A Green Vehicle Routing Problem with Simultaneous Delivery and Pickup with Time Windows for Cost Optimization

Mst. Anjuman Ara

Bangladesh Army University of Science and Technology, Saidpur, Nilphamari, Bangladesh
anjuman[at]baust.edu.bd

Abstract: ***This paper provides a green vehicle routing problem with simultaneous pickup and delivery with time windows. The objective of this study is to minimize total costs including fuel cost and carbon emission cost while satisfying customer pickup and delivery demands simultaneously with time windows and capacity constraints. In this paper, fuel consumption is computed considering vehicle load and distance. Firstly, a mathematical model is developed to describe the VRPSPDTW problem. This study proposes a genetic algorithm to optimize cost. The computational experiments are conducted under three crossover (one point, two point and cyclic crossover) and two mutation (swap and inverse) operator. The computation between swap and inverse mutation under three crossover are compared and the results show that swap mutation perform better than inverse mutation under every crossover operator.***

Keywords: Vehicle routing problem, Genetic algorithm, Fuel cost, Carbon emission cost

1. Introduction

The VRP was developed as a combinatorial optimization problem in 1959 with the objective of finding the optimal delivery route for serving a number of customers with a number of vehicles (Dantzig, and Ramser, 1959). Vehicle routing problem (VRP) consists of several components such as a set of customers, number of vehicles, demand, depot etc. with many applications. VRP can be divided into different problem with the variation of constraints and requirements. For example, VRP with time windows where customer service completes within time windows, CVRP with capacity constraint of vehicle, VRPB with backhauls, VRBSPD with both deliveries and collections; MDVRP with Multiple Depot that each vehicle can start or end its route at any of these depots.

Among different variants of VRP, VRP with simultaneous delivery and pickup draw great attention of researchers focusing on many practical applications. Reverse logistics is another most important strategy of logistics management which is integral part of vehicle routing problem with delivery and pickup. During the last 20 years, the awareness to protect environment has been increased by developing different laws and legislation of different industries. In reverse logistics, both delivery and pickup operations are performed simultaneously so that recycled or reused products can be took back for further processing. The objectives is to reduce the proportions of waste produced and energy consumed for green environment. The reduction of waste can be achieved through some activities such as recycled, disassembled and remanufactured of used economic goods for the purpose of re-use at the end of their lifecycle. Moreover, it is also possible to either recycled or re-used of wrapping and carrying devices. VRPSPDTW in further extended to VRPSPD with time windows which considers simultaneous pickup and delivery at each customer such that a customer is visited only once within the specified time window with vehicle capacity limitation.

Recently, green manufacturing are considered as new agenda of supply chain management where green transportation objectives are introduced in VRP models to convert transportation problems as environment friendly system from an environmental point of view. The traditional problem of VRP normally concentrates on minimizing different types of operational costs including distance, fleet size or time. By considering environmental safety, Vehicle routing problem is extended to Green Vehicle Routing Problem (GVRP) with the objectives of minimizing carbon emissions and fuel consumption. In this paper, green vehicle routing problem is incorporated with VRP with simultaneous delivery and pickup with time windows (VRPSDPTW) called green VRP with simultaneous delivery and pickup. The main contributions of the current paper are developed a mathematical model for green vehicle routing problem with simultaneous pickup and delivery and time windows (GVRP-SPDTW) and proposed genetic algorithm for the solution of the problem. The proposed problem intends to minimize the total cost including fuel consumption cost during travel and waiting time and carbon emissions cost. The paper is arranged as follows. Section 2 presents the literature on GVRPSPDTW. In Section 3, mathematical model for the problem is given. Section 4 describes the proposed solution algorithm. Computational results are provided in section 5 and finally, section 6 describes conclusion.

