Multi-phase Method for Geographical Transportation

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Abstract
In this paper, the Multi-phase method has been proposed to work on the geographical transportation. The first phase of this work applies the constructive heuristics to obtain routes number. Then, the improvement of evolutionary algorithm is implemented in another phase to find the best result. The proposed algorithm is tested on the three different geographical problem sets from Solomon benchmark dataset. The computational results are shown in comparison with other algorithms and also demonstrate as an example of effective routing map. The findings from the experiment indicate that the proposed algorithm provides distinctive performance to solve the problem. It shows that the proposed algorithm is very effective and obtains the best solution for all testing problem instances. In addition, the proposed method can provide routes map to serve customers in the different geographical areas efficiently.

1. Introduction

Transportation provides convenience to people's lives and impact to organizations such as logistics business, military transportation, distribution of goods, public transportation and others. For the business part, transportation not only delivers raw material to factories but also deliver goods from factories to stores, and to business warehouses sites or their customers. In particular, it is a significant part for business development. In the academic area, Vehicle Routing Problem (VRP) is a combinatorial optimization problem. It is the NP-hard problem which has challenged researchers in the world and been widely studied after it introduced by Dantzig and Ramser, 1959.

Transportation cost resulted in an increasing of goods price for 70% (Backer et al., 1997, Golden and Wasil, 1997 and Bräysy and Gendreau, 2005). Rodrigue and Notteboom (2017) pointed that 10%-15% of the household expenses are related to the transportation cost in average, while it accounts to the cost of each output unit in manufacturing around 4%. More significantly, 76% of the products have been transferred from places to places by vehicle transportation in 1989 (Halse, 1992) which confirm the significance of the vehicle routing planning.

The VRP is a well-known geographical problem arises in many real world applications to minimize cost. The high complexity and significance of the problem have been attracting researchers to study this disciple extensively. A massive number of existing literatures have been published by many researchers. In real world problem, there are many variants of the VRP incorporating constraints and conditions e.g. the Capacitated VRP (CVRP) that the vehicles have a limited freight capacity and the Vehicle Routing Problem with Time Windows (VRPTW) which time interval of each customer is specified.

Many methodologies have been brought to solve vehicle routing problems in recent times. Exact algorithm has been proposed to solve the problem in the earliest time. The methods can only be solved in small sized instances (Baldacci et al., 2012). Although it can provide optimal value for many instances, some other concepts cannot be solved which is a drawback of the algorithm. Heuristics, Meta-heuristics and Hybrid Algorithms have been proposed to figure out the drawback of the exact method, they can solve the problem efficiently. The hybrid algorithm is the newest technique which has attracted researchers in the world to develop a proper method for solving VRP problem. Due to the significant of this problem, it apparently that construct the new methodologies to solve this problem domain still attract researchers around the world. Therefore, this study aims to design a new effective methodology for the geographical routing map construction which is necessary for transportation part.

The proposed methodology was implemented by the multi-phase method including the first phase that the construction heuristics of Solomon (1987) is adopted to find number of routes. Then the improvement of genetic algorithm is taken to find the best result. The proposed algorithm is tested on the benchmark instances and compared with other algorithms. It found that the proposed algorithm yield better or equal to the comparing algorithms for all problem instances. In addition, the results illustrate that the proposed algorithm provides outstanding and competitive results and also shows the benefit of the proposed method for constructing effective routing map. The paper is organized as follows: the geographical transportation is introduced in section 2. Section 3 describes the multi-phase algorithm which is the proposed algorithm of this work. The computational results and discussions are presented in section 4. Finally, conclusions and suggestions for future works are provided in section 5.

2. Geographical Transportation

Geo-information can provide land use perceptions for transportation in depth. Geographic Information System (GIS) has been pervasive applied in transportation research and management from the late 1980s (Thill, 2000). Miller and Shaw (2001) described in their text book that the geographic information involved in the planning and running of transportation infrastructure and systems. It connects software for analyzing information about area of earth that is used for transportation activities. Goodchild (1992) claims that there are three classes model of GIS relevant to transportation context including field model, discrete model and network model. Off-line routing procedures are the representative of network model in GIS model class (Thill, 2000) and transport geography is traditionally more engaged in long distance trade issues (Hesse and Rodrigue, 2004).

The representative of problem set which are taken to test the proposed algorithm shown in Figure 1. In the Figure, there are 100 customers waiting for service in different locations. Each customer has their own demand and can be served by only one vehicle within their time windows. That means the vehicle cannot service customer before the earliest service time and after the latest service time. To serve customers in the route, the vehicle starts and ends its service at the depot. The aim of service is to minimize total distance while total of customers demand in the route not exceed the maximum of the vehicle capacity.

