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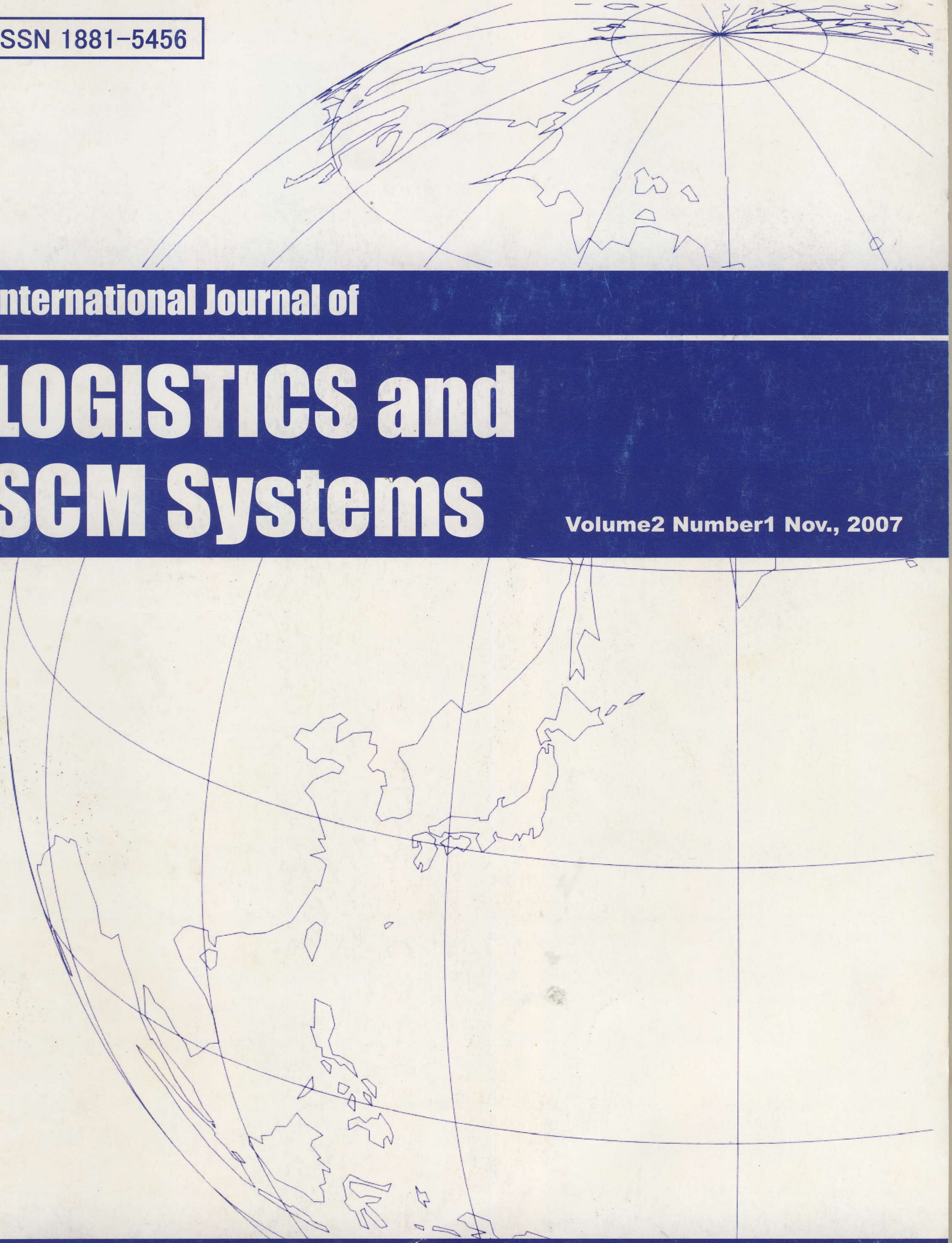

