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Solving Capacitated Vehicle Routing Problem Using Variant Sweep and Swarm Intelligence

M. A. H. Akhand[1]*, Zahrul Jannat Peya[1], Tanzima Sultana[1] and M. M. Hafizur Rahman[2]

[1]*Department of Computer Science and Engineering, Khulna University of Engineering & Technology, Khulna-9203, Bangladesh*
[2]*Xiamen University, Malaysia, Sunsuria City, Sepang 43900 Selangor, Malaysia*

Abstract

Capacitated vehicle routing problem (CVRP) is a real life constraint satisfaction problem in which customers are optimally assigned to individual vehicles (considering their capacity) to keep total travel distance of the vehicles as minimum as possible while serving customers. Various methods are used to solve CVRP in last few decades, among them the most popular way is splitting the task into two different phases: assigning customers under different vehicles and then finding optimal route of each vehicle. Sweep clustering algorithm is well studied for clustering nodes. On the other hand, route optimization is simply a traveling salesman problem (TSP) and a number of TSP optimization methods are applied for this purpose. This study investigates a variant of Sweep algorithm for clustering nodes and different Swarm Intelligence (SI) based methods for route generation to get optimal CVRP solution. In conventional Sweep algorithm, cluster formation starts from smallest angle and consequently advances to consider all the nodes. In variant Sweep of this study, cluster formation are considered from different starting angles. On the other hand, four TSP optimization methods including recent ones are considered for route optimization. The experimental results on a large number of benchmark CVRPs revealed that clustering with proposed variant Sweep and route optimization with Velocity Tentative Particle Swarm Optimization is able to produce better solution. Finally, the proposed mythology is found to achieve better solutions for several CVRPs when compared with prominent existing methods.

Key Words: Capacitated Vehicle Routing Problem, Sweep Clustering, Genetic Algorithm, Ant Colony Optimization, Producer-scrounger Method, Velocity Tentative Particle Swarm Optimization

1. Introduction

Vehicle routing problem (VRP) is to determine optimal routes for several vehicles to serve a number of customers. In general, customers with known demands are visited by a homogeneous fleet of vehicles with limited capacity. Capacity constraint of vehicles limit the number of customers to serve in its route. Due to importance of capacity constraint, the problem is alternatively called capacitated VRP (CVRP) [1].

In general, CVRP considers one depot and several vehicles with equal capacity. All vehicles depart from the depot and return to the depot at the end. All customers have known demands and known locations for the delivery. The delivery for a customer cannot be split and must be satisfied via only one visit by a vehicle. CVRP is a complex optimization task and its objective is to minimize the total travelling distance for all vehicles to serve all customers.

CVRP is a real life constraint satisfaction problem in

*Corresponding author. E-mail: akhand@cse.kuet.ac.bd

which customers are optimally assigned to individual vehicles (considering their capacity) to keep CVRP cost as minimum as possible. Various methods are already studied to solve CVRP in last few decades; among them a number of methods assign customer nodes under vehicles and generate routes of vehicles together [2–5]. On the other hand, the most popular way of solving CVRP is splitting the task into two different phases: assigning customers under different vehicles and then finding optimal route of each vehicle [6–12]. Among several ways for customer assignment, Sweep clustering algorithm is widely used due to its simplicity. The algorithm calculates polar angles of all the nodes and then assigns nodes into different clusters according to their angles. Finally, a vehicle is assigned for each individual cluster nodes and its route is optimized as of traveling salesman problem (TSP).

A number of CVRP studies are available using traditional TSP optimization methods with Sweep clustering. A Sweep based CVRP is investigated for public transport optimization in [6] where route optimization is accomplished using nearest neighbor algorithm. Another method, called Hybrid Heuristic Approach [12], also used Sweep based node assignment and nearest neighbor algorithm to generate optimal routes of individual vehicles. The method applied on benchmark CVRPs. Sweep with integer programming based TSP optimization is investigated in [8] for bus service optimization of an education institute; 2-opt exchange is also used in the method to improve TSP routes.