Figure 1: The Locations of Customers who are waiting for service

In this study, the VRPTW is chosen to examine the algorithm. The associated explanation of VRPTW, the objective function and constraints of the problem is mentioned as follows:

2.1 Vehicle Routing Problem with Time Windows (VRPTW)

The VRPTW can be reviewed as a combinatorial of vehicle routing and scheduling problem. A set of customers will be satisfied by a fleet of vehicles which start and end service at the depot. Each customer will be served by a vehicle within their time windows in order to minimize the cost and total of customers demand in the route not exceed the maximum of vehicle capacity.

Toth and Vigo (2001) define VRPTW as follows: it is a complete graph $G=(V,E)$. There is a set of vertices $V=\{v_0,v_1,...,v_{n+1}\}$, $v_0 \in V$ represents depot, N is a sub set of vertices represents customers, $N=\{v_1,...,v_n\}$. The location of customer v_i represents by (x_i,y_i) and the representation location of the depot, v_0 is (x_0,y_0). For each customer $v_i \in N$, there is a demand q_i, service time or unloading time t_i and a time window $[e_i,l_i]$ where e_i is the earliest time to begin service and l_i is the latest time. Accordingly, s_i denotes the starting time service at customer v_i, the vehicle must wait with the waiting time w_i if the arriving time at customer v_i before time e_i and it's not allow to arrive after latest time l_i. Each pair of customers, there is $t_{i,j}$ represents a time that takes to go from customer v_i to v_j. Customer v_i is served by a vehicle at the beginning time s_i takes time t_i to unload or pickup goods. At the depot, $v_0 \in V$, there are m homogenous vehicles. Every vehicle starts and end service to customer with the specific quantity Q at the depot. The objective of VRP is to find a set of $K=\{k_1,k_2,...,k_m\}$ routes which serve all customers by m vehicles at the minimum cost. The cost can be the sum of travel distances or times of all routes, this paper considers travel distance. From the geographical position of customer v_i (position is (x_i,y_i)) and customer v_j (position is (x_j,y_j)), the distance between a pair of them is denoted by $d_{i,j}$ calculated by the Euclidean distance:

$$d_{i,j}=\sqrt{(x_i-x_j)^2+(y_i-y_j)^2}$$

Equation 1

Each vehicle serve a route, and each customer is served by only one vehicle and all customers demand in the route cannot exceed maximum capacity Q of vehicle. The objective function and constraints of the problem shown as follows:

$$\textit{Minimise} \sum_{(i,j,k)} d_{ij}x_{ijk}$$

Equation 2

Subject to:

$$\sum_{k=1}^{m}\sum_{j=1}^{n}x_{ijk} \le m, \textit{for}\, i=0$$

Equation 3

$$\sum_{j=1}^{n}x_{ijk}=\sum_{j=1}^{n}x_{jik}=1\, \textit{for}\, i=0\, \textit{and}\, k\in K$$

Equation 4

$$\sum_{k=1}^{m}\sum_{j=0,j\ne i}^{n}x_{ijk}=1, \textit{for}\, i\in N$$

Equation 5

$$\sum_{k=1}^{m}\sum_{i=0,j\ne i}^{n}x_{ijk}=1, \textit{for}\, j\in N$$

Equation 6

$$\sum_{i=1}^{n}q_i\sum_{j=0,j\ne i}^{n}x_{ijk}\le Q, \textit{for}\, k\in K$$

Equation 7

$$e_j \le s_i+t_i+t_{ij}+w_j \le l_j$$

Equation 8

The objective function (Equation 2) minimizes overall distance. x is a decision variable, $x_{ijk}=1$ if the path i to j is traveled by vehicle k, otherwise 0. Equation 3 guarantees that there are m vehicles at the depot (v_i; $i=0$), to serve all customers. Equation 4 ensures that all vehicles start and end their routes at the depot.

Equation 5 and equation 6 assure that each customer is served by only one vehicle. Equation 7 guarantees that all customers demand in the route does not exceed vehicle capacity and Equation 8 ensure that the summation of the arrival time at v_i, service time of v_i, travel time v_{ij} and the waiting time at v_j of each customer is not less than earliest time window e_j and not more than latest time window l_j.

3. Multi-Phase Method

3.1 First Phase

The aim of this phase is using sequential insertion heuristics (Solomon, 1987) to obtain number of routes. One feasible solution is constructed and local search heuristic will be applied to find the minimum route numbers.