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CONTENTS

A Particle Swarm Optimization for the Capacitated Vehicle Routing Problem

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Abstract

This paper proposed a random-key based solution representation and decoding method for solving the Capacitated Vehicle Routing Problem (CVRP) using Particle Swarm Optimization (PSO). The solution representation is $(n+2m)$-dimensional particle for CVRP with n customers and m vehicles. The decoding method starts with transforming the particle to a priority list of customer to enter route and priority matrix of vehicle to serve each customer. The vehicle routes are constructed based on the customer priority list and vehicle priority matrix. The proposed representation is applied using GLNPSO, a PSO algorithm with multiple social learning structures. The proposed algorithm is tested using the benchmark data set provided by Christofides. The computational result shows that this representation and decoding method is promising to be applied for CVRP.

Keywords: Capacitated Vehicle Routing Problem, Particle Swarm Optimization, Random Key Representation, Decoding Method

1. Introduction

The Capacitated Vehicle Routing Problem (CVRP), which was firstly introduced by Danzig and Ramser [1], is a problem to design a set of vehicle routes in which a fixed fleet of delivery vehicles of uniform capacity must service known customer demands for a single commodity from a common depot at minimum cost. In the literature [2]–[4], CVRP can be formally defined as follows. Let $G=(V,A)$ be a graph where $V=\{v_0,v_1,\ldots,v_n\}$ is a vertex set, and $A=\{(v_i,v_j)|v_i,v_j\in V, i\neq j\}$ is an arc set. Vertex v_0 represents a depot, while the remaining vertices correspond to customers. Associated with A are a cost or distance matrix (d_{ij}) and a travel time matrix (t_{ij}). Each customer has a non-negative demand q_i and a service time s_i. A fleet of m identical vehicles of capacity Q is based at the depot. The number of vehicles is either known in advance or treated as a decision variable. The CVRP consists of designing a set of at most m delivery or collection routes such that (1) each route starts and ends at the depot, (2) each customer is visited exactly once by exactly one vehicle, (3) the total demand of each route does not exceed Q, (4) the total duration of each route (including travel and service times) does not exceed a preset limit D, and (5) the total routing cost is minimized.

CVRP is an NP-hard problem, which means that any optimization algorithm for their solution has worst case running time which is likely to grow exponentially with problem size [5]. In other words, there is a high possibility that an optimal solution of a large VRP problem may only be found with excessively long solution time. To overcome this situation, evolutionary computing methods have been used to find a near optimal solution in a reasonable amount of time, for example: Genetic Algorithm [6]–[7], Ant Colony Optimization [8]–[9], and Particle Swarm Optimization [10].

Particle Swarm Optimization (PSO) is a population based search method proposed by Kennedy and Eberhart [11], which were motivated by the group organism behavior such as bee swarm, fish school, and bird flock. PSO imitated the physical movements of the individuals in the swarm as a searching method, altogether with its cognitive and social behavior as local and global exploration abilities. In the PSO, a solution of a specific problem is being represented by n-dimensional position of a particle. The ability of particles to search for solution is represented by means of velocity vector. The PSO algorithm starts with population of particles with random initial position and velocity. The population of particles is usually called a swarm. In one iteration step, every particle is moved from previous position to the new position based on its velocity; and its velocity is updated based on its personal best position and the global best position obtained so far. Once a particle reach a position which has a better objective function than the previous best objective function for this particle, the personal best position is updated. Also, if it found better objective function than the previous best objective function for whole swarm, the global best position is updated. A brief and complete survey on PSO mechanism, technique, and application is provided by Kennedy & Eberhart [12] and also Clerc [13].

