Particle Swarm Optimization for Post Box Collection Routing Problem

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Abstract

Nowadays, in spite of advanced communication technology, the post box collection activity is still operating by the agents of a country's postal service. Thus, this activity needs to be operated at minimum cost with smart decision making. The aim of this study is to find the optimal routing in post box collection activity with an objective to minimize the total traveling time. To deal with large-scale problem in the real-world practice, particle swarm optimization (PSO) algorithm are applied to solve the complexity of the problem. The experiments are executed using the case study of post box collection in Chiang Mai city, Thailand. The results showed that the proposed PSO can effectively find the new routing which helps to reduce the total travelling time by 11.14%, the total travelling distance by 7.11%, and the total cost by 13.86%.

Keywords
Post box collection routing, Vehicle routing problem, Particle swarm optimization, Metaheuristic

1. Introduction

In the world toward industry 4.0 and advance communication technology, the postal service receives drastic popularity especially on parcel collection and delivery. Even though much less number of people using post box for letter dropping, post box collection service is still operating in several countries. Thus, post box collection activity must be operated at minimum cost with smart decision making using high-technology computing techniques. Post box collection routing problem is one of the postal service problems that has been studied for several decades. The goal of the problem is to find the optimal routing to satisfy some certain objectives.

The post box collection routing problem is a kind of the generalized vehicle routing problem (GVRP). The GVRP, introduced by Ghiani and Improta (2000), is an extension of the vehicle routing problem (VRP). The GVRP is the problem of designing optimal delivery or collection routes from a given depot to a number of predefined, mutually exclusive and exhaustive node-sets (clusters) which includes exactly one node from each cluster, subject to capacity restrictions. Several solution methods for GVRP include exact algorithms and approximate algorithms, such as Kara and Bektas (2003) and Pop et al. (2009, 2010). Pop et al. (2012) proposed the two new modes of GVRP based on integer programming to reduce the complexity of the problem. The results showed the efficiency of the proposed models.

The post box collection routing problem described in Laporte et al. (1989) becomes as an asymmetric GVRP if more than one vehicle is required. Oliver (1964) presented the concept of calculus of variations to derive a solution for the post box collection routing problem to minimize the delay of mails in the system. Ritzman et al. (1976), proposed a heuristic program and simulation model to maximize service for a given volume of mail input. Laporte et al. (1989), studied the mailbox collection routing problem at the Canada post cooperation. They proposed a generalized travelling saleman problem (GTSP) algorithm based on branch and bound method to improve the current clustering and routing algorithm. The result showed that the proposed algorithm yield the better routing with shorter distance for each cluster.

This study aims to solve post box collection routing problem with an objective to minimize the total traveling time. Due to the fact that the problem is NP-hard, an effective evolutionary algorithm called particle swarm optimization (PSO) is proposed to deal with the complexity of the problem. The proposed PSO is implemented in the case study of post box collection activity in Chiang Mai city, Thailand. The remainder of this paper is organized as follows. Section 2 presents a mathematical model of the problem and a description of the case study. Section 3 provides the application of particle swarm optimization to the problem. The numerical experiment and conclusion are given in section 4 and section 5, respectively.

2. Problem Formulation

2.1 Mathematical Model

This study presents a mathematical model for post box collection routing problem as an integer programming problem. The model aims to find the optimal route with minimum total traveling time. The notations and variables used in the models are listed as the following.

Index

i, j : The index of post office (i, j = 1) and post box (i, j = 2, 3, …, n)

k : The index of vehicle (k = 1, 2, … n)

Decision variable

x_{ijk} : 1 if vehicle k travels from i to j or 0 in otherwise

Parameter

t_{ij} : Travelling Time from i to j

q_j : Number of letter in post box j

c_k : Capacity of vehicle k

o_j : Operating time at post box j

TW_k : Time window of vehicle k

U_i, U_j : Constant value used to eliminate sub-tours

N : A set of post boxes; N = {0, 1, 2,…, n}

Objective function:

$$Min\ Z = \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n}(t_{ij} + o_j)\, x_{ijk} \quad (1)$$