The sequential insertion heuristics includes two important steps. First, the initialization step which aims to find the first customer, called seed, to the new route. Second, the insertion step which targets to consider the insertion place for the remaining customers. The unrouted customers will be chosen to the route by this step until it is full with respect to the problem constraints. These two steps will be continued until all customers are added to the route. After all customers are scheduled by the sequential insertion heuristics, the swap (1-0) operator is adopted to find proper number of route. To explain the process of swap (1-0) operator, the routes example is shown as follows:

$$k_1 : v_0 \to v_1 \to v_2 \to v_3 \to v_4 \to v_5 \to v_0$$
$$k_2 : v_0 \to v_6 \to v_7 \to v_8 \to v_9 \to v_0$$
$$k_3 : v_0 \to v_{10} \to v_0$$

There are three routes served by vehicle k_1 , k_2 and vehicle k_3 start and end their service at the depot v_0. Customer v_1, v_2, v_3, v_4, and v_5 are served by vehicle k_1 respectively. v_6 , v_7 , v_8 , and v_9 are customers visited by vehicle k_2 in the sequence while vehicle k_3 serves customer v_{10}. The following displays the new sequences of each route that could be happened after apply the local search swap 1-0.

$$k_1 : v_0 \to v_1 \to v_2 \to v_4 \to v_5 \to v_{10} \to v_0$$
$$k_2 : v_0 \to v_6 \to v_7 \to v_3 \to v_8 \to v_9 \to v_0$$

In this example, customer v_3 from route k_1 is chosen to insert before customer v_8 in route k_2 and the route k_3 is eliminated while customer v_{10} is moved to k_1. These could be happened after the swap 1-0 is applied.

3.2 Second Phase

After number of routes is established from the first phase, the improved genetic algorithm is taken to approach in the second phase. In the first step, the fuzzy technique is applied to construct P numbers of feasible solutions (population). Then, the nearest neighborhood search is applied to improve the population. The evolutionary processes are used to handle the second step. Each individual is improved iteration by iteration until the stopping condition is met and the best found result will be returned. The second phase workflow is demonstrated in Figure 2.

3.2.1 The first step

The first step of the second phase aims to generate P numbers of feasible solutions (population). Fuzzy technique is applied in this step. The Fuzzy theory was presented by Zadeh in 1965, whereas many different research areas have found that it is a useful tool to describe subjective opinions, Tang et al., (2009). In applications, basic fuzzy inference algorithm is a generalized implementation of fuzzy logic. The membership function provides a measure of the degree of similarity of an element to a fuzzy set. The design of membership functions for the fuzzy variables and rules are the design elements of the basic fuzzy inference. For each fuzzy variable, problem domain has to be determined. Problem domain represents the extent of validity of the fuzzy inference rule on each variable domains, the next stage is to fix the shape of the membership functions then the number of members (or number of mapping categories) and their locations on the universe of discourse has to be found. There are different shapes of membership functions e.g. triangular, trapezoidal, piecewise-linear, Gaussian and bell-shaped. In this work, the membership function is assumed to be triangular in shape and this assumption is continued in this study. The triangular membership function is applied to find the preference of customers as a triangular fuzzy number under the following Equation:

$$\theta_i(s_i) = \begin{cases} 0; s_i < e_i \text{ or } s_i > l_i \\ \dfrac{(s_i - e_i)}{(u_i - e_i)}; e_i \le s_i \le u_i \\ \dfrac{(l_i - s_i)}{(l_i - u_i)}; u_i < s_i \le l_i \end{cases}$$