It is obviously seen that the PSO works on

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finding the best position and the position is represented by real number. To make PSO applicable to specific problem; the relationship between the position of particles and the solutions of that problem must be clearly defined. In CVRP case, the particle's position represents the vehicle route. This paper proposed a specific solution representation and its decoding method to relate position in PSO with CVRP solution. The proposed representation is different from representation of Chen *et al.* [10] in two aspects. First, the proposed representation is designed for the classic variant of PSO, i.e. directly using real value of position, instead of the discrete version. Second, the proposed representation is implemented in a pure PSO without any local search or other hybrid method.

The remainder of this paper is organized as follow: Section 2 explains the proposed solution representation and decoding method. Section 3 reviews PSO framework for solving CVRP. Section 4 discusses the computational experiment of PSO that applied the proposed solution representation on benchmark data set. Finally, Section 5 discusses the result of this study and suggests further improvement of proposed algorithm.

2. Proposed Solution Representation and Decoding Method

In PSO, a problem specific solution is represented by position of particle in multi-dimensional space. The proposed solution representation of CVRP with n customers and m vehicles consists of $(n+2m)$ dimensional particle. Each particle dimension is encoded as a real number. The first n dimension is related to customers, each customer will be represented by one dimension. The last $2m$ dimension is related to vehicles, each vehicle will be represented by two dimensions as the reference point in Cartesian diagram/map.

In order to decode this solution representation into the CVRP solution, three steps are taken. First, extract the information from the first n dimension to make a priority list of customers. Second, extract the information from the last $2m$ dimension to set the reference point of vehicles and use this information to create priority matrix of vehicles. Third, construct the vehicle routes based on the customer priority list and vehicle priority matrix.

For illustration, consider CVRP problem with 6 customers and 2 vehicles. A particle representation for the solution of this problem will consist of $(6+2.2) = 10$ dimensions. The first six dimensions are related to the customers and the four remaining are related to the vehicles. Suppose a particle has certain positional values as describe below in part (a) of Figure 1 The decoding process of this particle begins by constructing a priority list of customers by sorting in ascending order the position value and taking the dimension index as the list.

The next step is extracting the reference point

Dimension (d)	1	2	3	4	5	6	7	8	9	10
Value(x_{id})	0.4	0.2	0.9	0.5	0.6	0.1	0.8	1.5	0.4	1.0
	Customers						Vehicles			

(a) Particle position

d	6	2	1	4	5	3
x_{id}	0.1	0.2	0.4	0.5	0.6	0.9
Customer Priority List	6	2	1	4	5	3

(b) First Step: Customer Priority List

Vehicle Reference Points

Vehicle 1	(0.8, 0.4)
Vehicle 2	(1.5, 1.0)

Customer	Relative Distance		Vehicle Priority	
	Vehicle 1	Vehicle 2	Priority 1	Priority 2
1	0.66	0.26	2	1
2	0.70	0.40	2	1
3	0.13	1.05	1	2
4	0.21	0.84	1	2
5	0.35	0.59	1	2
6	0.35	1.08	1	2

(c) Second Step: Vehicle Priority Matrix

Vehicle Routes

Vehicle 1	0	6	3	4	5	0
Vehicle 2	0	2	1	0		

(d) Third Step: Vehicle Route

Figure 1: Conversion Process of Solution Representation to Vehicle Routes

for vehicles; In this case, the 7^{th} and 9th dimension of the particle will be the reference point of Vehicle 1 and the 8^{th} and 10^{th} dimension of the particle will be the reference point of Vehicle 2. The priority matrix of vehicles is constructed based on the relative distance between these points and customers location. The distance could be calculated in every case of CVRP, since the location of customer is usually placed in a Cartesian map. A customer is prioritized to be served by vehicle which has closer distance. For example, the vehicle priority of customer 1 is vehicle 1 then vehicle 2, since customer 1 location is closer to the vehicle 2 reference point than to vehicle 1. This conversion result is illustrated in the part (b) of Figure 1.

