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Modified ant colony optimization with selecting and elimination customer and re-initialization for VRPTW

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ABSTRACT

Vehicle routing problem with time windows (VRPTW) is a special kind of vehicle routing with adding time windows constraints and has a variety of applications in logistics. Many researchers have attacked the VRPTW by approximate solutions. Ant colony optimization (ACO) is a classical method to solve the VRPTW problem but the constraints of VRPTW are not used to consider customer selection. Most ACO-based optimization algorithms can suffer from the complexity of the VRPTW such as trapping in local optimum. In this paper, we present a novel ACO-based optimization method for VRPTW by using customer selection in order to decrease or solve the inefficiency of the customer selection of the ACO process. Moreover, we enhance performance searching of ACO in order to eliminate these small routes from the ACO process. Finally, we proposed the re-initialization technique in order to decrease or solve trapping in local optimum. Experiments conducted on fifty-six maps dataset have shown that the proposed method achieves encouraging performance compared to other ACOs.

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1. INTRODUCTION

Vehicle routing problem (VRP) is a problem of transporting goods from a depot to all customers through the shortest route regarding vehicle capacity constraints. Many logistic companies encounter these problems because they have limited resources. VRP plays an important role in many businesses and many industries. It first appeared in Dantzig and Ramser [1]. The VRP with time windows can be defined as the VRP with time window (VRPTW). The objective of VRPTW is to find the lowest-cost routes for a group of customers within time and limited capacity constraints [2], [3]. VRPTW is a non-deterministic polynomial-time hardness (NP-hard) problem [1]–[3]. Therefore, the VRPTW is hard to be solved by using exact optimization techniques.

For many years, many researchers have attempted to solve the problem of VRPTW by using meta-heuristic algorithms, including genetic algorithms (GA) [4]–[7], tabu search [8] and ant colony optimization (ACO) [9]–[15]. ACO has successfully solved VRP [16], [17]. Motivated by [18]–[20], ACO has much potential for the VRPTW. First, ACO has been successfully to solve many optimization problems such as job scheduling problems, traveling salesman problems (TSP), network routing, and VRP. Despite this, the main drawback of ACO is that it has a propensity for trapping in the local optimum. To overcome the drawback of ACO, many researchers [14], [15], [21], [22] increase searching diversity by adding the mutation technique and reset technique to the ACO process. In addition, many researchers [13]–[15], [22] have added the neighborhood search technique or local search technique to the ACO process to improve answers.

The local search or neighbourhood search is conducted by changing or swapping one or two customer routes in order to improve the answer [23]. Many researchers proposed the local search to improve answers from ACO searching. This paper uses three well-known local search techniques as follows: the first technique, customer exchange technique [13] is all possible valid permutations from exchanging customers between two routes. The reason is to obtain the best answer from the exchanging mechanism. The second technique, one move operator technique [13] is all possible valid permutations from inserting customers between two routes. The reason is to obtain the best answer from the insertion mechanism. The third technique, two-opt technique [24] is all possible valid permutations from the swapping of two customers in the same route. The reason is to obtain the best answer from the swapping mechanism.

Yu *et al.* [13] proposed a hybrid ACO and tabu search for VRP with time windows (HACOTS). Tabu search (TS) is used to prevent trapping in local optimum, search new answers, and maintain the diversity population. Two-opt techniques, customer exchange technique, and one move operator technique are applied to HACOTS to improve the answer of HACOTS. Gupta and Saini [14] proposed an enhanced ACO algorithm and pheromone reset for VRP with time windows (EACOR). The effect from pheromone reset can decrease or solve trapping in local optimum. In addition, EACOR adds the new technique of creating new answers by choosing a customer that differs from the previous answer. Two-opts technique is applied to EACOR to improve the searching performance of EACOR. Zhang *et al.* [15] proposed a hybrid ACO and mutation operator for a VRP with time windows (HACOM). HACOM added a new technique for updating pheromone and new three mutation operators such as the interchange operator, the shifting operator, and the inverse operator. The results from new three mutation operators can increase the local search ability, the global search ability, and prevent trapping in local optimum. HACOTS, EACOR, and HACOM are tested with the well-known benchmark Solomon problems. The results from the experiment show that answers of these algorithms are better than that of competitive algorithms.

To handle trapping local optimum and the searching performance of ACO, this paper offers the novel selecting customer technique, the novel dynamic population, the novel customer elimination technique, and re-initialization technique applied to ACO. A set of the Solomon fifty-six maps [25], [26] is used for comparison to other ACOs, and the proposed algorithm. The best paths of the Solomon fifty-six maps were presented by [27]. The results show that the quality and reliability of the answers to the proposed technique were better than other comparative algorithms. The rest of this paper is organized as follows: section 2 explains the comprehensive theoretical basis such as VRPTW and ACO, section 3 explains the literature review or the previous modified ACO to VRPTW, section 4 explains the proposed technique, section 5 explains the experiment results, and section 6 explains the conclusion of this paper.