Equation 9

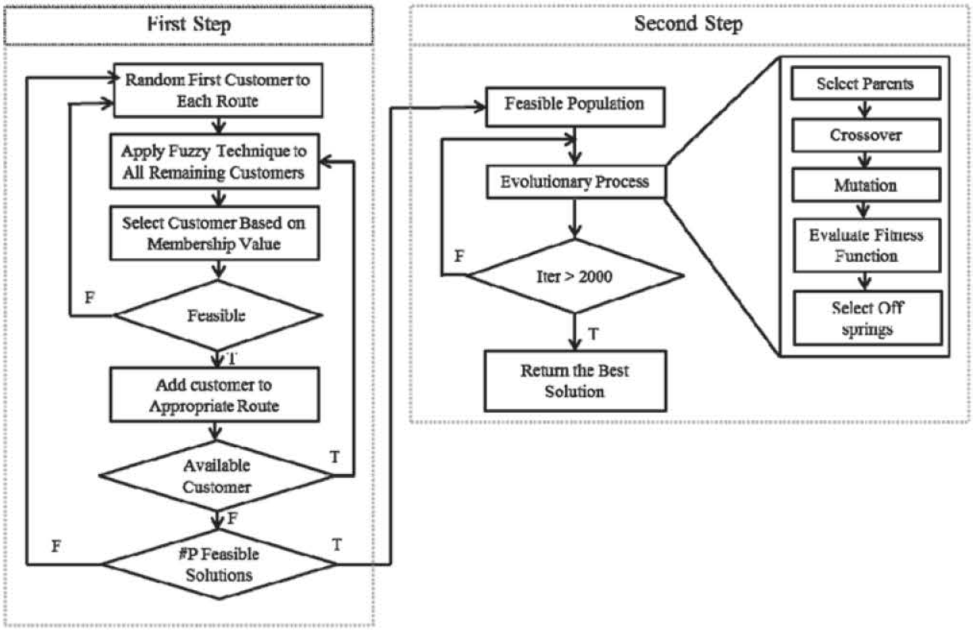


Figure 2: The Second Phase Workflow

Figure 3: Fuzzy due time

Where s_i represent the time at which the customer is served, u_i represent fuzzy due time, $u_i = e_i + t_i$; t_i is the time spent to service at customer v_i. The satisfaction area is shown in Figure 3. In vehicle routing problem, fuzzy membership function has been applied to the problem in several papers. The fuzzy theory has been applied to the Chinese postman problem with time windows in 2002 by Wang and Wen (2002). They considered two cases in fuzzy time constrained of the problem. 1) the arrival time at a node may be fuzzy to describe the degrees of possibility and 2) the upper and lower bounds of time window constraints are uncertain. Their objectives are to minimize the total time to finish the tour and maximize the satisfaction level. Zheng and Liu (2006) proposed a hybrid solution algorithm: they consider a vehicle routing problem in which the traveling times are assumed to be fuzzy variables. Tang et al., 2009 proposed and solved vehicle routing problem with fuzzy time windows (VRPFTW). The paper applies fuzzy membership functions to characterize the service level issues associated with time window violation in a vehicle routing problem and proposes VRPFTW. VRPFTW is formulated as a multi-objective model with two goals which are to minimize the travel distance and to maximize the service level of the supplier to customers. To solve this multi-objective model, a two-stage algorithm is developed to obtain a Pareto solution for VRPFTW. In 1996, Teodorovi and Pavkovi developed a model to design vehicle routing when the demand at the nodes is uncertain. The model is based on the heuristic sweeping algorithm, the rules of fuzzy arithmetic and fuzzy logic. Sandhya and Katiyar (2014) considered fuzzy VRPTW with an uncertainty time windows. Fuzzy credibility theory was applied.

The triangular fuzzy number represents fuzzy travel time in their chance constrained proposed model for the problem and found the optimal solution through the ant colony optimization algorithm. Lin (2008) consider travel distance, service satisfaction, waiting time, delay time and space utility are considered in Lin's formulation as the fuzzy vehicle routing and scheduling problem (FVRSP). After that, Gupta et al., (2009) include the fuzzy service time under time windows and capacity constraints to Lin's formula and then based on this extended model, a real time application is added by them in 2010 to produce the FVRPTWC.

In this work, the triangular membership function based on the concept of fuzzy due time from Gupta et al., (2010) is applied. To grade the satisfaction of a service time of customers, the membership function of service time, $\theta_i(s)$ can be defined for any service time $(s > 0)$ as the following Equation:

$$\theta_i(s) = \begin{cases} 1; e_i < s < l_i \\ 0; otherwise \end{cases}$$

Equation 10

It is noted that e_i is the earliest time and l_i is the latest time that the vehicle can service customer. To explain the work process of fuzzy membership function approach to time dependent VRP, some example data are shown in Table 1. To create each feasible individual, this step begins with adding the first customer to each route randomly. To select the next customer for each route, the membership function of service time (Equation 10) is applied to consider the satisfaction of the service time for all remaining customers.

The satisfied customers will be calculated their membership value by the triangular membership function (Equation 9). All constrains are determined and then the satisfied customer will be added to be the next customer in the proper route. In Table 2, suppose there are 10 customers waiting to be served by 2 vehicles. In this example, customer 3 and customer 8 presented in bold are randomly selected to be the first member of the first and the second empty routes respectively. As a result, the value S $(e_i + t_i)$ of the first route is 115 and the value s of the second route is 393. To select the next customer for each route, the membership function of service time (Equation 10) is applied to consider the satisfaction of the service time, $\theta_i(s)$, for all remaining customers. From Table 2, due to the satisfaction value, $\theta_i(s)$, customer 4 and 5 are satisfied for the first route and customer 1 is satisfied for the second route, therefore, they will be selected to calculate by the triangular membership function (Equation 9) and the results, $\theta_i(s_i)$, are shown in column 7 and 9 of Table 2. In this example, customer 5 and customer 1 are chosen because of their $\theta_i(s_i)$ value and the value of s is changed to be 205 and 393 in the first and second route successively. All constrains will be determined and after all of them are satisfied the customer will be added to be the next customer in the route. The example result of these processes is shown in Figure 4. The processes will be continued until all customers are added to the proper routes. However, if the feasible solution cannot be constructed the process will start from the beginning until the feasible solution is produced.