The last decoding step is to construct a route based on the customer priority list and the vehicle priority matrix. One by one each customer in the customer priority list is assigned to a vehicle based on its priority, vehicle capacity constraint, and route time constraint. This newly assigned customer is inserted to the best sequence in the existing vehicle route based on the least additional cost or distance. This heuristic is usually called the cheapest insertion heuristic. In the illustration in Figure 1: customer 6 is assigned to vehicle 1, customer 2 to vehicle 2, customer 1 to vehicle 2, customer 4 to vehicle 1, customer 5 to vehicle 1, and customer 3 to vehicle 1. Hence, the final vehicle route is displayed in the bottom part of Figure 1. In this figure, '0' represents the depot. Note that the cheapest insertion heuristic may make the customer sequence in the route different from the order of customer assignment, for example: customer 3, which is the last assigned customer, appeared in the middle of the route because of this heuristic. The process and final result of this example are illustrated in Figure 2. The details of this decoding procedure are described in Algorithm 1.

Algorithm 1: Decoding Method

Decode from Particle Position (x_{id} – position of the i^{th} particle at the d^{th} dimension) into Vehicle Route (R_{ij} – route of the j^{th} vehicle corresponding to the i^{th} particle)

```
1. Construct the priority list of customers ($U$)
   a. Build set $S = \{1,2,...,n\}$ and $U = \varnothing$
   b. Select $c$ from set $S$ where $x_{ic} = \min(x_{id}), d \in S$
   c. Add $c$ to the last position in set $U$.
   d. Remove $c$ from set $S$.
   e. Repeat step 1.b. until $S = \varnothing$
2. Construct the vehicle priority matrix ($V$)
   a. Set the vehicle reference position. For $j$=1…$m$, set $xref_j = x_{i,n+j}$ and $yref_j = x_{i,n+m+j}$
   b. For each customer $i$, $i$=1…$n$
      i. Calculate the distance between customer $i$ and vehicle reference points using following formula
         $\delta_j = \sqrt{\left(xpos_i - xref_j\right)^2 + \left(ypos_i - yref_j\right)^2}$
      ii. Build set $S = \{1,2,...,m\}$ and $V_i = \varnothing$
      iii. Select $c$ from set $S$ where $\delta_c = \min(\delta_d)$, $d \in S$
      iv. Add $c$ to the last position in set $V_i$
      v. Remove $c$ from set $S$
      vi. Repeat step 2.b.iii until $S = \varnothing$
3. Construct vehicle route.
   a. Set $k$=1
   b. Add customer one by one to the route
      i. Set $l = U_k$ and $p$=1
      ii. Set $j = V_{l,p}$. Evaluate the vehicle load if customer $l$ is added to the route $R_{ij}$.
      iii. Make a candidate of new route by inserting customer $l$ to the best sequence in the route $R_{ij}$, which has the smallest additional cost (cheapest insertion heuristic).
      iv. Check the capacity and route time
```