2. Literature Review

Vehicle routing problem with pickup and delivery can be extended into three types of problems such as VRP with backhauls, VRP with mixed pickup and delivery and the VRP with simultaneous pickup and delivery (VRPSPD) (Belgin et al. 2017; Wassan et al. 2008); Reil et al. 2018). In the VRPSPD, the vehicles are responsible for two duties at a a time, one is to deliver materials from the Depot to customers and another one is to simultaneously pickup materials back to the depot (Osaba et al. 2017).VRPSDP is studied first by Min (1989). He developed a model based on real world application with a case study of public library distribution system and solved the problem by Cluster First - Route Second approach. Belgin et al. (2018) introduce two-echelon simultaneous pickup and delivery vehicle routing problem (2E-VRPSPD). In the first echelon of 2E-VRPSPD, the pickup and delivery activities are completed simultaneously through depot to satellites by the same vehicles and in the second echelon, the same operations are performed from satellites to customers. To solve the problem, a variable neighborhood descent (VND) and local search (LS) is used for medium- and large-size instances of the 2E-VRPSPD. Finally, the heuristic method is applied for a supermarket chain of Turkey. Chen and Fang (2019) propose a two-layer discrete particle swarm optimization (DPSO) for solving two sub-problems of VRPSPD-customer bases determination and best routes decision. In the customer bases determination phase, the optimal allocation of vehicles of customers (customer bases) is determined by outer layer DPSO to meet the requirements of customers for delivery and pickup. In the second sub problem, the optimal routes of vehicles are obtained by inner DPSO. VRPSPD is solved effectively by two layer DPSO method. Tasan and Gen (2012) propose a genetic algorithm to solve VRPSPD with the objective to minimize total travelling distance. Park et al., (2021) propose a hybrid genetic algorithm with waiting strategy to solve vehicle routing problem with simultaneous delivery and pick. The objective is to minimize the total cost calculated by the sum of vehicles' distance traveled and the amount of pickup and delivery products transported.

Vehicle routing problem with simultaneous delivery and pickup (VRPSPD) is extended based on the constraints of time windows and known as VRPSPDTW. Angelelli and Mansini (2002) introduce VRPSPDTW first and solve the problem by combining a branch-and-price with branch-and-bound approach. Lai and Cao (2010) apply an Improved Differential Evolution (IDE) algorithm on small scale instances to carry out some experiments for solving this problem. Boubahri et al. (2011) constructed a multi-agent colonies algorithm for VRPSPDTW, but the method has not been tested with the instances. Wang and Chen (2012) proposed a co-evolution genetic algorithm with variants of the cheapest insertion method for VRPSPDTW. They also developed 65 instances revised from the well-known Solomon benchmark (1987) for VRPTW. Recently, the terminology green is incorporated to vehicle routing problem with awareness of environmental protection. The carbon emission from fuel consumption is considered as great threat to environment. So, researchers pay much attention on environment and study green vehicle routing problem. Majidi et al. (2017) present a fuzzy green vehicle routing problem with simultaneous delivery and pickup and time windows and develop a model to minimize the cost of carbon emission and fuel consumption. An adaptive large neighborhood heuristic is applied on a set of benchmark instances to conduct computational experiments.

Green vehicle routing problem with simultaneous delivery and pickup with time windows is proposed in this study to minimize carbon emission and fuel consumption cost. The mathematical model is developed under certain constraints. For the solving the problem, a genetic algorithm is suggested with two mutation and three crossover operator.

3. Cost Optimization Model

The vehicle routing problem with simultaneous pickup and delivery with time windows are proposed in this study as follows. A fleet of vehicles in the distribution center are set to deliver and pickup demand simultaneously to a certain number of customers. The locations of the distribution center and the customers are all known previously. Each vehicle has a fixed capacity and provide service within allowable duration. Each customer requires a fixed amount of delivery and returning operation that will be delivered by a fixed vehicle and pickup by the same vehicle simultaneously. Each customer must be assigned by a vehicle and visited exactly once. The travel times between the customers depend on the travelling distances between them. The customer must be serviced within time windows. The objective of this problem is to minimize the total cost including fuel consumption cost and carbon emission cost under capacity and time windows constraints. The settings and notations of cost optimizing model are given as follows:

Notation & definition

Sets

J = Set of customer nodes {1, 2, 3, 4,.....................n}
J_0 = Set of all nodes including customer locations and depot {0, 1, 2, 3, 4.............n}
V = Set of vehicles {1, 2, 3,............m}

Parameters:

(X_i , Y_i) = Coordinates of node, i= 0, 1, 2, 3,..........n, node 0 represents the depot
C_{ij}= Distance between node i and j, i, j∈J, i≠j
d_j = Delivery amount demanded by customer node j, j∈J
p_j = Pickup amount of customer node j, j∈J
n =Number of nodes, $n = |J_0|$
Q = Vehicle capacity
M = A very large number used in Big-M technique
$M = \max\{\sum_{j\in J}(d_j + p_j), \sum_{i\in J_0}\sum_{j\in J_0} C_{ij}\}$
r = Number of routes; the same as the number of vehicles being used
D_n = Total delivery amount
P_n = Total pickup amount
µ = Carbon emission rate
C_f = fuel cost
C_e = Carbon emission cost
A_i = arrival time of assigned vehicle at node i
D_i= departure time of assigned vehicle at node i
W_i = waiting time
T_i = tardiness time
S_i = service time
t_{ij}= time taken to vehicle v to travel from node i to j
e_i= the earliest time that node i can be serviced by a vehicle
l_i= the latest time that node i can be serviced by a vehicle