Constraints:

$$\sum_{i=1}^{n}\sum_{k=1}^{m} x_{ijk} = 1 \qquad \forall j;\ j = \{2,3, \dots, n\} \quad (2)$$

$$\sum_{j=1}^{n}\sum_{k=1}^{m} x_{ijk} = 1 \qquad \forall i;\ i = \{2,3,\dots,n\} \tag{3}$$

$$\sum_{i=1}^{n} x_{ipk} - \sum_{j=1}^{n} x_{pjk} = 0 \qquad \forall_p \forall_k;\ p = \{1,2,\dots,n\}, k = \{1,2,\dots,m\} \tag{4}$$

$$\sum_{i=2}^{n} x_{i1k} = 1 \qquad \forall_k;\ k = \{1,2,\dots,m\} \tag{5}$$

$$\sum_{j=2}^{n} x_{1jk} = 1 \qquad \forall_k;\ k = \{1,2,\dots,m\} \tag{6}$$

$$U_i - U_j + N\sum_{k=1}^{m} x_{ijk} \le N - 1 \qquad \forall i, \forall j;\ i,j = \{2,3,\dots,n\} \tag{7}$$

$$\sum_{j=1}^{n}\sum_{i=1}^{n} q_j x_{ijk} \le C_k \qquad \forall_k;\ k = \{1,2,\dots,m\} \tag{8}$$

$$\sum_{j=1}^{n}\sum_{i=1}^{n} (t_{ij} + o_j) x_{ijk} \le TW_k \qquad \forall_k;\ k = \{1,2,\dots,m\} \tag{9}$$

$$x_{ijk} \in \{0,1\} \qquad \forall_i \forall_j \forall_k;\ i,j = \{1,2,\dots,n\}, k = \{1,2,\dots,m\} \tag{10}$$

Equation (1) is an objective function that aims to minimize the total time of post box collection process. Constraints (2) and (3) ensure that each post box is collected by only one vehicle. Constraint (4) guarantees the route continuity. Constraints (5) and (6) ensure that all routes depart from and return to the post office. Constraint (7) eliminates the sub-tours. Constraint (8) imposes that the vehicle capacity does not exceed its limit. Constraint (9) ensures that each post boxes is visited within the operational time window. Constraint (10) states that decision variables can be either 0 or 1.

2.2 Case Study

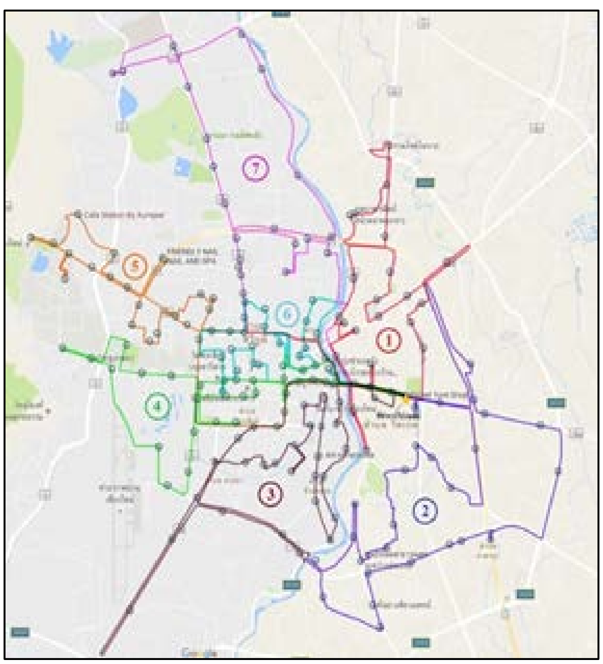

Figure 1. Current post box collection routing

To employ the proposed solution method, this paper studies the post box collection routing problem in Chiang Mai city, Thailand. Currently, seven postmen travels along different routes to collect mails from 175 post boxes as shown in Figure 1. The problem is a single-depot vehicle routing problem in which each postman starts and finishes his trip at the post office. In addition, all post boxes must be visited within a certain time period.

3. Application of Particle Swarm Optimization

3.1 Particle Swarm Optimization (PSO)

PSO, originally proposed by Kennedy and Eberhart in 1995, is a population-based random search method that imitates the physical movements of the individuals in the swarm as a searching mechanism. Several variants of PSO have been proposed to improve the search efficiency and remedy the common problem of premature convergence.

This study adopts Global Local and Near-Neighbor Particle Swarm Optimization (GLNPSO), improved version of PSO proposed by Pongchairerks and Kachitvichyanukul (2005). The GLNPSO introduces two additional social learning structures which are local best and near neighbor best to enhance the search efficiency. It has been successfully applied in many application areas such as Pongchairerks and Kachitvichyanukul (2009), Wisittipanich and Meesuk (2015) and Wisittipanich and Hengmeechai (2017). In addition, this paper also proposes the local search technique with swap strategy in order to improve the solution quality. The framework the proposed algorithm is shown in Figure 2.