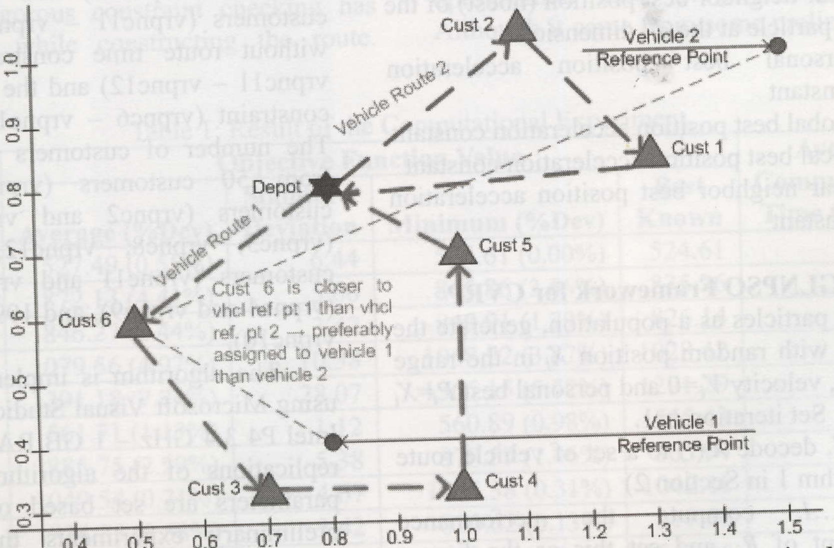

Figure 2: Graphical Illustration of Vehicle Routes Construction on Cartesian Map

```
        constraint of the candidate route.
    v. If a feasible solution is reached, update
       the route $R_{ij}$ with the candidate route; go
       to step 3.c.
    vi. If $p=m$, go to step 3.c. Otherwise, set
        $p=p+1$ and repeat 3.b.ii
  c. If $k=n$, stop. Otherwise, set $k=k+1$ and repeat
     3.b.
```

3. PSO Framework for Solving CVRP

The proposed representation is applied using GLNPSO, a PSO Algorithm with multiple social structures [14], with slight modification on the velocity and position limitation. In this application, no velocity and position limitation is incorporated. It can be done due to the flexibility of this representation in which all real value can be converted into vehicle route. By applying no restriction on velocity and position value, the additional effort for checking and adjusting these values can be eliminated. The details of the GLNPSO for solving CVRP are explained below.

Notation

t : Iteration index, $t=1\ldots T$

i : Particle index, $i=1\ldots I$

d : Dimension index, $d=1\ldots D$

u : Uniform random number in the interval [0,1]

$w(t)$: Inertia weight in the t^{th} iteration

$v_{id}(t)$: Velocity of the i^{th} particle at the d^{th} dimension in the t^{th} iteration

$x_{id}(t)$: Position of the i^{th} particle at the d^{th} dimension in the t^{th} iteration

p_{id} : Personal best position (pbest) of the i^{th} particle at the d^{th} dimension

p_{gd} : Global best position (gbest) at the d^{th} dimension

p_{id}^{L} : Local best position (lbest) of the i^{th} particle at the d^{th} dimension

p_{id}^{N} : Near neighbor best position (nbest) of the i^{th} particle at the d^{th} dimension

c_p : Personal best position acceleration constant

c_g : Global best position acceleration constant

c_l : Local best position acceleration constant

c_n : Near neighbor best position acceleration constant

Algorithm 2: GLNPSO Framework for CVRP

```
1. Initialize $I$ particles as a population, generate the
   $i^{th}$ particle with random position $X_i$ in the range
   $[X^{\min}, X^{\max}]$, velocity $V_i=0$ and personal best $P_i=X_i$
   for $i=1\ldots I$. Set iteration $t=1$.
2. For $i=1\ldots I$, decode $X_i(t)$ to a set of vehicle route
   $R_i$. (Algorithm 1 in Section 2)
3. For $i=1\ldots I$, compute the performance
   measurement of $R_i$, and set this as the fitness
   value of $X_i$, represented by $\varphi(X_i)$.
4. Update pbest: For $i=1\ldots I$, update $P_i=X_i$, if
   $\varphi(X_i)<\varphi(P_i)$.
5. Update gbest: For $i=1\ldots I$, update $P_g=P_i$, if
   $\varphi(P_i)<\varphi(P_g)$.
6. Update lbest: For $i=1\ldots I$, among all pbest from $K$
   neighbors of the $i^{th}$ particle, set the personal best
   which obtains the least fitness value to be $P^L{}_i$.
7. Generate nbest: For $i=1\ldots I$, and $d=1\ldots D$, set
   $p^N{}_{id}=p_{jd}$ that maximizing fitness-distance-ratio
   ($FDR$) for $j=1\ldots I$. Where $FDR$ is defined as
   $FDR=\frac{\varphi(X_i)-\varphi(P_i)}{|x_{id}-p_{jd}|}$ which $i \neq j$
8. Update the velocity and the position of each $i^{th}$
   particle:
   $w(t)=w(T)+\frac{t-T}{1-T}[w(1)-w(T)]$
   $v_{id}(t+1)=c_p u(p_{id}-x_{id}(t))+c_g u(p_{gd}-x_{id}(t))$
   $\quad +c_l u(p_{id}^{L}-x_{id}(t))+c_n u(p_{id}^{N}-x_{id}(t))$
   $\quad +w(t)v_{id}(t)$
   $w(t)=w(T)+\frac{t-T}{1-T}[w(1)-w(T)]$
   $x_{id}(t+1)=x_{id}(t)+v_{id}(t+1)$
9. If the stopping criterion is met, stop. Otherwise,
   $t=t+1$ and return to step 2.
```