Table 1: An example data of customers

Customer number	x_i	y_i	q_i	e_i	l_i	t_i
1	53.00	30.00	10.00	308	468	90.00
2	50.00	30.00	10.00	401	561	90.00
3	42.00	65.00	10.00	25	185	90.00
4	28.00	52.00	20.00	22	207	90.00
5	25.00	50.00	10.00	112	276	90.00
6	23.00	52.00	10.00	209	369	90.00
7	20.00	50.00	10.00	398	558	90.00
8	20.00	55.00	10.00	303	463	90.00
9	10.00	40.00	30.00	593	753	90.00
10	48.00	30.00	10.00	493	653	90.00

Table 2: The membership value of an example data of customers

Customer number	e_i	l_i	t_i	u_i	Customer 3		Customer 8	
					$\theta_i(s)$	$\theta_i(s_i)$	$\theta_i(s)$	$\theta_i(s_i)$
1	308	468	90	398	0	-	1	0.944
2	401	561	90	491	0	-	0	-
3	**25**	**185**	**90**	-	-	-	-	-
4	22	182	90	207	1	0.957	0	-
5	112	276	90	202	1	0.999	0	-
6	209	369	90	299	0	-	0	-
7	398	558	90	488	0	-	0	-
8	**303**	**463**	**90**	-	-	-	-	-
9	593	753	90	683	0	-	0	-
10	493	653	90	583	0	-	0	-

First route: $v_0 \to v_8 \to v_1$

Second route: $v_0 \to v_3 \to v_5$

Figure 4: the example routes after customer 5 and customer 1 are added

3.2.2 The second step

After the feasible population is generated in the first step, the second step of this phase is continued. The following details explain relating processes.

Genetic algorithm (GA) is one of the effective evolutionary algorithms which have been applied to solve the VRPTW in the literature. Genetic algorithm, the improvement of genetic algorithm and the hybrid of genetic algorithm and other have been published to solve VRPTW. The two-phase hybrid of a genetic algorithm and an evolutionary algorithm was proposed by Bräysy et al., (2000). In their work, genetic algorithm was applied in the first phase to find feasible solutions and then the best solution was produced by evolutionary algorithm in the second phase. The hybridization of genetic algorithm and constructive heuristic was proposed by Berger et al., 1998. In their work, the nearest neighbor heuristic of Solomon (1987) was used to create the initial population. Then, the genetic algorithm processes were applied to find the solution. Another published paper is the multi-criteria genetic algorithm, it was announced by Rahoual et al., 2001. The initial population of this work is randomly generated, the 2-opt* from Potvin and Rousseau (1993) applied in crossover operation while random reinsertions of customers between routes applied in mutation stage. They choose the probability selection based on the rank of individual to select the off-springs.

In this step, the genetic algorithm concept is applied to improve the population from the previous step. The roulette wheel selection method (Goldberg, 1989) is applied to select parents and then the crossover operator in this work is working between them based on 2-opt*, swap 2-2 and swap 1-1. After that the worse individual will be selected and mutation operator will be operated based on or-opt operator. To evaluate each offspring, the fitness function is determined by the objective function (Equation 2). The new generation will be selected based on their fitness value ranking.

4. The Computational Results

To evaluate the performance of the algorithm, all problem instances are test in the same environment. The following table illustrates the control parameters in this work (Table 3). In the first part of this work, the performance of the proposed algorithm is tested on Solomon benchmark dataset and is available on the internet at http://w.cba.neu.edu/~msolomon/problems.htm. As mentioned in the previous part of this paper that transportation in remote area plays an important role for organizations in this era. Therefore, twenty seven problem instances, including C20x (C201 to C208), R20x (R201 to R211) and RC20x (RC201 to RC208) are chosen to examine the proposed algorithm because they have wide time windows, and the vehicle capacity which serve in the routes are large. In addition, these three problem sets consist of three different geographical positions of customers. The geographical positions of customers are classified, random and mixed of classified and randomly generated for problem set C20x, R20x and RC20x respectively (Solomon, 1987).

In this part, the experiment aims to evaluate the performance of the proposed algorithm comparing to best known solutions in the literature and the Optimized Crossover Genetic Algorithm (OCGA). The OCGA was proposed to solve VRPTW by Nazif and Lee in 2010. The algorithm applies the optimized crossover of Aggarwal et al., (1997) in genetic algorithm. The algorithm provides competitive results for VRPTW (Nazif and Lee, 2010).

Firstly, the experiment considered the number of routes and then the proposed algorithm is applied in order to minimize the total distance. The comparative computational results are shown in comparison in Table 4. In Table 4, number of vehicle (NV) and total distance (TD) of the best known and the OCGA results are taken from Nazif and Lee (2010). The experiment found that the initialization stage provide effective searching area and the operator in the improving stage can improve the population efficiently. The solutions converge to the optimum effectively by the crossover, mutation and the selection methods in evolutionary processes. As shown in Table 4, the proposed algorithm provides the best results equal to the best known solutions in the literature and the OCGA for problem set C20x. Regarding the distance of problem sets R20x and RC20x in this table, the proposed algorithm conducts almost equal to best known results and almost better than the OCGA.