Decision variables:

l_v' : Initial loads of Vth vehicle when leaving the depot

l_j: Load of vehicle after having serviced customer $j, \quad j \in J$

K_j: Intermediate variable used to prohibit sub tours; can be interpreted as position of node $j \in J$ in the route

X_{ijv}: Binary decision variable that indicates whether V[th] vehicle travels from node i to j

X_{ijv} = 1, if vehicle V traverses arc (i, j)

X_{ijv} = 0, if vehicle V does not traverses arc (i, j)

Amount of fuel consumption and carbon emission depends on several factor such as speed, load, distance etc. The model of fuel consumption is developed based on load and distance similar to Huang et al., (2012). The fuel consumption is proportional to the driving distance and linear with the vehicle load. That is,

Fuel consumption = $d_{ij}[\alpha(\gamma_{ij} + \delta_{ij}) + \beta]$ and

Carbon emissions = μd_{ij} $[\alpha(Y_{ij} + Z_{ij})$

Where α and β are the coefficients of vehicle fuel consumption and μ is the carbon emission rate of fuel consumption.

X_{ij} = the binary variable to indicate whether arc (i, j) is visited on the route

γ_{ij} = the demand picked up from customers routed up to node i and transported on arc (i, j);

δ_{ij} = the demand to be delivered to customers routed after node i and transported on arc (i, j)

Considering the environmental effect, the complete objective function for the vehicle routing problem with simultaneous delivery and pickup and time windows is presented in the following:

Objective Function:

Minimize C_{cost} = $C_f \sum_{i\in J_0} \sum_{j\in J_0} \sum_{v\in V} d_{ij} X_{ij} \, [\alpha(\gamma_{ij} + \delta_{ij}) + \beta] + C_e \, \mu \sum_{i\in J_0} \sum_{j\in J_0} \sum_{v\in V} d_{ij} X_{ij} \, [\alpha(\gamma_{ij} + \delta_{ij}) + \beta]$

Subject to,

$$\sum_{i\in J_0}^{n} \sum_{v\in V}^{m} X_{ijv} = 1, \qquad j \in J \tag{1}$$

$$\sum_{i\in J_0}^{n} X_{isv} = \sum_{j\in J_0}^{n} X_{sjv}, \qquad s \in J, v \in V \tag{2}$$

$$l'_v = \sum_{i\in J_0} \sum_{i\in J} d_j X_{ijv}, \quad v\in V \tag{3}$$

$$l_j \geq l'_v - d_j + p_j - M(1 - X_{ojv}), j \in J, v \in V \tag{4}$$

$$l_j \geq l_i - d_j + p_j - M\left(1 - \sum_{v\in V}^{m} X_{ijv}\right), i \in J, j \in J \tag{5}$$

$$l'_v \leq Q, \quad v \in V \tag{6}$$

$$l_j \leq Q, \quad j \in J \tag{7}$$

$$S_j \geq S_i + 1 - n\left(1 - \sum_{v\in V}^{m} X_{ijv}\right), i \in J, j \in J, j \neq i \tag{8}$$

$$S_j \geq 0, \quad j \in J \tag{9}$$

$$X_{ijv} \in \{0,1\}, \quad i \in J_0, \quad j \in J_0, \quad v \in V \tag{10}$$

$$(A_{iv} + W_i + S_i + t_{ij})X_{ijv} \leq A_{jv} \tag{11}$$

$$A_i \leq l_i \qquad i \in J_0 \tag{12}$$

$$e_i \leq A_i + W_i \leq l_i \qquad i \in J_0 \tag{13}$$

Constraint (1) ensures that each customer is serviced exactly once. Constraint (2) guarantees that every vehicle that arrives to a customer node must leave that customer node. Constraint (3) defines the vehicle's initial load that is the accumulated demand of all customer nodes assigned to this vehicle. Constraint (4) means that the amount of vehicle load after it has serviced the first customer node on their route. Constraint (5) gives the amount of vehicle load en route. Constraint (6) guarantees that the initial vehicle loads do not exceed the vehicle capacity. Constraint (7) means that the vehicle loads en route do not exceed the vehicle capacity. Constraint (8) ensures sub tour elimination. Constraint (9) ensures the non-negativity of intermediate variables used to prohibit sub-tours. Constraint (10) states the decision variable is a binary variable. Equation 11, 12 & 13 are time windows constraints.