2. PRELIMINARIES

2.1. VRP with time windows

The objective of VRPTW is to search a set of the least distance routes to transport goods to all customers within due time without overloading the vehicle capacity and each customer is visited only once [28], [29]. All vehicle routes begin and finish at the supplying depot. The VRPTW formulations can be explained as follows:

$$Min \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{K} C_{ij} x_{ijk} \tag{1}$$

$$x_{ijk} = \begin{cases} 1 & if\_the\_vehicle\_k\_travels\_from\_i\_to\_j \\ 0 & else \end{cases} \tag{2}$$

$$\sum_{k=1}^{K} \sum_{j=1}^{N} x_{ijk} \leq K \quad for\ i = 0 \tag{3}$$

$$\sum_{i=1}^{N} x_{ijk} = \sum_{j=1}^{N} x_{jik} \leq 1 \quad for\ i = 0, k \in \{1, \dots, K\} \tag{4}$$

$$\sum_{j=0, j\neq i}^{N} \sum_{k=1}^{K} x_{ijk} = 1 \quad for\ i \in \{1, \dots, N\} \tag{5}$$

$$\sum_{i=0, j\neq i}^{N} \sum_{k=1}^{K} x_{ijk} = 1 \quad for\ j \in \{1, \dots, N\} \tag{6}$$

$$\sum_{i=1}^{N} \sum_{j=0, j\neq i}^{N} x_{ijk} \times q_i \leq Q \quad for\ k \in \{1, \dots, K\} \tag{7}$$

$$t0 = w0 = 0 \tag{8}$$

$$\sum_{i=1}^{N} \sum_{j=0,j\neq i}^{N} x_{ijk} = x_{ijk}(t_i + t_{ij} + w_i) \leq t_j \quad for\ k \in \{1, \ldots., K\} \tag{9}$$

$$T_{Ei} \leq t_i \leq T_{Li} \tag{10}$$

where xijk is i customers and j customers that are assigned to transport goods by vehicle k. Cij is a euclidian distance between customer i and j. K is the total number of vehicles. Qi indicates a quantity of item transported to customer i for the depot. The depot is defined as the number 0. N is a set of customers. Q denotes the maximum vehicle capacity. Ti is the arrival time for i customer. Tij is the travel time between i and j customers. wi is the waiting time at i customer. TEi is the earliest arrival time at i customer and if the vehicle visits before TEi, ti is set TEi. TLi is the latest arrival time at i customer and the vehicle cannot arrive at i customer after TLi.

In (1) explains the objective of VRPTW to the least total transporting distance (Cij). In (2) explains each customer that is assigned to transport goods by only one vehicle. In (3) explains the maximum number of routing constraint. In (4) explains all vehicle tours begin and finish at the depot. In (5) and (6) explains a customer that is visited only once. In (7) explains the total quantity of goods that a vehicle can be loaded cannot exceed the Q capacity. In (8) and (9) are the time constraint. In (10) is the vehicle serving the customer within due time.

2.2. Ant colony optimization

ACO is inspired by the behavior of searching food of genuine ants. Each ant attempts to search for shortest paths from ant's nest to feeding sources. The begin step, each ant random walk from its nest to feeding sources. Each ant walks along density of pheromone and releases pheromone among walking. The pheromone of the far distance is much evaporated while the pheromone of the short distance is less evaporated. Other ants choose to walk along the rest pheromone. Hence, the short distance increases density of pheromone while the far distance decrease density of pheromone. Finally, almost ants choose walk along the short distance.

ACO can be described as follows: Initially, each edge has an initial pheromone □$_{ij}$(0) between two cities. The next step is to select a customer of ant. The first customer of each ant is randomly selected, and then each ant selects the next customer according to the probability function as (11).

$$P_{ij}^{k} = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}[n_{ij}]^{\beta}}{\sum_{t\in allowed}[\tau_{ij}(t)]^{\alpha}[n_{ij}]^{\beta}}, j \in allowed \\ 0, otherwise \end{cases} \tag{11}$$

Where P_{ij}^{k} denotes the probability of k[th] ant choosing to move from customer i to customer j, $\tau_{ij}(t)$ is the number of pheromones, which will be found in inter-customer routes in iteration t, $n_{ij} = \frac{1}{d_{ij}}$ is the inverse of the distance, β is a parameter which determines the relative importance of pheromone versus distance (β > 0). The result from (11) is use to select a path that is shorter and has a greater amount of pheromone. After the customer selection of ant process is completed, the fitness of each ant is used to update pheromones and the fitness of the ant is calculated in (12).

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{L_k}, \text{if the } k^{th} \text{ant uses edge}(i, j) \text{in its tour} \\ 0, \text{otherwise} \end{cases} \tag{12}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{13}$$

$$\tau_{ij}(t) = (1 - \rho)\, \tau_{ij}(t - 1) + \Delta\tau_{ij}(t) \tag{14}$$

Where $\Delta\tau_{ij}^{k}(t)$ is the amount of pheromones left by an ant on a route that it is calculated in (12); Q is a consistent value; k representing the k[th] ant in the colony; L_k is the fitness of ant k; $\Delta\tau_{ij}(t)$ denotes the total amount of pheromones that ants use the route between customers i and j have left; m is the amount of ant population; ρ is the coefficient of evaporation which receives a value between [0-1]. The next step is to repeat this process until the stop condition is reached. In terms of VRPTW, each ant starts at the depot and creates a route by selecting a customer under the capacity constraints and the time window constraints until the capacity of the vehicle cannot be further loaded. It is then returned to the depot. Customer selection is based on pheromone [27]. The process is repeated until all customers are selected.