Population based metaheuristic methods are found efficient for TSP in the recent studies [13−17] and several studies conceived such methods to generate optimal vehicle route in solving CVRPs. In [7], genetic algorithm is combined with Sweep algorithm to optimize routes and hence produce CVRP solution. Ant colony optimization (ACO) is the prominent Swarm Intelligence (SI) method for TSP and adapted with Sweep in [10] for solving CVRPs. In the method, ACO is used to generate route among the nodes of individual vehicles assigned by Sweep; and 3-opt local search is also used to exchange the vehicle's nodes for further improvement of the solutions. Particle Swarm optimization (PSO), the most studied SI method in the recent time, is also used in solving CVRPs. Standard PSO is used in [18] to optimize routes from the outcome of Sweep algorithm. On the other hand, a modified version of PSO, called Nested PSO, is investigated in [11].

A few methods are also investigated for CVRPs with modification in Sweep. Including time constraint, a modified Sweep algorithm is used to solve morning newspaper delivery problem through CVRP in [19]. In [9], a cluster adjustment is adapted with Sweep and Lin-Kernighan heuristic TSP method is used to generate CVRP solution. Recently, an extension of Sweep algorithm, called Sweep Nearest (SN) algorithm, has been investigated in [20]. SN combines the idea of Sweep and Nearest Neighbor concept. SN considers sorted polar angle of the nodes and starts a cluster with smallest polar angle like Sweep; but it considers other customers to complete the cluster which are nearer to the already assigned customer(s). In the method, 2-opt edge exchange is used to optimize each individual vehicle's route.

The main objective of this study is to identify the effective CVRP solving method. A variant version of Sweep is considered in this study for better vehicle wise clustering the nodes. Route optimization is a traveling salesman problem; and therefore, prominent SI based TSP methods, including most recent ones, are considered in this study.

The outline of the paper is as follows. Section 2 explains variant Sweep algorithm and SI methods for route optimization briefly. Section 3 is for experimental studies which presents as well as compares the outcomes of the methods on a suite of benchmark CVRPs. At last, section 4 gives a brief conclusion of the paper.

2. Solving CVRP Using Variant Sweep and Swarm Intelligence

This section explains proposed CVRP solving method using variant Sweep and SI methods. At first it investigates deficiency of standard Sweep and explains proposed variant Sweep clustering. To make the paper self-contained, considered TSP route optimization methods are also explained briefly.

2.1 Variant Sweep Clustering

It is already described in the previous section that standard Sweep considers polar angle of nodes and capacity of vehicle. In general, standard Sweep considers depot located at (0,0) co-ordinate in two dimensional plane. It first calculates polar angle of each individual node and order the nodes according to polar angle. Finally, cluster formation starts from 0° and consequently advances toward 360° to assign all the nodes under different vehicles considering vehicle capacity [8,18]. Problem with such rigid starting from 0° is identified that total clusters formation may exceeds total number of available vehicles for some instances. It is worth mentionable that cluster formation may differ for different starting angles and explores chance to get better CVRP solution after route optimization.

Figure 1 demonstrates the inadequacy with standard Sweep and its improvement way for a sample CVRP. The CVRP consists with 10 nodes with different demands around the depot and the total demand of the nodes 157 will be served vehicles having capacity 100. Figure 1(a) shows the cluster formation with standard Sweep starting from 0°: Cluster 1 covers demand 64 with two nodes, Cluster 2 covers demand 80 with two nodes, Cluster 3 covers demand 95 with four nodes; and remaining demand 18 is assigned to Cluster 4. Therefore, required number of vehicles in standard Sweep is 4. But three vehicles (total capacity 100*3 = 300) might be enough to serve all the nodes having total demand 157. Figure 1(b) shows cluster formation with Sweep technique but starting from 90° in which all the nodes are assigned into three clusters each one demand is below vehicle capacity: Cluster 1 covers demand 80 with three nodes, Cluster 2 covers demand 95 with four nodes, Cluster 3 covers remaining three nodes with demand 82. Three clusters also found sufficient to cover all the nodes for starting angle 135°. It is obvious that total CVRP cost for three vehicles will be less than the cost for four vehicles. Therefore, this study considers the starting angle of cluster formation as user defined parameter and the method called variant Sweep.

Algorithm 1 shows the steps of proposed variant Sweep algorithm. First three steps of the initialization section are same as standard Sweep: update nodes' coordinates considering depot location as (0,0), compute polar angle of each node and order the nodes according to polar angle to a list *ONL*. The basic difference of the proposed variant method takes starting angle of cluster formation (θ_s) as user defined parameter.