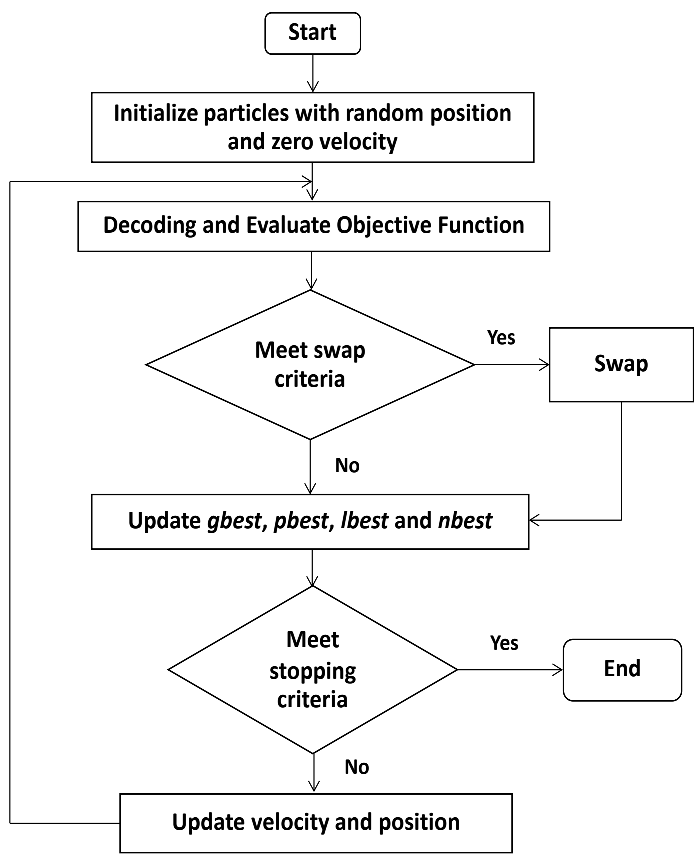

Figure 2. The proposed framework of GLNPSO with swap

Similar to the original PSO, GLNPSO begins by generating a population of particles with random position and zero velocity. Then, each particles is decoded to obtain the objective value. If the swap condition is met, each particle performs the swap strategy. It is noted that a randomly selected swap strategy would be performed by each particle with each strategy being applied for every certain number of iterations. After that, each particle updates the cognitive knowledge of its experiences and the social knowledge of the swarm which are global, local, and near-neighbor to guide the particle to the better position. A particle moves to a new position using the updated velocity. Once a new position is reached, the best position of each particle and the best position of the swarm are updated as needed. These processes are repeated until a stopping criterion is met.

3.2 Solution Representation of GLNPSO to the problem

Since PSO is originally designed for continuous domains, in order for PSO to deal with combination problems, a solution in PSO must be transformed into a practical solution. The solution representation of GLNPSO to the problem in this study is illustrated in Figure 3.

The encoding procedures used in this study starts from defining the number of particle dimension to be equal to twice as much as the number of post boxes. Consider an example of eight post boxes and two postmen. Since there are total of 8 post boxes, the dimensions of a particle are set to be 16. Each value in a vector dimension is initially generated with a uniform random number between 0 and 1. As shown in Figure 3(a).The dimensions of a vector are divided into two parts in which the first eight dimensions represent the post boxes and the other eights dimensions represents the vehicle assignment. To decode a particle dimension into a routing solution, a sorting list rule is applied to the first part of a particle dimension. Then, a roulette wheel rule is applied to the second part of a particle dimension to determine the vehicle assignment. Since there are two vehicles in this example, a random value between 0 and 0.5 is assigned to vehicle 1 and a random value between 0.5 and 1.0 is assigned to vehicle 2. As a result, a routing for each vehicle is determined accordingly as shown in Figure 3(b).