3. METHOD

3.1. Modified ACO with novel selecting customer

According to literature review, the methods HACOTS, EACOR, and HACOM seem promising for VRPTW. However, their results are not satisfying because of improper customer selection. Typically, the ACO generation process involves selecting a customer based on pheromone influence. As the searching progresses, the better is the path, the stronger the pheromone will be, influencing on the selection of the next cycle. The answer will be good to some extent but the selection is not considered constraint, chances of choosing a customer is inappropriate. In order to understand, we show example as Figure 1. From Figure 1, there are 4 customers, the first has the earliest arrival time (TE)=5, the second customer has TE=10, the third customer has TE=15, the fourth customer has TE=20. Assuming the transit time from customer to customer is 5. If we consider the constraint of TE, we should choose 0, 1, 2, 3, 4, 0, but since ACO does not take the constraint of TE. Let's consider. There is a chance that the ACO causes car 1 to choose 0, 1, 4, 0 and car 2 is 0, 2, 3, 0, causing longer mileage and using more cars. From the problem of choosing ACO's customer as previous mentioned.

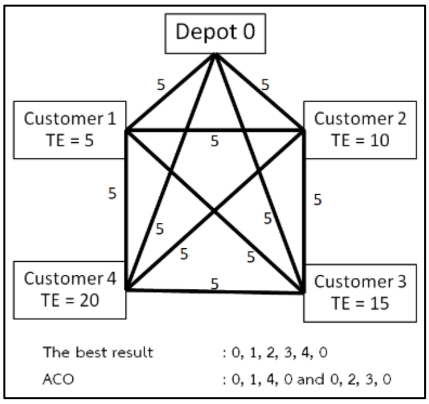

Figure 1. The example of choosing inappropriate customer

The purpose of this paper is to bring the constraint of the VRPTW for consideration to search for an answer. ACO's customer selection is based on the greedy algorithm for its application dividing the ant population into four equal parts which each ant uses only one criterion. Each section uses the following criteria for selecting a customer: criteria 1 is the nearest distance from the current customer to the selected customer (ND), criteria 2 is the minimum time of the earliest arrival time (TE) from the current customer to the selected customer, criteria 3 is the least time of the latest arrival time (TL) from the current customer to the selected customer, criteria 4 is the least goods quantity of the selected customer (LG). The selection of suitable customers is selected from all customers and sorted according to the criteria mentioned above. These top rank customers are selected to increase pheromone than customers that does not appear in the rank. The results from pheromone are enhanced, these top rank customers have the probability to be selected than any other customers. In order to understand, we show example as Figure 2. From Figure 2, there are all customers selected into the ant list: 1, 2, 3, 4, and 5 respectively being sorted by TE criteria, they are arranged in the following order: 3, 4, 5, 2, 1. If the number of suitable lists is 2 and the pheromone multiplier is 5, then the pheromone of 3, 4 will be increased by 5 times, while the pheromone of 5, 2, 1 will remain the same. The probability of being chosen 3 and 4 will be higher in the same time that 5, 2, 1 will have lower probability of being chosen.

Normally, according to the ACO answer creation process, a customer is added to a vehicle until the customer cannot be added. A new vehicle is created if unselected customers remain. The technique is called the sequential addition. If a customer is added by the greedy algorithm, the first vehicles will get a good answer but the later vehicles get a very bad answer. A good selection should be a good answer for all vehicles. Hence, we propose a parallel addition. All customers are added to all vehicles alternately. In order to understand, we show exmaple as Figure 3. From Figure 3, the number of vehicles is two and the number of all customers are 10 (0 to 9). In case of the sequential addition, First addition, the first vehicle is added and supposes its path is 0, 1. Next, the first vehicle is added and supposes its path is 0, 1, 2. Next, the first vehicle is added and supposes its path is 0, 1, 2, 3. Next, the first vehicle is added and supposes its path is 0, 1, 2, 3, 4. In case of the parallel addition, first addition, the first vehicle is added and supposes its path is 0, 1. Next, the second vehicle is added and supposes its path is 0, 2. Next, the first vehicle is added and supposes its path is 0, 1, 3. Next, the second vehicle is added and supposes its path is 0, 2, 4.

Customer	TE
1	30
2	20
3	5
4	10
5	15

Sort by TE

Customer	TE	status	pheromone
3	5	suitable	× 5 (multiplier)
4	10	suitable	× 5 (multiplier)
5	15	unsuitable	× 1
2	20	unsuitable	× 1
1	30	unsuitable	× 1