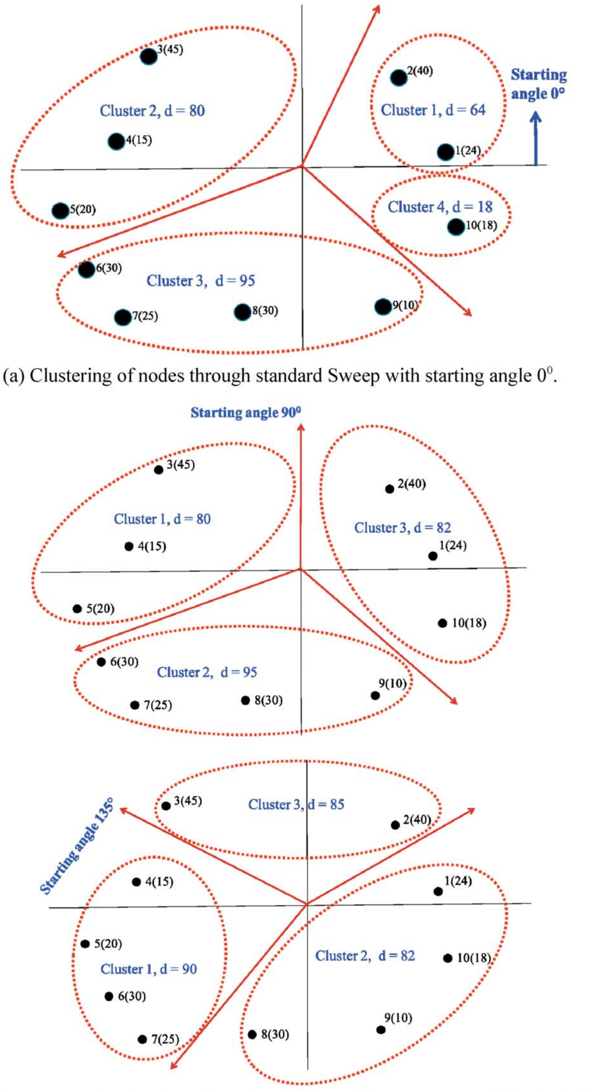
Algorithm 1: Variant Sweep Algorithm

1. Initialization

a. Update coordinates of the nodes considering depot as (0,0).
b. Compute the polar angle of each node.
c. Order the nodes according to polar angle, *ONL*.
d. Take starting angle of cluster formation, θ_s.
e. Cluster $C = 1$.

2. Clustering

a. Identify position of θ_s in *ONL*.
b. Sweeping nodes to current cluster C by increasing



(a) Clustering of nodes through standard Sweep with starting angle 0^0.

(b) Clustering of nodes through variant Sweep with starting angle 90^0 and 135^0.

Figure 1. Clustering of nodes with standard Sweep and variant Sweep algorithms.

polar angle.

c. Stop when adding the next node would exceed vehicle capacity.

d. Create a new cluster C+1 by resuming the sweep where the last one left off.

e. Repeat Steps 2b-2d, until all customers have been included in a cluster.

Outcome

All the nodes are assigned into total C clusters.

Cluster formation starts in variant Sweep from the defined angle θ_s and nodes are assigned into different clusters considering vehicle capacity. First the method identifies the position of θ_s in *ONL* (Step 2a). As like standard Sweep, variant method assigns nodes into a cluster while vehicle capacity does not exceed (Steps 2b and 2c) otherwise new cluster forms for unassigned nodes (Step 2d). Since the variant Sweep may starts any location of *ONL*, Step 2e transforms node assignment from bottom of *ONL* to the beginning of *ONL*. It is notable that for $\theta_s = 0°$ the proposed method will be standard Sweep.

2.2 Optimal Vehicle Route Generation

In solving CVRP, optimal route generation of each individual vehicle is a crucial part while any clustering method is used to cluster nodes. In general, a clustering method divides total CVRP nodes into clusters, whereby number of clusters is equal to the number of vehicles. The aim of route generation is the optimal path finding of each vehicle starting from the depot and returning to depot after serving all of its assigned nodes. Therefore, route generation of individual vehicle is simply a small sized TSP considering the depot as a common city point; and any TSP optimization method may be used for this purpose. To generate route for a vehicle, a TSP cost matrix considering nodes for a particular vehicle is prepared and then a TSP optimization is employed to work with the cost matrix as an independent TSP. More specifically, in sample case of Figure 1(b), Cluster 1 belongs nodes 4, 5, 6 and 7 for $\theta_s = 135°$ and therefore algorithm will prepare TSP cost matrix of five cities including depot as a TSP city. Algorithm 2 depicts the steps of vehicle route generation of individual vehicles and provide CVRP solution.