Table 3: Parameters used in the experiment

Parameters	Values
Number of individuals (N)	10
Crossover rate	0.8
Mutation rate	0.3
Number of iterations (Iter)	2000

Table 4: The computational results show in comparison with other results

Problems	Best Known		OCGA		Results	
	NV	TD	NV	TD	NV	TD
C201	3	591.56	3	591.56	3	591.56
C202	3	591.56	3	591.56	3	591.56
C203	3	591.17	3	591.17	3	591.17
C204	3	590.60	3	590.60	3	590.60
C205	3	588.88	3	588.88	3	588.88
C206	3	588.49	3	588.49	3	588.49
C207	3	588.29	3	588.29	3	588.29
C208	3	588.32	3	588.32	3	588.32
R201	4	1252.37	8	1248.87	4	1252.37
R202	**4**	**1088.07**	**6**	**1079.36**	**3**	**1191.70**
R203	3	939.54	5	965.79	3	939.50
R204	2	825.52	4	813.90	2	825.52
R205	3	994.42	6	994.88	3	994.42
R206	3	906.14	5	928.96	3	906.14
R207	**3**	**814.78**	**4**	**847.54**	**2**	**890.61**
R208	2	726.75	4	725.42	2	726.75
R209	3	909.16	6	890.27	3	909.16
R210	3	939.34	6	946.55	3	939.34
R211	**2**	**892.71**	**5**	**888.73**	**2**	**885.71**
RC201	4	1406.91	8	1387.55	4	1406.94
RC202	**4**	**1165.57**	**7**	**1176.98**	**3**	**1365.65**
RC203	3	1049.62	5	1082.94	3	1049.62
RC204	3	798.41	4	836.13	3	798.42
RC205	4	1297.19	7	1270.69	4	1297.19
RC206	3	1146.32	6	1149.73	3	1146.32
RC207	3	1061.14	6	1053.58	3	1061.14
RC208	3	828.14	5	816.10	3	828.14

Table 5: The Comparison of the proposed algorithms with the best known approaches for problem set C201 to C208, R201 to R211 and RC201 to RC208 of Solomon's dataset

C201-C208			R201-R211			RC201-RC208		
Authors	**CNV**	**Average Travel Distance**	**Authors**	**CNV**	**Average Travel Distance**	**Authors**	**CNV**	**Average Travel Distance**
[1]	3.00	749.13	[1]	3.18	1124.28	[1]	3.38	1411.13
[2]	3.00	590.00	[2]	3.00	1117.64	[2]	3.38	1368.13
[3]	3.00	594.25	[3]	3.09	1030.01	[3]	3.50	1284.25
[4]	3.00	624.31	[4]	3.09	1053.35	[4]	3.38	1256.80
[5]	3.00	589.86	[5]	2.73	969.95	[5]	3.25	1144.43
[6]	3.00	591.81	[6]	3.09	978.00	[6]	3.38	1170.23
[7]	3.00	589.86	[7]	2.73	967.75	[7]	3.25	1129.19
[8]	3.00	589.86	[8]	2.73	969.57	[8]	3.25	1134.52
The proposed algorithm	3.00	589.86	The proposed algorithm	2.73	951.03	The proposed algorithm	3.35	1237.34

Note: [1] Thangiah (1995), [2] Potvin and Bengio (1996), [3] Berger (1998), [4] Bräysy (1999), [5] Homberger and Gehring (1999), [6] Bräysy et al. (2000), [7] Cordeau et al. (2000), [8] Bräysy (2001).

In the case that the proposed algorithm provide worse distance, the proposed algorith use less vehicle number than them. It is noteworthy that the proposed algorithm produce better or equal results comparing to the best known and provides better results comparing to the OCGA for problem sets R20x and RC20x in terms of vehicle number.

The computational results from this table claims that the proposed algorithm is appropriate to serve a set of customers who live in different geographical position and their time windows are wide.

Table 5 illustrates the cumulative results in comparison. The table provides the results from the proposed algorithm and other eight algorithms which are taken from Bräysy (2001). The CNV in this table is the cumulative number of vehicles and the Distance refers to the average distance produced by the vehicles to serve all customers. The table shows that the algorithm provides the results equal to the best known solutions for all problem instances in problem C20x. This claims that the proposed algorithm work efficiently for the customers who are classified by geographical position.

For problem set R20x, the proposed algorithm uses less or equal number of vehicles comparing to the other eight algorithms while produces the best results in terms of distance. With regard to problem set RC20x, the proposed algorithm provides better results than Thangiah (1995), Potvin and Bengio (1996), Berger et al., (1998) and Bräysy (1999). It seems that the result for Thangiah (1995) is not competitive with the other approaches in this table. More significantly, the results in Table 5 demonstrate that the proposed algorithm is competitive comparing to other eight algorithms.