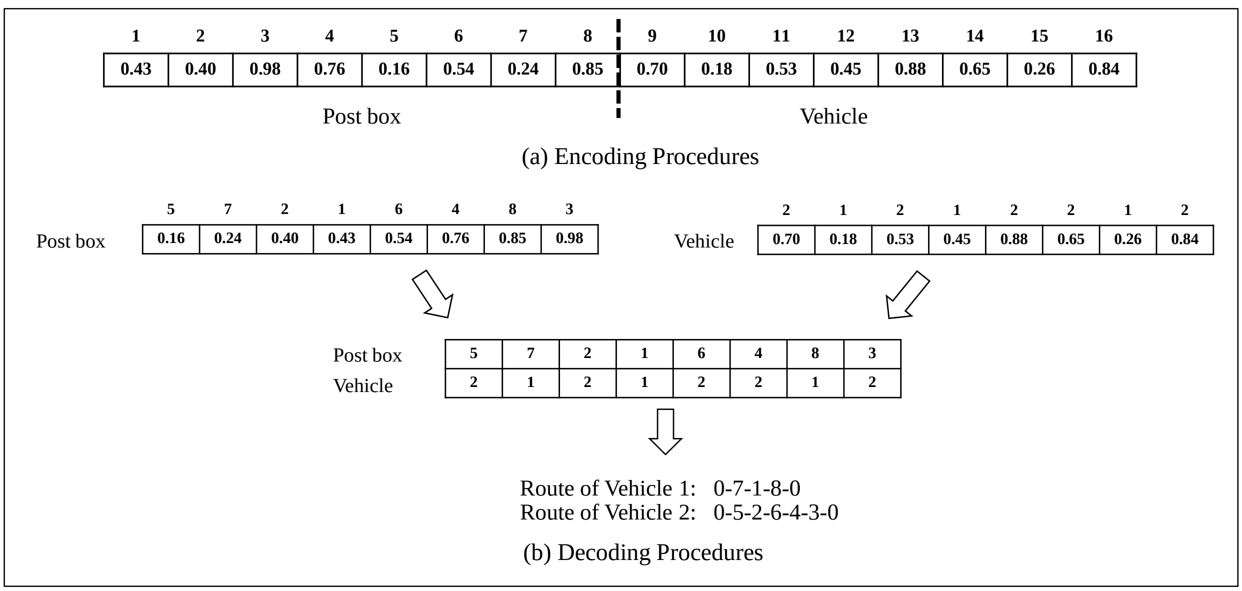

Figure 3. Solution representation of GLNPSO to the problem

3.3 Local Search

In this study, three swap-based local search strategies are proposed to improve the solution quality and help t. Each strategy is explained as follows.

1) Swap1: The idea of Swap1 is to find the better routing by exchanging the sequence of two post boxes within one vehicle for all possibilities.
2) Swap2: The concept of Swap2 is to exchange the sequence of two post boxes from two randomly selected vehicles.

3) Swap3: Swap3 is executed when more than two vehicles is in consideration. Similar to Swap2, the exchanging process in Swap3 is performed between two different vehicles. However, in Swap3, all possible pairs of two vehicles are taken into account for swapping.

For each swap strategy, when a better solution is found, it will replace its parent. This process continues until all swap possibilities are exhaustedly searched. The best solution from the swap strategy will be used for the next generation.

4. Results and Discussion

4.1 Parameter Setting

Based on some preliminary experiments, the setting of GLNPSO parameters that are suitable for the problem in this study are shown in Table 1.

Table 1. Parameters of GLNPSO

Parameter	Parameter Value
Number of Iteration	1,000
Number of Particle	100
Inertia Weight	Linearly increase from 0.5 to 0.9
Swap criteria	Every 50 iterations
Personal Best Position, C_p	0.25
Global Best Position, C_g	0.25
Local Best Position, C_l	0.25
Near Neighbors Best Position, C_n	0.25

4.2 Experimental Results

In order to verify the performance of the proposed PSO, the preliminary experiments are conducted using small to medium sample size problems. The results obtained from the proposed PSO are compared with those obtained from the LINGO optimization solver as shown in Table 2.

Table 2. Comparison results between GLNPSO and LINGO

Number of Postbox	Number of Vehicle	LINGO		GLNPSO with Swap		
		Optimal solution	Computing time (hr:min:sec)	Solution	Computing time (hr:min:sec)	%diff
5	1	25.25	00:00:01	25.25	00:00:07	0%
10	1	37.50	00:00:01	37.50	00:01:21	0%
10	2	51.50	00:03:26	51.50	00:01:04	0%
15	1	52.75	00:00:02	52.75	00:06:27	0%
15	2	64.75	01:58:49	64.75	00:06:04	0%
20	1	64.00	00:00:02	64.00	00:20:20	0%
20	2	N/A	> 12:00:00	77.00	00:20:09	-
25	1	68.25	00:02:09	68.25	00:21:21	0%
25	2	N/A	> 12:00:00	83.25	00:30:09	-