4. Methodology

This section of study described the procedure of the proposed genetic algorithm for the green VRPSPDTW. The concept of the genetic algorithm was first proposed by Holland (1975). It is random search and self-adaptive algorithms derived by the natural evolution of biological organisms. The procedure of genetic algorithm firstly generates an initial population randomly and selects a better population (chromosomes) based on the survival principle of the fittest. At the time of iteration, different genetic operator such as crossover and mutation operator are performed upon the individuals and chromosomes are evaluated based on fitness function. Thus, after several iterations, the best individuals are find out and obtained the final solution of the optimization problem. The procedure of the proposed genetic algorithm is illustrated in the flowchart given in fig. 1.

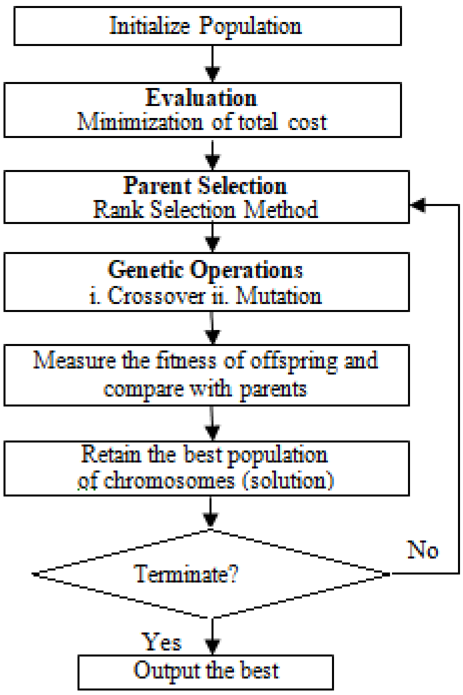

Figure 1: Flowchart of proposed genetic algorithm

4.1 Chromosome representation

In the genetic algorithm, chromosome is represented to describe the individual of VRPSPDTW model. Chromosomes are represented by permutation representation, instead of binary representation. Direct representation is used to encode routing solution into chromosome. The length of the chromosome determined by the number of customer nodes which are served by the vehicles. Routes are determined based on capacity and time windows constraints.

4.2 Initialization of the population

The desired number of individuals is generated to obtain a population with desired size. In the proposed methodology, the initial population is generated based on random permutation.

4.3 Fitness Function

In this study, the objective function (minimization of total cost) is used as a fitness function. The initial population created is evaluated based on fitness function. The cost function in this study is equal to sum of total cost including fuel cost and carbon emission cost.

The objective function (fitness function) of VRPSPDTW is as below:

Minimize $C_{cost} = C_f \sum_{i \in J_0} \sum_{j \in J_0} \sum_{v \in V} d_{ij} X_{ij} \, [\alpha(\gamma_{ij} + \delta_{ij}) + \beta] + C_e \, \mu \sum_{i \in J_0} \sum_{j \in J_0} \sum_{v \in V} d_{ij} X_{ij} \, [\alpha(\gamma_{ij} + \delta_{ij}) + \beta]$

4.4 Parents Selection

Selection technique used in this research is rank selection operator that is selection done by sorting population based on its fitness value. The rank selection operator was introduced by Baker (1985) to select best chromosomes to undergo the genetic operations. The chromosome of fitness value that is less cost incurred will rank first, and so on. Selection is chosen to reduce the possibility of an individual with a very large fitness dominating the population. By using the rankings, then the value of fitness is too large will not greatly affect the selection process is done randomly.

4.5 Genetic Operator

A crossover is the main genetic operator, which simulates reproduction between two parents. It acts on a pair of solutions and recombines them, producing one or more offspring in a certain way. Some of the parents' traits are shared by the offspring and the characteristics are thereby passed on to future generations. The crossover operator is not in a position to generate new functionality. Mutation, which is applied to a single solution of a certain probability, is the other genetic operator which makes random changes in the solution.

4.5.1 Crossover

Crossover plays a vital role in GAs, which simulates a reproduction between two parents. It works on a pair of solutions and recombines them in a certain way generating one or more offspring's. In this study, three crossover operator are adopted- one point crossover, two point crossover and three point crossover.

(a) One point crossover

This crossover uses the single point fragmentation of the two parents randomly and designates the fragmentation point as crossover point. The tails to the right of the crossover point are swapped between the two parent chromosomes and then combine the parents at the crossover point to create the offspring or child.

