent particles, and the near neighbor best, which is a social learning behavior concept proposed by Veeramachaneni *et al.* [11], besides the global best as components for social learning behavior. The PSO framework is briefly reviewed in Algorithm 1. It is noted that the problem specific steps are located in Step 2.a and 2.b. Therefore, it is also possible to use this framework for solving HVRP.

Algorithm 1: PSO Framework for VRP

Step 1. *Initialization*

a. Generate particles as member of the swarm.
b. Set the initial position and velocity of each particle.

Step 2. *Iteration Process*

a. Decode each particle position to a set of vehicle routes (see Section 2.2).
b. Evaluate the performance of each set of vehicle routes and set the performance value as the fitness value of the corresponding particle.
c. Update personal best, global best, local best and near neighbor best values.
d. Update the velocity and position of each particle based on the updated values.

Step 3. *Stopping*

Stop if the stopping criterion is met, otherwise repeat Step 2.

In this framework, L particles are initialized in st ep 1.a in which each particle dimension is randomly g enerated between a minimum and a maximum value. The initial velocity vector is zero vectors for all partic les. In the iteration process, following equations are u sed to update the velocity and position of each positio n:

$$\begin{aligned}\omega_{lh}(\tau+1) = w(\tau)\omega_{lh}(\tau) + c_p u\left(\psi_{lh} - \theta_{lh}(\tau)\right) \\ + c_g u\left(\psi_{gh} - \theta_{lh}(\tau)\right) \\ + c_l u\left(\psi_{lh}^{L} - \theta_{lh}(\tau)\right) \\ + c_n u\left(\psi_{lh}^{N} - \theta_{lh}(\tau)\right)\end{aligned} \tag{1}$$

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

where:

$\omega_{lh}(\tau)$	:	Velocity of the l^{th} particle at the h^{th} dimension in the τ^{th} iteration
$\theta_{lh}(\tau)$	:	Position of the l^{th} particle at the h^{th} dimension in the τ^{th} iteration
$w(\tau)$	:	Inertia weight in the τ^{th} iteration
ψ_{lh}	:	Personal best position (pbest) of the l^{th} particle at the h^{th} dimension
ψ_{gh}	:	Global best position (gbest) at the h^{th} dimension
ψ_{lh}^{L}	:	Local best position (lbest) of the l^{th} particle at the h^{th} dimension
ψ_{lh}^{N}	:	Near neighbor best position (nbest) of the l^{th} particle at the h^{th} dimension
c_p	:	The acceleration constant for personal best position
c_g	:	The acceleration constant for global best position
c_l	:	The acceleration constant for local best position
c_n	:	The acceleration constant for near neighbor best position
u	:	Uniform random number in the interval $[0,1]$

2.2 Solution Representation

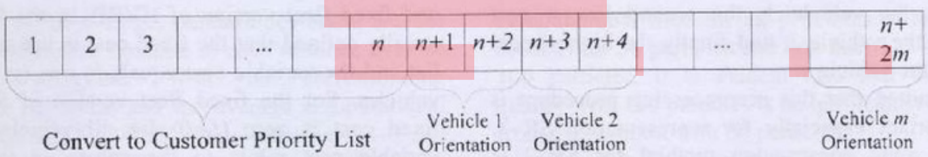

Figure 1: Solution Representation SR–1

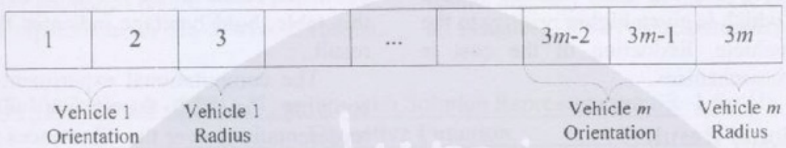

Figure 2: Solution Representation SR–2

Two solution representations had been proposed in previous works of Ai and Kachitvichyanukul [5–7], which are called solution representation SR–1 and SR–2. For representing VRP with n customers and m vehicles, the representation SR–1 is using particle with (n+2m) dimensions and the representation SR–2 is using 3m dimensions.