Figure 2. The example of the proposal method of selection customer

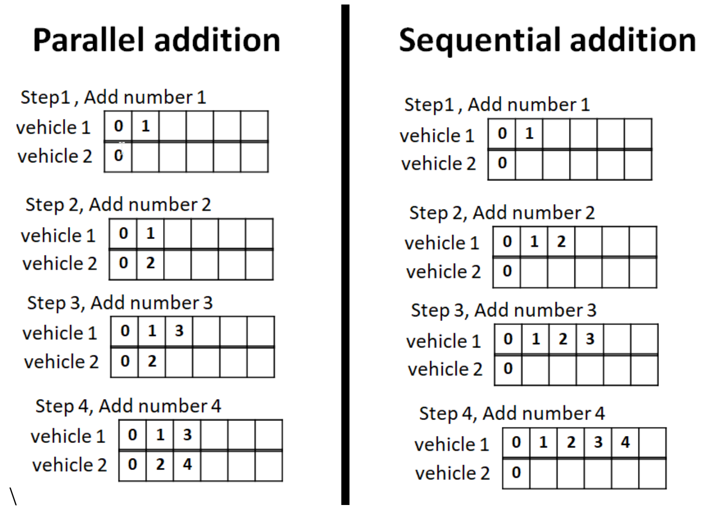

Figure 3. The example of the sequential addition and the parallel addition

The addition is swapped as mentioned earlier until all customers are selected. However, this technique requires evaluating a number of vehicles (NV) that are used. NV is calculated by (15). If vehicles are not enough, a new vehicle will be created and uses the sequential addition. As mentioned earlier, this proposed technique is called modified ACO with novel selecting customer technique or the novel selecting customer technique or ACOs.

$$NV = \frac{\sum_{i=1}^{N} Q_i}{Q} \quad (15)$$

3.2. Modified ACO with novel dynamic population

As mention earlier, using multi criterion (ND, TE, TL, and LG) that can increase searching performance of ACO is better than using only one criterion. Each criterion is suitable for solving different problems. If amount of population of the most suitable criteria for solving problems are increased, the performance of searching is increased in order to maintain searching resource, the population of the most unsuitable criteria should decrease equal to quantity that is increased. This idea can increase chances of finding better answers. Hence, this paper proposed any criterion that is able to generate the best answer in the current round, the population of that criteria are increased in the next round. On the other hands, any criteria generate the worst answer in the current round, the population of criteria are reduced in the next round. This proposed technique is called modified ACO with novel dynamic a number of criteria population for selecting a customer technique or the novel dynamic population technique or ACOSD.

3.3. Modified ACO with novel customer elimination

As mentioned previously, neighbourhood search can improve ACO's answer. However, neighbourhood search technique cannot be designed to solve the problem of the excess customers. In order to understand, we show example as Figure 4. From Figure 4, ACO's searching results are: vehicle 1 has the following routes: 0, 1, 4, 6, 5, 2, 0. Vehicle 2 has the following path 0, 3, 0. Assuming customer 3 can be inserted into vehicle 1 with constraints that do not exceed. The result of inserting causes the distance to be increased more than using 2 vehicles. In case of one move operator technique, insertion will not be performed. In fact, if the customer 3 is inserted into the first vehicle and is arranged by two-opt technique, the distance will be obtained that is a shorter path. The customer 3 is called an excess customer.

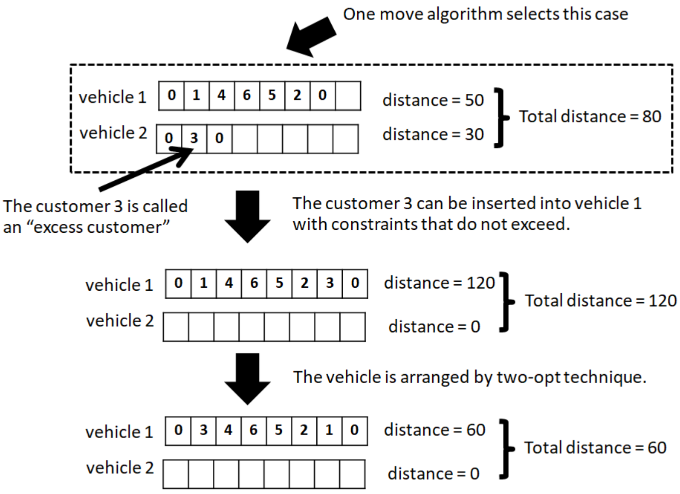

Figure 4. The example of the customer elimination

Managing excess customer can greatly improve ACO's answer by this improvement. Therefore, this research proposed the novel excess customer elimination technique. The excess customer elimination process is using one move operator technique constraints are not considered. Normally, the excess customer is only 1-3 customers. After the ACO searching is completed, the customer elimination will be executed following by the neighbourhood search technique.

The result from customer elimination, a number of routes decrease and obtain better answer. The answers are used to update pheromone, and then pheromone is used to create answers in the next round. This technique can enhance searching performance of ACO and obtain better answer. The technique is called modified ACO with novel customer elimination or the novel customer elimination technique or ACOC.

3.4. Modified ACO with re-initialization

As mentioned previously, the novel selecting customer technique, the novel dynamic population technique, and the novel customer elimination technique can improve the answers of ACO searching; however, trapping in local optimum is possible for the length of search time. When trapping in local optimum, the search answer will not be improved. It seems like the search is over. Therefore, the searching for further answers will be a waste of resources. To preventing searching after trapping in local optimum, the ACO should re-run or re-initialization the searching. Therefore, the simple technique to indicate trapping in local optimum is to monitor the unchanged number of consecutive best answers [27]. For these reasons, this paper proposed re-initialization when the unchanged number of the best consecutive answer is more than the threshold value. This proposed technique is called modified ACO with re-initialization or the re-initialization technique or ACOI.