Parent-1	0	1	2	3	4	**5**	**6**	**7**	**8**	**9**
Parent-2	5	8	9	7	3	**1**	**0**	**6**	**4**	**2**

Figure 1: One point crossover

(b) Two point crossover

The two-point crossover selects two crossover points within a chromosome and then the bits in between the two points are swapped between two parent chromosomes to produce two new offsprings.

Parent-1	0	1	2	**3**	**0**	**5**	6	7	8	9
Parent-2	0	8	9	**7**	**0**	**3**	5	6	1	2

Offspring-1	0	1	2	**7**	**0**	**3**	6	7	8	9
Offspring-2	0	8	9	**3**	**0**	**5**	5	6	1	2

Figure 2: Two point Crossover

(c) Cyclic Crossover

The cycle crossover (CX) operator attempts to create offspring in such a way that each gene and its position is occupied by a corresponding element from one of the parents. Cycle crossover occurs by picking some cycles from one parent and the remaining cycles from the alternate parent. All the elements in the offspring occupy the same positions in one of the two parents. First a cycle of alleles from parent 1 is created. Then the alleles of the cycle are put in child 1. Other cycle is taken from parent 2 and the process is repeated.

Parent-1	1	2	3	4	5	6	7	8	9
Parent-2	9	3	7	8	2	6	5	1	4

Offspring-1	1	3	7	4	2	**6**	5	8	9
Offspring-2	9	2	3	8	5	**6**	7	1	4

Figure 3: Cyclic Crossover

4.5.2 Mutation

The mutation operator is used to maintain a certain level of diversity from one generation to another. It helps avoid the local optimal solution by preventing solutions from being too similar. A scramble mutation operator is used for this study. The genetic mutation operators i.e. inverse and swap mutation are adopted in this study.

(a) Inverse mutation

The inversion operator is a mutation operation, which is used to increase the diversity of the population. The inversion operator selects a substring from a parent and flips it to form an offspring. However, the inversion operator works with one chromosome only.

Parent	3	9	**5**	**4**	**6**	**2**	7	1	8
Offspring	3	9	**2**	**6**	**4**	**5**	7	1	8

Figure 4: Inversion Mutation

(b) Swap mutation

The swap mutation randomly selects two alleles in the chromosome and interchanges their positions. It is also known as the exchange mutation operator, also known as reciprocal exchange mutation or swapping.

Parent	3	9	**5**	4	6	2	**7**	1	8
Offspring	3	9	**7**	4	6	2	**5**	1	8

Figure 5: Swap Mutation

5. Computational Result

This section reports the computational results obtained by applying the proposed approach. All experiments are executed on Intel Core i5 560 GHz CPU and 2.0 GB of RAM. The algorithms are coded in MATLAB language version 2016b and stochastic simulations are performed in fixed Computer hardware. For conducting the experiment, the well-known Solomon VRP-TW instances are used. These instances provide the geographical coordinates of the location, the service time, delivery load, earliest time and latest time of all nodes. The pickup loads for VRPSPDTW model are determined using the following relation: pickup load = delivery load* r, where r = random number distributed over the range 0.5 to 1. The crossover and mutation operations are applied with probabilities 85% and 5% respectively. The problem is solved for 25, 50 and 100 customer size. There are six test cases in the database (R1, C1, RC1, R2, C2 and RC2), and this paper randomly selects one problem from each type for algorithm testing. The experiments of VRPSPDTW problem are conducted under six scenario with three crossover and two mutation operator such as one point crossover with swap mutation, one point crossover with inverse mutation, two point crossover with swap mutation, two point crossover with inverse mutation, cyclic crossover with swap mutation and cyclic crossover with inverse mutation. Moreover, the comparative analysis is carried out between swap and inverse mutation under three crossover operators. The experimental results in each table (1-3) show that the result from swap mutation is better than inverse mutation in terms of cost and distance.