Algorithm 2: Vehicle Route Generation

1. Input

Vehicle wise nodes from variant Sweep clustering with Algorithm 1.

2. Route Generation for Each Vehicle

a. Include depot as a node in the cluster.

b. Prepare a TSP cost matrix with the nodes of the cluster.

c. Employ TSP optimization method to generate optimal route for the vehicle.

Outcome

CVRP solution with optimal routes of all the vehicles.

Figure 2 illustrates the complete flowchart of CVRP solving method integrating Algorithm 1 and Algorithm 2. The initialization step accomplishes preprocessing of given data of a problem as well as setting of SI algorithm parameters. SI method takes vehicle wise clusters from variant Sweep and generates TSP routes of clusters individually. Finally, CVRP solution is achieved with the TSP routes of individual vehicles.

In this study, three prominent SI based methods are investigated for route optimization. Genetic algorithm is also considered along with SI methods as it is a prominent and pioneer optimization method. Among the SI methods, ant colony optimization is the well-known prominent method for TSP; and producer-scrounger method and velocity tentative particle swarm optimization are two very recent well performed methods for TSP. Brief descriptions of the methods are explained in the following subsections to make the paper self-contained.

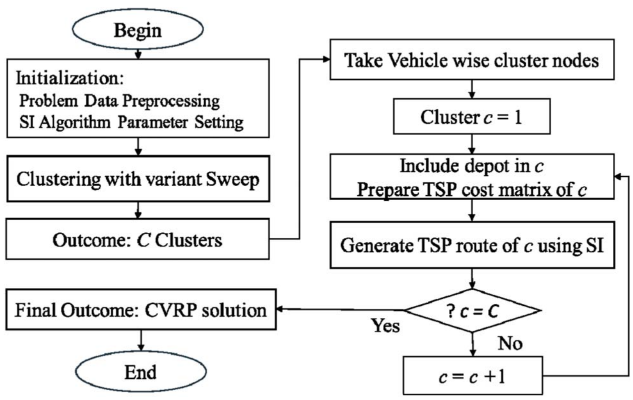


Figure 2. Flowchart of solving CVRP using variant Sweep and Swarm Intelligence.

2.2.1 Genetic Algorithm (GA)

GA is the pioneer optimization method inspired by biological systems' fitness improvement through evolution [13]. Common features of GA are: populations of chromosomes (i.e., solutions), selection according to fitness, crossover to produce new offspring, and random mutation of new offspring. GA is used to solve various optimization tasks and a number of studies used GA with different modifications in solving vehicle routing problems [4,7,21,22].

2.2.2 Ant Colony Optimization (ACO)

ACO is the prominent SI based search and optimization method based on the behavior of ants while seeking the shortest path between their colony and a food source through an indirect interaction via pheromone on the path [14]. In solving TSP, a particular ant considers next city to visit based on the visibility heuristic (i.e., inverse of distance) and intensity of the pheromone on the path. After the completion of a tour, each ant lays some pheromone on the path. Pheromone evaporation is also adopted by reducing pheromone of all the links which allows the artificial ants to forget bad choices made in the past. Finally, all the ants follow the same route after certain iteration. A large number of studies are available with ACO and its variants to solve TSP [14,15] and others scheduling problems including CVRPs [3,10,23,24].

2.2.3 Producer-scrounger Method (PSM)

PSM [17] is a new SI technique to solve TSP inspiring from the animal group living behavior. It models roles and interactions of three types of animal group members: producer, scrounger and dispersed [25]. PSM considers a producer having the best tour, few dispersed members having worse tours and scroungers. In each iteration, the producer scans for better tour, scroungers explore new tours while moving toward producer's tour; and dispersed members randomly check new tours. For producer's scanning, PSM randomly selects a city from the producer's tour and rearranges its connection with several near cities for better tours. Swap operator (SO) and swap sequence (SS) based operation is employed in PSM to update a scrounger towards the producer. A SS is a collection of several SOs and each one indicates two positions in a tour those might be swapped. Finally, producer is consider as the TSP solution of a given problem. The detailed description of PSM for TSP is available in [17].