3.5. The modified proposed ACO

As mentioned previously, we incorporate four proposed techniques into ACO to enhance the efficiency as well as to solve trapping in local optimum. The proposed technique is called modified ACO with novel selecting customer technique, novel dynamic population technique, novel customer elimination technique, and re-initialization technique (ACOSDCI). Pseudo code of ACOSDCI is shown in algorithm 1:

Algorithm 1:

```
Initialize edges (i, j) and pheromone (τij)
Calculate NV in (15)
reset GR, TG = 0
m1 = 25, m2 = 25, m3=25, m4=25
While termination condition ≠ true do
process of novel selecting customer technique
MV = NV
 For ant x begin 1 to a number of all ants
  For until customers in list of ant x is full
   For car k begin 1 to MV
    If car k can add the next customer
     The chosen customer is not repeat customer in list of ant x
     The chosen customer passes condition of capacity and time Windows
     If 1 <= x <= m1
      The chosen customer is according to the goods quantity criterion (sort min to
max)
     Else If m1 +1 <= x <= m1+ m2
      The chosen customer is according to the earliest arrival time criterion (sort
min to max)
     Else If m1+ m2+1 <= x <= m1+ m2+m3
      The chosen customer is according to the latest arrival time criterion (sort
min to max)
     Else If m1+ m2+m3+1 <= x <= m1+ m2+m3+m4
      The chosen customer is according to the distance criterion (sort min to max)
     End If
     A number of chosen customers in the top lists are not over SN
     choose the next customer with probability according to (11) but customer in
list, the probability × MN
     Insert chosen customer into list of ant x
    End If
    If no one vehicle cannot add the next customer and some customers are not stay in
list ant x
     Add the new vehicle and MV = MV + 1
    End If
   End For
  End For
 End For
 Evaluate the fitness of each ant
 process of novel customer elimination
 For ant x begin 1 to a number of all ants
  If ant x has the excess customers
   Apply one move operator without considering results
   Apply 2-opt
  End If
 End For
 process of neighborhood search
 Apply customer exchange with each ant
 Apply one move operator with each ant
 Apply 2-opt with each ant
 Update pheromone according to (14)
 process of re-initialization
 If GR is not improve
  TG++
 End If
 If TG >= RP
  All Initialize edges and pheromone
  Reset GR, TG = 0
  Reset m1, m2, m3, m4
 End If
 process of novel dynamic a number of criteria population for selecting a customer
 If the number of criterion population (m1, m2, m3, m4) of the worst answer > 1
  The number of criterion population of the best answer in the current iteration + 1
  The number of criterion population of the worst answer in the current iteration - 1
 End If
 Apply the evaporation
End While
```

Where m_1 is the number of the goods quantity criterion population, m_2 is the number of the earliest arrival time criterion population, m3 is the number of the latest arrival time criterion population, and m4 is the number of the distance criterion population. NV is a number of vehicles that is evaluated. MV is a number of vehicles. GR is the best answer of each round reset. RP is the round reset. TG is the number of GR that is not improved continuously. SN is the maximum amount of customers that is selected from the top list. MN is the constant values to increase chance of selecting this customer.

4. RESULTS AND DISCUSSION

4.1. Parameters setting

Parameters of all algorithms are as follows: Q=0.6, β=4, α=1, ρ=0.7. For these parameters are suggested by [15]. The number of population of ants is 100. The number of experiments on each map is 10 runs. The maximum number of generation is 5,000. The non-ACO parameters for all proposal algorithms (ACOS, ACOSD, ACOSDC, and ACOSDCI) are set as RP=20, SN=20, MN=10. This value of RP, SN, and MN gets from the results from experiment. The experiments start defining them equal 0 then increase 5 until 100 and select value of them that can create the best result. The non-ACO parameters for the compared algorithms (HACOTS, EACOR, and HACOM) are set according to the original papers. All maps are used in this experiments come from the Solomon fifty-six maps [28].

The detail of the Solomon fifty-six maps is showed as Table 1 (in appendix). From Table 1 show that C101 to C109 use the constant amount that are 10 vehicles for the best solutions and the capacity of vehicles are 200. C201 to C208 use the constant amount that is 3 vehicles for the best solutions and the capacity of vehicles are 700. R101 to R112 and RC101 to RC108 has the capacity of vehicles are 700. R201 to RC201 and RC201 to RC208 has the capacity of vehicles are 1000. R101 to RC208 use the amount of vehicles that are varied for the best solutions.

The algorithm performance in the experiment can be indicated as follows: The average best fitness value (ABF) is the average of best fitness in the final generation from all running. ABF measures the efficiency of answer searching of an algorithm. The closer the ABF to the optimum point of a method, the better the algorithm is. SD is the standard deviation. SD measures the answer searching reliability of an algorithm.

4.2. Experiment of proposed algorithm

The experimental results of Table 2 (in appendix) show that the quality answer of ACOSDCI is better than that of HACOTS, EACOR, HACOM, ACOS, ACOSD, and ACOSDC because of its lowest ABF of all tested maps. The reliability of ACOSDCI is better than that of HACOTS, EACOR, HACOM, ACOS, ACOSD, and ACOSDC because of its lowest SD in all tested maps. From this experiments, it shows that the proposed novel selecting customer technique can obtain the answer better than the standard ACO process, because the results of all tested maps (the quality answers and the reliability answers) of ACOS are better than those of HACOTS, EACOR, and HACOM. From this experiments, it shows that the proposed novel dynamic population technique can enhance searching performance of ACOS, because the results of all tested maps (the quality answers and the reliability answers) of ACOSD are better than those of ACOS. From this experiments, it shows that the proposed novel customer elimination technique can enhance searching performance of ACOSD, because the results of all tested maps (the quality answers and the reliability answers) of ACOSDC are better than those of ACOSD.