In brief, both representation SR–1 and SR–2 are using real number in each dimension. In the representation SR–1, the first n dimensions represent priorities of customers and the other 2m dimensions represent the orientation point of vehicles (Figure 1). While in the representation SR–2, 2m dimensions represent the orientation point of vehicles and another m dimensions represent the coverage radius of vehicles (Figure 2).

In the PSO application for VRP, a specific decoding method must be defined to transform a particle with specific representation into vehicle routes. For representation SR–1, the decoding method starts with creating a priority list of customers based on the first n dimensions of a particle. The priority list is constructed by sorting in ascending order the position values and taking the dimension index as the list. The priority matrix of vehicle is then created based on the last 2m dimensions that are used as the route orientation point of vehicles, in which a customer is prioritized to be served by vehicle with closer distance between customer location and the vehicle route orientation. Finally, the vehicle routes are constructed based on the customer priority list and vehicle priority matrix. One by one, each customer in the customer priority list is assigned to a vehicle based on its priority and such problem constraints as vehicle capacity constraint and service duration constraint. This newly assigned customer is inserted to the best position in the existing vehicle route based on the least additional cost. Another effort to improve solution quality of the route is to re-optimize the emerging route using local improvement procedure, i.e. 2-opt.

The decoding method for solution representation SR–2 is slightly different with SR–1. It starts by transforming a particle into the vehicle orientation points and the vehicle coverage radius. The vehicle routes are then constructed based on these points and radius. For each vehicle, starting from the first to the last vehicle, a feasible route is constructed by including customers that are located within the coverage radius and are not yet assigned to other vehicle. Afterward, local improvement procedures, such as 2-opt, 1-1 exchange, and 1-0 exchange, are applied to the constructed routes. If there are remaining customers that have not been assigned to any vehicle, the customers are inserted one by one to the existing routes as long as the route feasibility is maintained. Finally, the local improvement procedures are re-applied to all of the routes.

It is noted that the differences among VRP variants are in the problem constraints. Therefore, both representations SR–1 and SR–2 can deal with the HVRP. Slight modification is needed in the route construction steps to form feasible routes that did not violate the problem constraints. To be more specific, the HVRP has the same problem constraints as the CVRP, however, different vehicles may have different capacity and duration limit for the HVRP.

2.3 Preprocessing Vehicle List

In the HVRP, different vehicles may have differe nt fixed and variable cost. This characteristic is not pr esent in the CVRP case where all vehicles are identic al. To deal with different cost scheme among vehicles , an additional procedure is proposed here to preproce ss the vehicle list based on a cost parameter ς_k, that i s calculated using following formula:

$$\varsigma_k = \frac{f_k}{0.5 \cdot D_k} + g_k \tag{3}$$

An ideal formula is to use the expected travel distance of vehicle as the denominator of fixed cost. However, it is difficult to estimate the expected travel distance so half of the time duration limit is set as the denominator. A vehicle with lower cost parameter will be preferred over one with higher cost, so that the routing cost will be reduced. In the solution representation SR–1 and SR–2, the result of this procedure is implemented by setting the lowest cost vehicle as the vehicle 1, the second lowest cost vehicle as the vehicle 2, and finally the highest cost vehicle as the vehicle m.

It is noted that this preprocessing procedure is very important especially for representation SR–2, since the route construction method for SR–2 is mainly based on the vehicle list. Therefore, the route is firstly constructed for the first vehicle in the preprocessed list, which is given higher priority to the least expensive vehicle. Reduction of the cost is expected from this mechanism.

3. Computational Result

A common benchmark data set for the HVRP for both VFM and fixed fleet version of HVRP is the data set of Taillard (1999), which is originally from Golden et al. [12]. This benchmark data set consists of 8 instances, with the number of customers varies from 50 to 100 customers and the number of vehicle types varies from 3 to 6. The positions of depot and customers are given in Cartesian coordinate map and the distances among them are defined as Euclidean distance. The specification of this benchmark data set is presented in Table 1. Although fixed and variable costs are clearly defined in this benchmark data set, both values are not used simultaneously for the VFM and fixed fleet version of HVRP. In the VFM, it is usually defined that the fixed cost is the same as the list and the variable cost equals to one (g_k=1) for all vehicles. For the fixed fleet version of HVRP, the fixed cost is zero (f_k=0) for all vehicles and the variable cost refers to the values in the list. In addition to this information, comparison of the published result on the HVRP is listed on Table 2. In this table, bold typeface indicates the best published result.