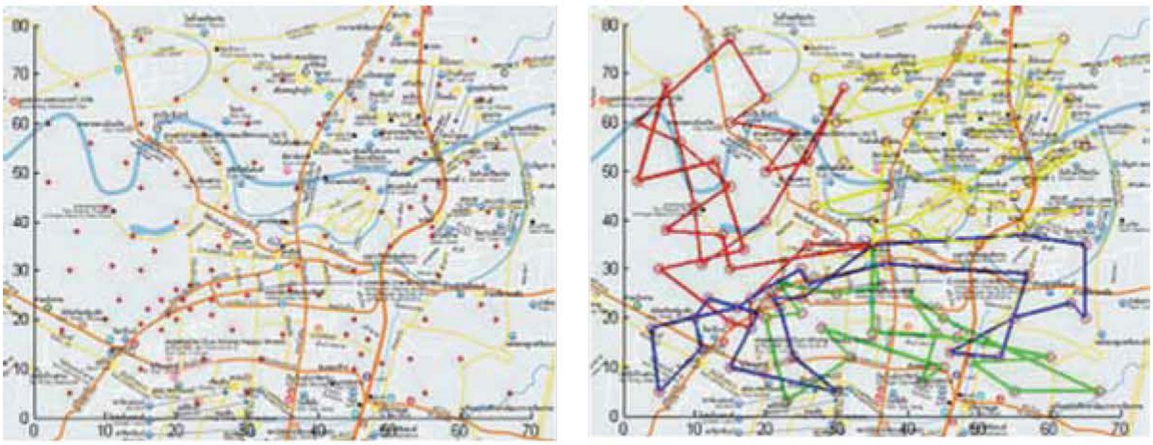
The last part of the experiment intends to evaluate the robustness of the proposed algorithm. In the experiment, the algorithm runs ten times in the same environment setting. The computational results over the ten runs are demonstrated in Table 6. The table shows the maximum distance (Max), minimum distance (Min), average distance (Avg), and standard deviations (SD) over ten runs of the proposed algorithm. The table also demonstrates vehicle capacity, vehicle number, Best Known and Authors who proposed the best known results of each problem instance. To evaluate the robustness of the proposed algorithm, vehicle capacity and number of vehicle are fixed over 10 runs. The standard deviation from Table 6 indicates that the robustness of the algorithm is acceptable for these problems.

In reality, customer's locations could be distributed in any area. To be easy to understand, some examples of results are shown as routing maps in the following figure. The routes in these figures are produced from the results of the proposed algorithm from Table 4. In Figure 5, the geographical position of customers and the shortest route to serve them can be seen. The proposed algorithm will choose the shortest routes to serve customers within their time windows while the maximum vehicle capacity is not exceed. To find the best geographical route, the vehicle can visit customers' position in any sequence and direction. In the figure, customers' positions of dataset C201 and RC201 are the same but the service routes are different. That is because the proposed algorithm generates appropriate routes depending on vehicle capacity, location, demand and the bound of time to service of each customer.

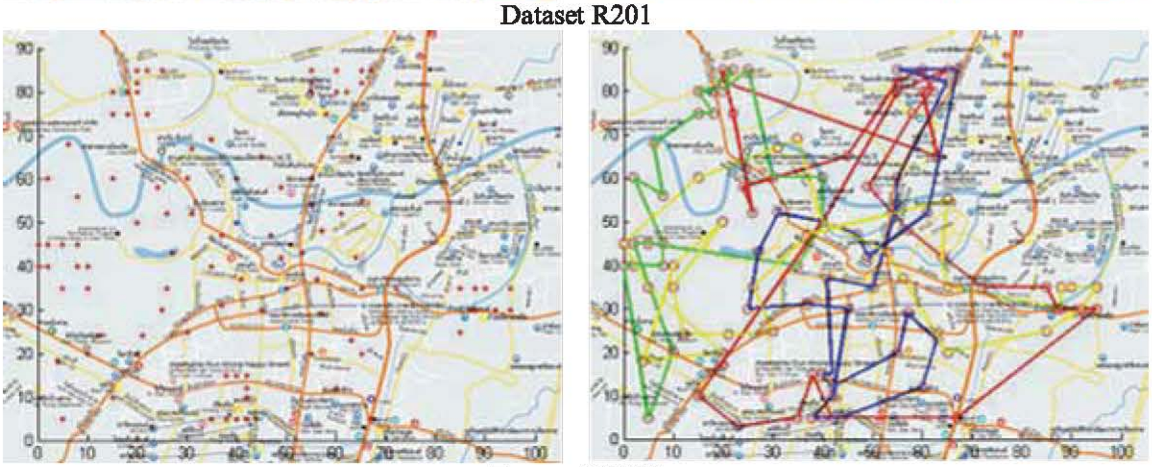
However, when the locations of customers are changed as the figure of dataset R201, the proposed algorithm still creates the effective routes to serve all of them.

These can be pointed that the proposed algorithm can respond to user's requirement for transport route design from different existing information.