4. Computational Experiment

A computational experiment is conducted by applying this proposed algorithm to the benchmark data set of Christofides et al. [15]. In this set of benchmark problem, the position of depot and customer are given in Cartesian coordinate map. Hence, no additional effort is needed to calculate distance in the proposed decoding method. This benchmark problem consists of problems with randomly distributed customers around the depot (vrpnc1 – vrpnc10) and problem with clustered customers (vrpnc11 – vrpnc14). Some problem is without route time constraint (vrpnc1 – vrpnc5, vrpnc11 – vrpnc12) and the other is with route time constraint (vrpnc6 – vrpnc10, vrpnc13 – vrpnc14). The number of customers in each problem varies from 50 customers (vrpnc1 and vrpnc6), 75 customers (vrpnc2 and vrpnc7), 100 customers (vrpnc3, vrpnc8, vrpnc12, and vrpnc14), 120 customers (vrpnc11 and vrpnc13), 150 customers (vrpnc4 and vrpnc9), and 199 customers (vrpnc5 and vrpnc10).

The algorithm is implemented in C# language using Microsoft Visual Studio.NET 1.1 on a PC with Intel P4 3.4 GHz – 1 GB RAM. For each data set, 5 replications of the algorithm are tried. The PSO parameters are set based on the result of some preliminary experiments that are conducted to observe the behavior of algorithm in different parameter setting. The parameters are: Number of particle, I=100; Number of iteration, T=1000; Number of neighbor, K=5; First inertia weight, $w(1)$=0.9; Last inertia weight, $w(T)$=0.4; Personal best position acceleration constant, c_p=0.5; Global best position acceleration constant, c_g=0.5; Local best position acceleration constant, c_l=1.5; Near neighbor best position acceleration constant, c_n=1.5. The range of initial position is $[X^{\min},X^{\max}]=[0,100]$, since the position of customer and depot in the map for all problem is located within this range.

Table 1 shows the experimental results for some problems that the algorithm could solve effectively. The average, standard deviation, and minimum objective function value of each problem are presented altogether with the percentage deviation (%Dev) of the value from the best known solution which is available in the VRP web (http://neo.lcc.uma.es/radi-aeb/WebVRP/index.html?/results/BestResults.htm). It is shown that the average percentage deviation for the problem with randomly distributed customer and without route time constraint (vrpnc1 – vrpnc5) is less than 8%, for the problem with randomly distributed customer and with route time constraint (vrpnc6 and vrpnc8), even only for two from five cases, is less than 3%, and for the problem with clustered customer (vrpnc11 – vrpnc14), both for problem with and without route time constraint, the average percentage deviation is less than 3%. In addition, the computational time also provide promising result, since all problems need less than 7 minutes for the iteration process.

5. Discussion and Further Study

The computational result shows that the proposed solution representation and decoding procedure is quite effective for solving the CVRP using pure PSO. This promising result may come from the following two reasons. First, the decoding scheme gives higher possibility to get feasible solution, since a rigorous constraint checking has already been done while constructing the route. Second, the solution quality is improved from the cheapest insertion heuristic which is applied during the route construction.