The computational experiment is conducted by applying the PSO framework with both solution representations over the 8 instances data set available for the HVRP. The PSO Algorithm is implemented using C# language on Microsoft.NET Framework version 1.1 and run on a PC with Intel P4 3.4 GHz processor and 1 GB of RAM. For comparison purpose, the same PSO parameters are incorporated for both representations: number of iteration 1000, number of neighbor 5, first inertia weight 0.9, last inertia weight 0.4, personal best position acceleration constant 1, global best position acceleration constant 0, local best position acceleration constant 1, and near neighbor best position acceleration constant 2.

The experiment is conducted on the PSO Algorithm with 50 and 100 particles. Table 3 and 4 shows the computational experiment result,

Table 1: Specification of the HVRP Benchmark Data Set [2]

Prob. No.	No. of Cust.	Vhcl. Type	Q	f	g	m
13	50	A	20	20	1.0	4
		B	30	35	1.1	2
		C	40	50	1.2	4
		D	70	120	1.7	4
		E	120	225	2.5	2
		F	200	400	3.2	1
14	50	A	120	1000	1.0	4
		B	160	1500	1.1	2
		C	300	3500	1.4	1
15	50	A	50	100	1.0	4
		B	100	250	1.6	3
		C	160	450	2.0	2
16	50	A	40	100	1.0	2
		B	80	200	1.6	4
		C	140	400	2.1	3

Prob. No.	No. of Cust.	Vhcl. Type	Q	f	g	m
17	75	A	50	25	1.0	4
		B	120	80	1.2	4
		C	200	150	1.5	2
		D	350	320	1.8	1
18	75	A	20	10	1.0	4
		B	50	35	1.3	4
		C	100	100	1.9	2
		D	150	180	2.4	2
		E	250	400	2.9	1
		F	400	800	3.2	1
19	100	A	100	500	1.0	4
		B	200	1200	1.4	3
		C	300	2100	1.7	3
20	100	A	60	100	1.0	6
		B	140	300	1.7	4
		C	200	500	2.0	3

Table 2: Comparison of the Published Result on HVRP

Instance	HCG [2]		LBTA [3]		BATA [1]		HRTR [4]	
	Objective	Time (s)	Objective	Time (s)	Objective	Time (s)	Objective	Time (s)
13	1518.05	473	1519.96	110	1519.96	843	**1517.84**	358
14	615.64	575	612.51	51	611.39	387	607.53	141
15	1016.86	335	1017.94	94	**1015.29**	368	**1015.29**	166
16	1154.05	350	1148.19	11	1145.52	341	**1144.94**	188
17	1071.79	2245	1071.67	221	1071.01	363	**1061.96**	216
18	1870.16	2876	1852.13	310	1846.35	971	**1823.58**	366
19	**1117.51**	5833	1125.64	309	1123.83	428	1120.34	404
20	1559.77	3402	1558.56	675	1556.35	1156	**1534.17**	447
Computer Specification	Sun Sparc workstation, 50 Mhz		Pentium III 550Mhz 128MB RAM		Pentium II 400Mhz 128MB RAM		Athlon 1Ghz 256MB RAM	

comprises of the average, standard deviation, and the minimum objective function of each instance over 10 iterations, altogether with its corresponding percentage deviation and the average computational time (in second) for solution representation SR–1 and SR–2, respectively. The percentage deviation is calculated as the ratio between the deviation of the result from the best published result.

For solution representation SR–1, overall results computational time for all problems is less than 74 seconds for 50 particles and less than 172 seconds for 100 particles. It is evident also that the solution quality with 100 particles is insignificantly better than from the solution with 50 particles.