Dataset C201



Dataset R201



Dataset RC201

Figure 5: The position of customers and the Constructed Route

Table 6: The computational results over 10 runs of problem set C20x, R20x, and RC20x

Problems	Distance				Vehicle Capacity	Vehicle Number	Best Known	Authors
	Max	Min	Avg	SD				
C201	592.10	591.56	591.83	0.38	700	3	591.56	[1]
C202	593.36	591.56	591.92	0.80	700	3	591.56	[1]
C203	593.32	591.17	591.98	0.84	700	3	591.17	[1]
C204	591.77	590.60	591.24	0.52	700	3	590.60	[1]
C205	591.56	588.88	589.85	1.25	700	3	588.88	[1]
C206	591.56	588.49	589.58	1.38	700	3	588.49	[1]
C207	588.88	588.29	588.50	0.27	700	3	588.29	[1]
C208	590.11	588.32	588.98	0.79	700	3	588.32	[1]
R201	1,258.11	1,252.37	1,256.22	1.67	1000	4	1,252.37	[2]
R202	1,197.75	1,191.70	1,194.70	2.01	1000	3	1,191.70	[3]
R203	944.88	939.54	940.88	1.72	1000	3	939.54	[4]
R204	829.56	825.52	827.10	1.75	1000	2	825.52	[5]
R205	1,000.98	994.42	996.35	2.12	1000	3	994.42	[3]
R206	909.45	906.14	907.79	1.35	1000	3	906.14	[6]
R207	893.33	890.61	891.94	1.07	1000	2	890.61	[5]
R208	729.11	726.82	728.09	1.04	1000	2	726.82	[4]
R209	917.78	909.16	913.58	2.96	1000	3	909.16	[7]
R210	942.22	939.34	941.24	1.12	1000	3	939.37	[4]
R211	898.23	885.71	895.78	1.86	1000	2	885.71	[8]
RC201	1,411.97	1,406.91	1,409.17	1.58	1000	4	1,406.94	[4]
RC202	1,372.69	1,367.09	1,369.01	1.78	1000	3	1,367.09	[9]
RC203	1,053.19	1,049.62	1,051.45	1.27	1000	3	1,049.62	[9]
RC204	798.42	798.42	799.71	1.66	1000	3	798.46	[4]
RC205	1,301.72	1,297.19	1,298.65	1.51	1000	4	1,297.65	[4]
RC206	1,150.21	1,146.32	1,148.25	1.30	1000	3	1,146.32	[7]
RC207	1,066.62	1,061.14	1,062.71	1.72	1000	3	1,061.14	[5]
RC208	832.23	828.14	829.39	1.45	1000	3	828.14	[10]

Note: [1] Rochat and Taillard (1995), [2] Homberger and Gehring (1999) , [3] Rousseau et al., (2002), [4] Mester et al., (2005), [5] Bent and Hentenryck (2001), [6] Schrimpf et al., (2000), [7] Homberger (2000), [8] Woch and Łebkowski (2009). [9] Czech and Czarnas (2002), [10] Ibaraki et al., (2001).

5. Conclusion and Future Works

This work aims to propose a multi-phase method for geographical transportation. The proposed method processes are described in details, tested on Solomon's benchmark dataset and the computational results are shown in comparison with the results obtained by other algorithms. The problem sets of testing data including problem set C201-C208, R201-R211 and RC201-RC208 which contains customers whose geographical locations are classified, generated randomly and mixed of classified and randomly respectively. The results also present the figure of routes produced by the proposed algorithm in example area which can help to understand the experiment results clearly. In the first part of the experiment, the computational results are presented in comparison with the results from Nazif and Lee (2010). For each different geographical problem set, the results in Table 2 confirm that the proposed algorithm works efficiently for all of them. In the second part of the experiment, the cumulative results of problem set C20x, R20x and RC20x are evaluated. The results in Table 3 verify that the proposed algorithm is the efficient approach for solving these three problem sets. Next, the computational results over ten runs of the proposed algorithm indicate that the quality and robustness of the algorithm are satisfied. More significantly, the proposed algorithm produces competitive average results for all problem sets comparing to other algorithms. Finally, the result demonstrates the location plot and the route produced by the proposed algorithm in example area. It point outs that the proposed algorithm can produce effective routes to serve customers in any areas. The effective routes could be produced in the different patterns depending on vehicle capacity, customers demand and their time windows.

The Geographical transportation should be emphasized in future research because of its significance. Effective transportation planning should be underlined for many relating situations such as to transfer food, medicine, workforce and other necessary elements to remote area, dangerous areas or disaster area. In Smart City scheme, the geographical transportation should be addressed. Traffic congestion, route planning for public and private transport must be concerned and prepared carefully. Future studies are planned to apply this methodology to Thailand's road. The target is to apply and improve the proposed algorithm to solve real routing data that will be useful to public or private organizations to plan their appropriate routing in the future.

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