ACOSDC can effectively solve VRPTW. However, some maps such as C104, C103, C108, C109, C204, R205, R206, R208, R210, and RC204, ACOSDC cannot search the best known point, because ACOSDC does not have the process in dealing with the problem of trapping in the local optimum. From this experiment, it shows that the proposed re-initialization technique can effectively solve trapping in the local optimum because ACOSDCI can search the best known point from all test maps and all rounds.

5. CONCLUSION

This research proposed a modified ACO, named ACOSDCI, which takes advantages of novel selecting customer, dynamic population, customer elimination, re-initaliziation mechanisms to effectively solve the VRPTW. The novel selecting customer technique, the novel customer elimination technique, and the novel dynamic population technique can enhance searching performance of ACO. However, three mentioned techniques are still trapped in local optimum. For this reason, the re-initialization technique is added to solve trapping in local optimum when the trapping already occurred. Thus, the concurrent application of four techniques (ACOS, ACOD, ACOC, and ACOI) is proposed to improve the searching performance of ACO. A set of the Solomon fifty-six maps: HACOTS, EACOR, HACOM, ACOS, ACOD, ACOC, ACOI and ACOSDCI are tested and the results are compared. The results indicate that the proposed ACOSDCI outperforms HACOTS, EACOR, and HACOM regarding the reliability and quality of answers in all the experiments.

The proposed technique is suitable for solving the problem of a dataset of the Solomon. However, the proposed technique is tested with other datasets or the real practical problem. The proposed technique must adjust many parameters suitable for the problem in order to get good results. The adjusting parameters are complicated. In the future, we have plan to develop the proposed technique can automatically adjust parameters to suitable for the problem.

APPENDIX

Table 1. The detail of the Solomon fifty-six maps

Problems	The number of vehicles for the best solutions	The maximun number of vehicles	The capacity of vehicles	The number of customers
C101	10	25	200	100
C102	10	25	200	100
C103	10	25	200	100
C104	10	25	200	100
C105	10	25	200	100
C106	10	25	200	100
C107	10	25	200	100
C108	10	25	200	100
C109	10	25	200	100
C201	3	25	700	100
C202	3	25	700	100
C203	3	25	700	100
C204	3	25	700	100
C205	3	25	700	100
C206	3	25	700	100
C207	3	25	700	100
C208	3	25	700	100
R101	19	25	200	100
R102	17	25	200	100
R103	13	25	200	100
R104	9	25	200	100
R105	14	25	200	100
R106	12	25	200	100
R107	10	25	200	100
R108	9	25	200	100
R109	11	25	200	100
R110	10	25	200	100
R111	10	25	200	100
R112	9	25	200	100
R201	4	25	1000	100
R202	3	25	1000	100
R203	3	25	1000	100
R204	2	25	1000	100
R205	3	25	1000	100
R206	3	25	1000	100
R207	2	25	1000	100
R208	2	25	1000	100
R209	3	25	1000	100
R210	3	25	1000	100
R211	2	25	1000	100
RC101	14	25	200	100
RC102	12	25	200	100
RC103	11	25	200	100
RC104	10	25	200	100
RC105	13	25	200	100
RC106	11	25	200	100
RC107	11	25	200	100
RC108	10	25	200	100
RC201	4	25	1000	100
RC202	3	25	1000	100
RC203	3	25	1000	100
RC204	3	25	1000	100
RC205	4	25	1000	100
RC206	3	25	1000	100
RC207	3	25	1000	100
RC208	3	25	1000	100

Table 2. Comparative ABF and SD of HACOTS, EACOR, HACOM, ACOS, ACOSD, ACOSDC, and ACOSDCI

Problem	Best known	HACOTS		EACOR		HACOM	
		ABF	SD	ABF	SD	ABF	SD
C101	828.93	1124.11	37.60	935.30	48.40	909.56	32.91
C102	828.93	1032.93	18.68	976.66	51.36	912.11	17.72
C103	828.06	949.40	17.77	966.28	36.76	924.75	7.08
C104	824.78	901.59	6.37	915.98	23.97	896.22	8.02
C105	828.94	1014.95	21.31	908.72	24.03	927.95	21.54
C106	828.94	1026.38	19.18	935.48	40.83	941.62	12.27

Table 2. Comparative ABF and SD of HACOTS, EACOR, HACOM, ACOS, ACOSD, ACOSDC, and ACOSDCI (continue)