Result for solution representation SR–2 is better than solution representation SR–1 result, in which the results are very close to the best known solution. For all instances, the average percentage deviation is less

Table 3: Result of PSO Algorithm with Solution Representation SR–1 for HVRP

Instance	Objective Function					Comp Time (s)
	Average	Average % Dev	Standard Deviation	Minimum	Minimum % Dev	
50 particles						
13	1743.16	14.84%	37.18	1694.17	11.62%	36
14	661.32	8.85%	17.25	640.90	5.49%	23
15	1072.13	5.60%	15.16	1054.13	3.83%	25
16	1200.69	4.87%	21.19	1170.82	2.26%	24
17	1148.72	8.17%	11.29	1127.66	6.19%	48
18	1988.60	9.05%	29.16	1937.73	6.26%	59
19	1203.62	7.71%	9.59	1191.04	6.58%	74
20	1712.00	11.59%	21.94	1672.87	9.04%	69
100 particles						
13	1744.84	14.96%	44.31	1660.20	9.38%	91
14	661.53	8.89%	15.10	641.91	5.66%	59
15	1067.03	5.10%	13.34	1045.53	2.98%	63
16	1204.62	5.21%	20.27	1171.63	2.33%	63
17	1152.29	8.51%	12.63	1137.72	7.13%	117
18	1973.98	8.25%	22.05	1944.36	6.62%	140
19	1194.69	6.91%	10.92	1168.62	4.57%	172
20	1683.80	9.75%	25.34	1640.24	6.91%	167

Table 4: Result of PSO Algorithm with Solution Representation SR–2 for HVRP

Instance	Objective Function					Comp Time (s)
	Average	Average % Dev	Standard Deviation	Minimum	Minimum % Dev	
50 particles						
13	1593.17	4.96%	16.22	1578.91	4.02%	48
14	614.66	1.17%	4.14	609.17	0.27%	28
15	1031.06	1.55%	7.50	1019.11	0.38%	32
16	1152.84	0.69%	4.36	1148.62	0.32%	31
17	1086.82	2.34%	12.60	1066.44	0.42%	70
18	1886.38	3.44%	24.46	1840.82	0.95%	85
19	1150.39	2.94%	9.46	1135.97	1.65%	104
20	1589.25	3.59%	17.03	1561.29	1.77%	115
100 particles						
13	1586.11	4.50%	14.80	1561.21	2.86%	107
14	613.29	0.95%	4.10	609.17	0.27%	58
15	1025.19	0.98%	4.56	1019.27	0.39%	66
16	1152.84	0.69%	3.82	1148.41	0.30%	66
17	1078.18	1.53%	7.83	1069.52	0.71%	143
18	1869.81	2.54%	13.18	1852.36	1.58%	175
19	1148.24	2.75%	10.25	1131.32	1.24%	206
20	1578.09	2.86%	9.58	1561.80	1.80%	233

are as follow: the average percentage deviation is less than 15%, standard deviation is less than 45, and the than 4%, standard deviation is less than 25, and the computational time for all problems is less than 115 seconds for 50 particles and less than 233 seconds for 100 particles. It is also shown that the solution quality with 100 particles is not significantly better than solution with 50 particles. Therefore, it can be concluded that the best combination of solution representation and number of particle is the SR–2 with 50 particles, since it is able to provide reasonable high quality solution in reasonable computational time.

4. Conclusion and Recommendation

This paper presents the application of Particle Swarm Optimization (PSO) for solving the Heterogeneous Fleet Vehicle Routing Problem (HVRP) by slightly modified an existing PSO application for CVRP. The computational results show that the proposed PSO with both representations SR–1 and SR–2 are effective for solving the HVRP in term of both solution quality and computational time. In term of solution quality, it is shown that the proposed PSO framework with representation SR–2 is better than the framework with representation SR–1. However, the representation SR–2 required more computational effort than the representation SR–1. In addition, the recommended combination of solution representation and number of particle that can be concluded from the computational results is the SR–2 with 50 particles.

Further researches are still possible to improve the result gained in this paper in two directions: improving solution quality and reducing computational time. Solution quality may be enhanced from the implementation of different improvement procedure in the route construction step or incorporating any other ideas in the whole decoding method, and also from the optimization of PSO parameters setting. The computational steps can also be further optimized to reduce the computational time.

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Paper 09 IJLSCM PSO for HVRP

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