2.2.4 Velocity Tentative Particle Swarm Optimization (VTPSO)

Particle swarm optimization (PSO) is a popular optimization method on metaphor of social behavior of flocks of birds or schools of fishes [26]. In PSO, each particle represents a potential solution and moves to a new position (i.e., search a new point) at every iteration based on the calculated velocity. PSO was proposed for continuous problems (e.g., function optimization) and has been proven to solve such problems effectively. It has also been found as an efficient method to solve combinatorial problems such as TSP [27–29]. To solve TSP with PSO, each particle represents a complete tour as a feasible solution and velocity is a measure to update the tour for better solution. A number of studies are also used PSO with different modifications in solving different vehicle routing problems [2,5,11,18,30,31]. In this study, VTPSO [29], the most recent TSP solving version of PSO, has been employed to solve CVRP. VTPSO calculates velocity SS similar to existing method [27] but apply the SS in a different and optimal way. It conceives partial search (PS) technique to apply calculated SS to update particle's position (i.e., TSP tour) and conceive comparatively better new tour with a portion or full SS. The detailed description of VTPSO for TSP is available in [29].

3. Experimental Studies

This section experimentally investigates the efficacy of variant Sweep algorithm and SI methods in solving benchmark CVRPs. Finally, an experimental analysis has been given for better understanding of the way of performance improvement in proposed method for solving CVRP.

3.1 Benchmark Data and General Experimental Methodology

In this study, total 51 benchmark CVRPs from two different sets of Augerat benchmark problems [32] of A-VRP and P-VRP have been considered. In A-VRP, number of customers varies from 32 to 80, total demand varies from 407 to 942, number of vehicles varies from 5 to 10 and capacity of individual vehicle is 100 for all the problems. For example, A-n32-k5 has 32 customers and 5 vehicles. On the other hand, in P-VRP, number of customers varies from 16 to 101, total demand varies from 246 to 22500 and vehicle capacity varies from 35 to 3000. The numeric value in a problem name presents the number of customer nodes and vehicles. The detailed description of the problems are available in provider's website [32]. The selected benchmark problems belongs large varieties in number of nodes, vehicles and demands; and therefore, provides a diverse test bed.

A customer node is represented as a co-ordinate in a problem. Therefore, the cost is found after calculating distance using the coordinates. The variant Sweep algorithm applied on each problem for different starting angles (θ_s) and those are 0°, 45°, 90°, 135°, 180°, 225°, and 270°. It is notable that conventional Sweep only considers θ_s = 0° for clustering.

A CVRP solution is considered after route optimization using GA, ACO, PSM or VTPSO. A fair experimental setting is maintained for each optimization method for better outcome in route optimization. In GA, enhanced edge recombination cross over is used and the positions of two nodes are interchanged for mutation operation. In ACO, alpha and beta are set to 1 and 3, respectively. On the other hand, the RNC (rate of near cities consideration) for producer scanning in PSM is set to 0.1. The algorithms are implemented on Visual C++ of Visual Studio 2013. The experiments have been carried out on a PC (Intel Core i5-3470 CPU @ 3.20 GHz CPU, 4GB RAM) with Windows 7 OS.

3.2 Detailed Experimental Observation on a Problem

This section presents detailed results for problem A-n53-k7. The population size of GA, PSM and VTPSO is 100; whereas, number of ants in ACO is equal to the number of nodes assigned to a vehicle as it desire. The number of iteration is set at 200 for the algorithms. Table 1 shows the total clusters for different starting angles (θ_s) in variant Sweep and optimized route costs with different methods for A-n53-k7 problem. The problem has 53 nodes and total 664 demand to be served with seven vehicles having capacity 100. From the table it is observed that total number of clusters for θ_s = 0° (i.e., in standard Sweep) is 8 which is more than available vehicles. Total clusters are also 8 for θ_s = 45°, 225° and 270°. On the other hand, number of clusters is equal to total vehicles (i.e., 7) for θ_s = 90°, 135° and 180°. It is also remarkable that total travel distances (i.e., CVRP costs) for 7 clusters are lower than the cases of 8 for route optimization with any method. The best CVRP cost for an algorithm for different θ_s is marked as bold-faced type. For the problem the best travel cost achieved after optimizing with GA, ACO, PSM and VTPSO are 1091, 1132, 1190 and 1090, respectively. The best values are found for θ_s = 180° where total cluster was 7. These results clearly indicate that variant Sweep starting with different angle has a positive effect on cluster formation and hence CVRP solution.