Problem	Best known	HACOTS		EACOR		HACOM	
		ABF	SD	ABF	SD	ABF	SD
C107	828.94	1041.44	18.93	945.03	65.98	928.90	13.52
C108	828.94	990.35	14.39	934.49	38.56	938.64	16.60
C109	828.94	921.64	13.31	933.41	30.92	905.38	7.68
C201	591.56	883.78	29.66	623.66	34.93	778.94	44.06
C202	591.56	863.28	46.48	685.83	64.62	819.00	32.07
C203	591.17	739.59	27.04	638.12	47.52	805.60	36.02
C204	590.60	773.74	14.89	651.70	32.31	780.01	33.23
C205	588.88	708.85	16.35	616.90	31.08	665.24	19.60
C206	588.49	680.86	14.47	599.69	6.79	626.10	18.71
C207	588.29	628.08	16.90	594.69	7.22	610.43	13.92
C208	588.32	624.95	9.60	611.30	20.26	607.12	9.40
R101	1650.80	1851.21	10.51	1853.51	36.12	1755.69	13.03
R102	1486.86	1648.35	14.14	1606.40	37.93	1577.99	17.28
R103	1292.67	1371.11	13.63	1361.34	46.05	1292.82	0.45
R104	1007.31	1047.46	15.13	1068.09	29.46	1046.80	16.48
R105	1377.11	1683.11	19.30	1593.39	60.38	1573.79	16.32
R106	1252.03	1439.56	12.27	1409.27	51.60	1423.91	9.10
R107	1104.66	1265.34	19.79	1203.02	53.41	1223.14	10.13
R108	960.88	1010.04	9.14	1026.92	31.32	991.86	13.79
R109	1194.73	1322.89	17.56	1264.99	60.36	1273.99	10.12
R110	1118.84	1176.59	13.43	1141.05	27.68	1153.86	14.56
R111	1096.73	1188.43	14.36	1160.80	30.47	1139.81	11.62
R112	982.14	982.14	0.00	984.83	6.64	982.14	0.00
R201	1252.37	1639.51	18.03	1592.88	79.78	1556.95	6.99
R202	1191.70	1415.24	18.61	1343.19	59.14	1370.51	10.08
R203	939.50	1187.25	61.40	1069.99	54.52	1111.59	35.94
R204	825.52	884.13	6.92	880.90	32.56	877.52	17.16
R205	994.43	1433.94	19.74	1293.21	46.07	1324.33	10.27
R206	906.14	1241.58	13.30	1158.68	67.94	1255.03	11.27
R207	890.61	1081.31	20.22	965.55	29.81	1078.10	11.44
R208	726.82	817.79	10.38	806.40	38.69	830.87	13.94
R209	909.16	1200.85	8.63	1036.25	42.62	1108.97	16.70
R210	939.37	1262.43	10.37	1111.82	46.93	1217.62	19.81
R211	885.71	885.71	0.00	885.71	0.00	885.71	0.00
RC101	1696.95	2043.77	15.75	1776.44	74.97	1839.79	23.98
RC102	1554.75	1691.03	23.47	1591.70	73.57	1653.11	23.37
RC103	1261.67	1419.78	15.52	1380.68	52.71	1390.79	18.44
RC104	1135.48	1162.72	19.84	1188.55	26.97	1142.13	7.58
RC105	1629.44	1719.35	21.98	1685.92	63.76	1669.09	20.43
RC106	1424.73	1614.40	23.65	1478.27	55.97	1448.61	22.16
RC107	1230.48	1263.93	14.90	1290.88	32.51	1232.45	3.42
RC108	1139.82	1139.82	0.00	1149.90	15.20	1139.82	0.00
RC201	1406.94	2068.87	33.09	1857.07	50.82	1831.15	13.19
RC202	1365.64	1619.28	20.19	1527.65	89.29	1590.89	17.60
RC203	1049.62	1286.61	23.18	1193.33	54.03	1237.64	18.78
RC204	798.46	948.16	13.86	904.73	28.53	922.03	9.08
RC205	1297.65	1769.91	36.48	1544.80	80.56	1590.37	18.70
RC206	1146.32	1788.35	20.75	1476.55	46.80	1541.82	16.18
RC207	1061.14	1460.15	15.07	1163.82	44.26	1360.77	34.59
RC208	828.14	830.09	3.08	830.57	7.28	828.14	0.00

Table 2. Comparative ABF and SD of HACOTS, EACOR, HACOM, ACOS, ACOSD, ACOSDC, and ACOSDCI (continue)

Problem	Best known	ACOS		ACOSD		ACOSDC		ACOSDCI	
		ABF	SD	ABF	SD	ABF	SD	ABF	SD
C101	828.93	886.31	31.21	857.09	20.88	828.93	0.00	828.93	0.00
C102	828.93	906.63	14.86	904.91	9.37	829.60	0.92	828.93	0.00
C103	828.06	889.35	6.70	884.95	6.59	835.47	4.80	828.06	0.00
C104	824.78	878.77	6.06	871.63	5.06	858.97	4.19	824.78	0.00
C105	828.94	897.37	20.32	884.18	18.95	828.94	0.00	828.94	0.00
C106	828.94	896.61	5.40	890.72	5.02	828.94	0.00	828.94	0.00
C107	828.94	892.55	10.56	881.19	9.35	830.90	6.21	828.94	0.00
C108	828.94	890.32	13.96	872.97	13.26	847.19	12.40	828.94	0.00
C109	828.94	891.45	3.82	881.58	3.08	846.23	2.78	828.94	0.00
C201	591.56	591.56	0.00	591.56	0.00	591.56	0.00	591.56	0.00
C202	591.56	591.56	0.00	591.56	0.00	591.56	0.00	591.56	0.00