Table 1: Computational results of one point crossover with swap and inverse mutation

Instances	Swap Mutation		Inverse Mutation		Deviation	
	Total distance	Total cost	Total distance	Total cost	Distance	Cost
R(101)/25	562	112820	715	142930	21%	21%
C(102)/25	370	73891	446	89267	17%	17%
RC(104)/25	655	129680	668	133130	2%	3%
R(203)/25	469	469230	561	561820	16%	16%
C(206)/25	317	221710	543	379360	42%	42%
RC(205)/25	261	260510	469	469510	44%	45%
R(103)/50	992	197960	1347	269530	26%	27%
C(105)/50	825	166200	1176	236320	30%	30%
RC(102)/50	1760	336070	1889	377030	7%	11%
R(206)/50	936	936050	1415	1414000	34%	34%
C(204)/50	580	406130	937	655550	38%	38%
RC(202)/50	1096	1094900	1929	1929200	43%	43%
R(103)/100	1891	379030	2469	493090	23%	23%
C(105)/100	2287	456740	3427	682340	33%	33%
RC(102)/100	2916	586070	4393	798390	34%	27%
R(206)/100	1603	1602100	2122	2121200	24%	24%
C(204)/100	2110	1475500	3224	2255000	35%	35%
RC(202)/100	2716	2717000	3922	3921500	31%	31%

Table 2: Computational results of two point crossover with swap and inverse mutation

Instances	Swap Mutation		Inverse Mutation		Deviation	
	Total distance	Total cost	Total distance	Total cost	Distance	Cost
R(101)/25	601	119640	716	122220	16%	2%
C(102)/25	352	70932	584	73435	40%	3%
RC(104)/25	680	134510	634	124980	-7%	-8%
R(203)/25	540	540940	725	595540	25%	9%
C(206)/25	294	204880	721	278300	59%	26%
RC(205)/25	331	331090	481	478470	31%	31%
R(103)/50	1284	257140	1367	270530	6%	5%
C(105)/50	1279	229350	1168	232730	-9%	1%
RC(102)/50	2027	398580	2231	427550	9%	7%
R(206)/50	1389	1318700	1337	1335500	-4%	1%
C(204)/50	1053	673180	1124	600560	6%	-12%
RC(202)/50	1658	1658000	1799	1789700	8%	7%
R(103)/100	2755	547920	2813	558530	2%	2%
C(105)/100	3512	695880	3524	692770	0%	0%
RC(102)/100	4266	821550	4254	834480	0%	2%
R(206)/100	2723	2707400	2379	2346000	-14%	-15%
C(204)/100	3347	2332600	3172	2219700	-6%	-5%
RC(202)/100	3340	3339100	3922	3893200	15%	14%

Table 3: Computational results of cyclic crossover with swap and inverse mutation

Instances	Swap Mutation		Inverse Mutation		Deviation	
	Total distance	Total cost	Total distance	Total cost	Distance	Cost
R(101)/25	732	146640	949	148650	21%	21%
C(102)/25	470	91363	469	91355	17%	17%
RC(104)/25	687	134480	853	156960	2%	3%
R(203)/25	677	672290	684	666040	16%	16%
C(206)/25	516	358040	785	312120	42%	42%
RC(205)/25	494	465420	551	524810	44%	45%
R(103)/50	1685	308080	2027	334470	26%	27%
C(105)/50	1379	269280	1528	288820	30%	30%
RC(102)/50	2473	444060	2514	494260	7%	11%
R(206)/50	1698	1619500	1680	1612900	34%	34%
C(204)/50	1366	854610	1291	889040	38%	38%
RC(202)/50	2482	2311300	2441	2324300	43%	43%
R(103)/100	3211	644630	3174	618520	23%	23%
C(105)/100	3860	767740	4155	812070	33%	33%
RC(102)/100	4695	921130	4853	935360	34%	27%
R(206)/100	3125	3078300	3167	3330200	24%	24%
C(204)/100	4002	2740000	4099	2793700	35%	35%
RC(202)	4486	4371200	4391	4373500	31%	31%

6. Conclusion

This work considers a vehicle routing problem with simultaneous delivery and pickup with time windows with the objective of minimizing the total costs including fuel cost and carbon emission cost with respect to the time windows and the vehicle capacity. The optimum result of VRPSPDTW model is computed with proposed a genetic algorithm. A two-point crossover and 2-opt mutation operations are used to maintain respectively the exploration and the diversity of the population. The simulation experiment results revealed that the proposed approach can find satisfactory solutions. One future issue may be the hybridization of the genetic algorithm with local search moves to improve the performance of the solution quality. The computational experiment of proposed GA are conducted by adopting genetic operators such as crossover operators (i.e. one point crossover, two point crossover and cyclic crossover) and mutation operators (i.e. inverse mutation and swap mutation) . The computational results of two mutation operators with three crossover operators under the GA are compared. The percentage of cost consumed and distance reduction are calculated and compared. The experimental results show that the GA under swap mutation is efficient to optimize the cost consumption compared to inverse mutation.

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