Especially for the problem with clustered customers, the effectiveness of proposed method is well proven. It is empirically shown that this method is more effective when it is applied to the problems with clustered customers than the problem with randomly distributed customer. The result is less than 3% in average deviation from the best known solution. It is not a surprising result since the nature of decoding process has a natural tendency to group customers for a vehicle that located surrounding its reference point.

In spite of the promising result, there are two findings from the result that must be further explored. First, there is a tendency that the percentage deviation is increasing while the number of customer is increasing. Second, the implementation result on problem vrpnc7, vrpnc9, and vrpnc10, which are problem with randomly distributed customers and with route time constraint, are not effective. The result of these problems with the same number of vehicles as the best known solution always gives a solution with some customers remain unserved by any vehicle. Since these two facts might be caused by the construction heuristic, the solution representation, or the problem case characteristics, further exploration on this area is still required.

Note again that the result on this paper is gained by pure PSO algorithm. Hence, it is possible to improve the result by the addition of effective local search method. Since the local search algorithm is usually computationally exhaustive, it may be done infrequently during the iteration process, for example, perform the local search only on the global best solution every 100 iterations. The implementation of local search needs to be further studied.

There is some other aspect that may improve the performance of the proposed algorithm, i.e. parameter optimization and programming implementation. Although it came from some preliminary experiment,

Table 1: Result of the Computational Experiment

Problem	**Objective Function Value**				**Average Computational Time (second)**
	Average (%Dev)	**Standard Deviation**	**Minimum (%Dev)**	**Best Known**	
vrpnc1	527.49 (0.55%)	6.44	524.61 (0.00%)	524.61	46.53
vrpnc2	872.13 (4.41%)	5.00	865.86 (3.66%)	835.26	98.83
vrpnc3	846.27 (2.44%)	3.42	840.91 (1.79%)	826.14	123.18
vrpnc4	1079.56 (4.97%)	10.38	1068.22 (3.87%)	1028.42	234.53
vrpnc5	1391.18 (7.74%)	28.07	1365.15 (5.72%)	1291.29	375.08
vrpnc6	561.71 (1.13%)	1.12	560.89 (0.98%)	555.43	51.49
vrpnc8	885.75 (2.29%)	5.38	878.59 (1.46%)	865.94	132.96
vrpnc11	1049.54 (0.71%)	4.67	1045.38 (0.31%)	1042.11	132.81
vrpnc12	824.35 (0.58%)	3.42	820.62 (0.13%)	819.56	127.94
vrpnc13	1585.05 (2.85%)	12.09	1569.14 (1.84%)	1541.14	176.71
vrpnc14	872.20 (0.67%)	7.98	866.37 (0.00%)	866.37	136.65

the parameter setting that has been used in this paper may not the best one. Also, the programming implementation of the algorithm has not been optimized. Since these efforts may yet contribute to better performance in both the solution quality and computational time, a further study on these aspects is still necessary.

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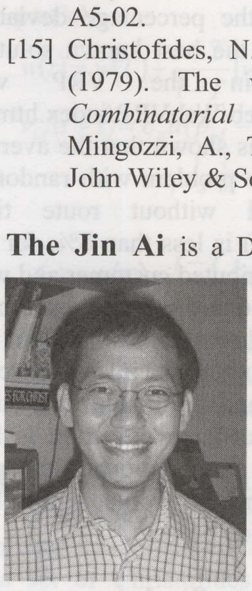

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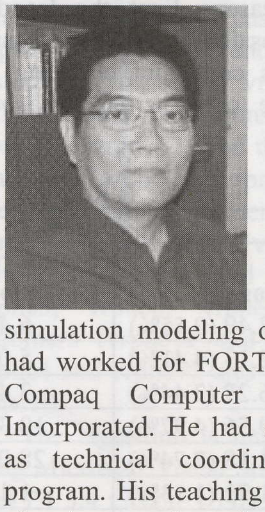

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