Table 2. Comparative ABF and SD of HACOTS, EACOR, HACOM, ACOS, ACOSD, ACOSDC, and ACOSDCI (continue)

Problem	Best known	ACOS		ACOSD		ACOSDC		ACOSDCI	
		ABF	SD	ABF	SD	ABF	SD	ABF	SD
C203	591.17	593.50	2.72	592.18	2.14	591.17	0.00	591.17	0.00
C204	590.60	606.81	7.59	597.49	2.29	592.85	2.14	590.60	0.00
C205	588.88	588.88	0.00	588.88	0.00	588.88	0.00	588.88	0.00
C206	588.49	588.49	0.00	588.49	0.00	588.49	0.00	588.49	0.00
C207	588.29	588.29	0.00	588.29	0.00	588.29	0.00	588.29	0.00
C208	588.32	588.32	0.00	588.32	0.00	588.32	0.00	588.32	0.00
R101	1650.80	1650.80	0.00	1650.80	0.00	1650.80	0.00	1650.80	0.00
R102	1486.86	1486.86	0.00	1486.86	0.00	1486.86	0.00	1486.86	0.00
R103	1292.67	1292.67	0.00	1292.67	0.00	1292.67	0.00	1292.67	0.00
R104	1007.31	1007.31	0.00	1007.31	0.00	1007.31	0.00	1007.31	0.00
R105	1377.11	1377.11	0.00	1377.11	0.00	1377.11	0.00	1377.11	0.00
R106	1252.03	1252.03	0.00	1252.03	0.00	1252.03	0.00	1252.03	0.00
R107	1104.66	1104.66	0.00	1104.66	0.00	1104.66	0.00	1104.66	0.00
R108	960.88	960.88	0.00	960.88	0.00	960.88	0.00	960.88	0.00
R109	1194.73	1194.73	0.00	1194.73	0.00	1194.73	0.00	1194.73	0.00
R110	1118.84	1118.84	0.00	1118.84	0.00	1118.84	0.00	1118.84	0.00
R111	1096.73	1096.73	0.00	1096.73	0.00	1096.73	0.00	1096.73	0.00
R112	982.14	982.14	0.00	982.14	0.00	982.14	0.00	982.14	0.00
R201	1252.37	1252.37	0.00	1252.37	0.00	1252.37	0.00	1252.37	0.00
R202	1191.70	1191.70	0.00	1191.70	0.00	1191.70	0.00	1191.70	0.00
R203	939.50	948.43	11.43	943.22	5.67	939.50	0.00	939.50	0.00
R204	825.52	825.52	0.00	825.52	0.00	825.52	0.00	825.52	0.00
R205	994.43	1054.40	9.96	1039.06	8.72	1008.75	7.13	994.43	0.00
R206	906.14	971.61	8.18	969.15	7.96	928.05	5.84	906.14	0.00
R207	890.61	892.02	3.21	891.33	1.54	890.61	0.00	890.61	0.00
R208	726.82	753.18	9.45	752.60	3.25	737.96	2.39	726.82	0.00
R209	909.16	928.17	6.20	924.55	5.45	909.16	0.00	909.16	0.00
R210	939.37	992.87	9.19	978.56	8.51	940.04	1.28	939.37	0.00
R211	885.71	885.71	0.00	885.71	0.00	885.71	0.00	885.71	0.00
RC101	1696.95	1696.95	0.00	1696.95	0.00	1696.95	0.00	1696.95	0.00
RC102	1554.75	1554.75	0.00	1554.75	0.00	1554.75	0.00	1554.75	0.00
RC103	1261.67	1284.71	14.14	1267.05	8.30	1261.67	0.00	1261.67	0.00
RC104	1135.48	1139.68	6.80	1138.01	5.34	1135.48	0.00	1135.48	0.00
RC105	1629.44	1629.44	0.00	1629.44	0.00	1629.44	0.00	1629.44	0.00
RC106	1424.73	1424.73	0.00	1424.73	0.00	1424.73	0.00	1424.73	0.00
RC107	1230.48	1230.90	1.34	1230.68	0.63	1230.48	0.00	1230.48	0.00
RC108	1139.82	1139.82	0.00	1139.82	0.00	1139.82	0.00	1139.82	0.00
RC201	1406.94	1407.47	1.66	1406.94	0.00	1406.94	0.00	1406.94	0.00
RC202	1365.64	1365.64	0.00	1365.64	0.00	1365.64	0.00	1365.64	0.00
RC203	1049.62	1049.62	0.00	1049.62	0.00	1049.62	0.00	1049.62	0.00
RC204	798.46	841.46	8.99	831.61	8.70	817.12	7.47	798.46	0.00
RC205	1297.65	1297.65	0.00	1297.65	0.00	1297.65	0.00	1297.65	0.00
RC206	1146.32	1191.15	14.00	1187.65	12.13	1146.32	0.00	1146.32	0.00
RC207	1061.14	1066.15	6.84	1063.33	4.93	1061.14	0.00	1061.14	0.00
RC208	828.14	828.14	0.00	828.14	0.00	828.14	0.00	828.14	0.00

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