Figure 3 is the graphical representation of the solution of A-n53-k7 for standard Sweep clustering (i.e., θ_s = 0°). The solution is infeasible because total clusters are eight against available seven vehicles. Cluster 8 covers only three nodes having total demand 29. Moreover, GA, PSM and VTPSO gave same solution with CVRP cost 1174 as shown in Figure 3(a). On the other hand, the CVRP cost for ACO is 1211 as seen in Figure 3(b). In some clusters, such as Cluster 4 and Cluster 6, ACO showed bad route cost. The reason might be inclination with pheromone in ACO.

Figure 4 is the graphical representation of the solution of A-n53-k7 problem for variant Sweep clustering for θ_s = 180°. In this case total demand is fulfilled by seven clusters that is equal to number of vehicles. Among the four route optimization methods, CVRP cost with ACO is the worst and the value is 1132. Similar to standard Sweep, it achieved worse solution for Cluster 4 and Cluster 6. The best CVRP solution for the problem is

Table 1. Clusters for different starting angle (θ_s) in variant Sweep and CVRP cost using GA, ACO, PSM and VTPSO for A-n53-k7 problem

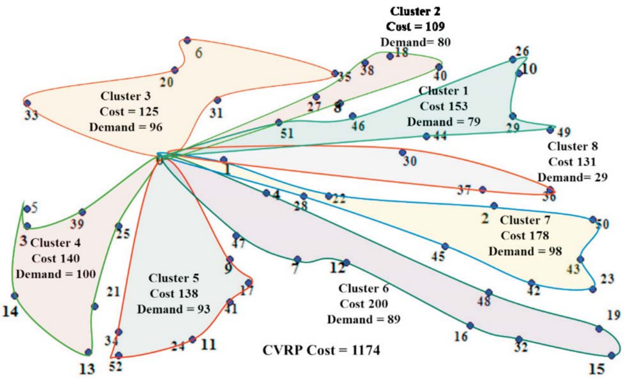
θ_s	Clusters	Before route optimizing	CVRP cost with			
			GA	ACO	PSM	VTPSO
0°	8	1604	1174	1211	1174	1174
45°	8	1571	1172	1207	1165	1165
90°	7	1654	1135	1152	1109	1109
135°	7	1654	1132	1160	1109	1109
180°	7	1504	**1091**	**1132**	**1090**	**1090**
225°	8	1558	1142	1184	1147	1142
270°	8	1775	1171	1195	1171	1171

achieved by PSM and VTPSO; and achieved CVRP cost is 1090. On the other hand, GA is showed competitive result with PSM/VTPSO achieving CVRP cost 1091; it differs only for Cluster 3 with different assignments of node 12. Finally, the comparative description with graphical representation in Figures 3 and 4 clearly depicted the superiority of proposed variant Sweep over standard Sweep.

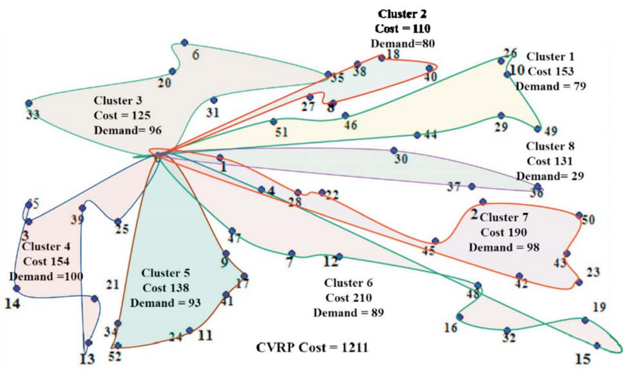
3.3 Experimental Results and Performance Comparison

This section first identifies the proficiency of variant Sweep clustering over standard Sweep clustering while using GA, ACO, PSM and VTPSO for route optimization. Finally, the outcome of the proposed method compares with the prominent methods in solving benchmark CVRPs. The population size of GA, PSM and VTPSO was 100; whereas, number of ants in ACO was equal to the number of nodes assigned to a vehicle. For the fair comparison, the number of iteration was set at 200 for the algorithms. The selected parameters are considered for simplicity as well as for fairness in observation.