Number of Postbox	Number of Vehicle	LINGO		GLNPSO with Swap		
		Optimal solution	Computing time (hr:min:sec)	Solution	Computing time (hr:min:sec)	%diff
30	2	N/A	> 12:00:00	94.50	00:35:22	-

It can be seen from Table 2 that, for small-size problems, LINGO can easily find optimal solutions with fast computing time, and the proposed PSO also obtains optimal solution as found by LINGO. The performance of the proposed PSO can be seen in the larger-size problems. While LINGO cannot find a solution within a reasonable time (12 hours), GLNPSO with swap is able to obtain solutions with relatively fast computing time. Therefore, in order to deal with real-world post box collection routing problem which consists of more than 100 post boxes, a metaheuristic is more appropriate to solve the problem.

As mentioned earlier, this paper studies the post box collection routing problem in Chiang Mai city, Thailand, which currently consists of 175 post boxes with the use of 7 postmen. The results of GLNPSO with swap are reported in two case scenarios. The first scenario is to use the same number of vehicles, and the second scenario is to reduce the number of vehicles from 7 to 6. The total travel time and the total travel distance of these two case scenarios o are shown in Table 3. It is noted that the solution is infeasible when the number of vehicles is 5. According to Table 3, the routing of 7 vehicles obtained from GLNPSO with swap algorithm can reduce the total travel time and total travel distance by 9.33% and 4.58% respectively. For the case of using 6 vehicles in post box collection activity, the total travel time and total travel distance are decreased by 11.14% and 7.11% respectively. In addition, with the use of 6 vehicles, the organization can reduce operating cost such as labor cost, fuel cost, maintenance cost, and vehicle insurance by 13.86% per year. The routing of 6 vehicles is illustrated in Figure 4.

Table 3. Results of GLNPSO with Swap for the case study

Current Situation			Results from GLNPSO with swap				
Number of Vehicle	Total travel time (min/week)	Total travel distance (km.)	Number of Vehicle	Total travel time (min/week)	% diff	Total travel distance (km.)	% diff
7	6793.00	2185.08	7	6159.00	9.33	2085.00	4.58
			6	6036.00	11.14	2029.80	7.11

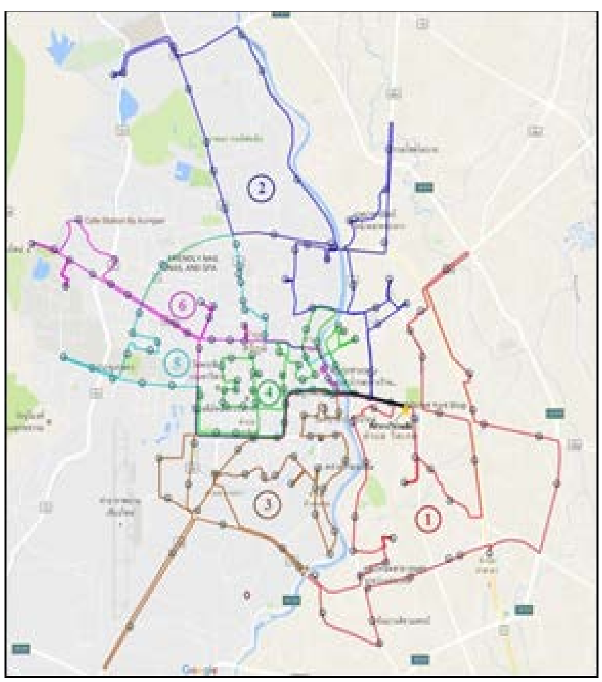

Figure 4. The routing of post box collection activity using six vehicles

5. Conclusion

The aim of this work is to find optimal routing in post box collection activity in Chiang Mai city, Thailand, with an objective to minimize the total traveling time.

While the exact method cannot provide solution in a reasonable time, Particle Swarm Optimization (PSO) is implemented to handling the complexity of the real-world problem. To solve the problem, the encoding and decoding procedures are developed for transform a particle solution into the routing of post box collection activity. Furthermore, several swap strategies are proposed to improve the solution quality. The experimental results show that the proposed PSO can effectively find the new post box collection routing which helps to reduce the total travelling time, the total travelling distance, and the total cost. In conclusion, the proposed PSO algorithm can be used as a smart decision making tool to solve similar vehicle routing problems.

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Biographies

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