Table 2 compares CVRP costs for clustering with standard Sweep and variant Sweep on A-VRP benchmark problems. Bottom of the table shows average and best/worst summary over all 27 problems. The results presented for variant Sweep with best result from seven different starting angles clustering. On the other hand, standard Sweep is for only clustering with $\theta_s = 0°$. From the Table 2, it is observed that any method based on vari-

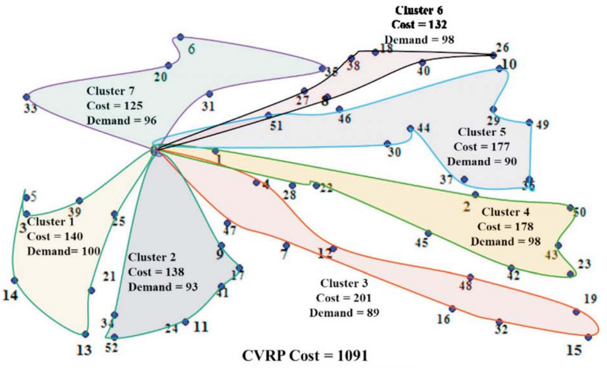


(a) Route optimization using GA, PSM or VTPSO.

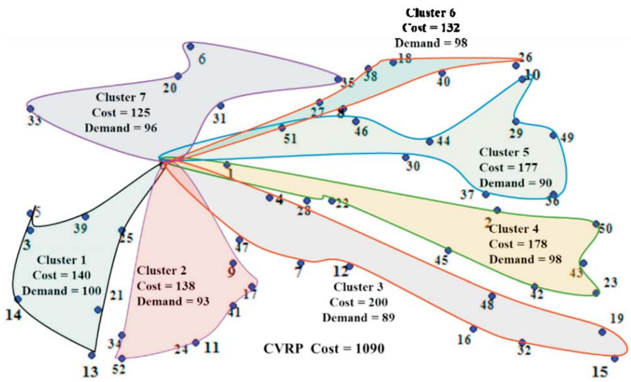


(b) Route optimization using ACO.

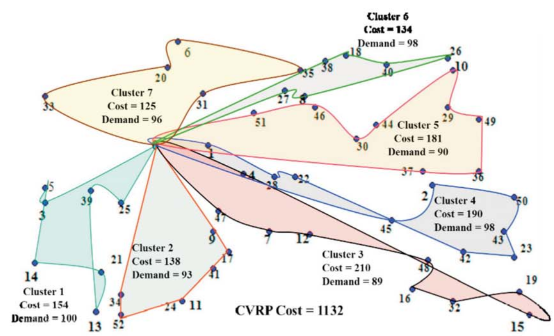
Figure 3. Graphical representation of A-n53-k7 solution with standard Sweep clustering (i.e., $\theta_s = 0°$).



(a) Route optimization using GA.



(b) Route optimization using PSM and VTPSO.



(c) Route optimization using ACO.

Figure 4. Graphical representation of A-n53-k7 solution with variant Sweep clustering with $\theta_s = 180°$.

Table 2. CVRP cost comparison for clustering with standard Sweep and variant Sweep on A-VRP benchmark problems

Sl.	Problem	Clustering with standard Sweep				Clustering with variant Sweep			
		GA	ACO	PSM	VTPSO	GA	ACO	PSM	VTPSO
1	A-n32-k5	882	897	882	882	882	897	882	882
2	A-n33-k5	788	808	788	788	*698*	*719*	*698*	*698*
3	A-n33-k6	874	877	874	874	*751*	*758*	*751*	*751*
4	A-n34-k5	867	897	867	867	*785*	*804*	*785*	*785*
5	A-n36-k5	945	965	942	942	*884*	*917*	*881*	*881*
6	A-n37-k5	795	840	795	795	*739*	*766*	*746*	*739*
7	A-n37-k6	1131	1141	1131	1131	*1097*	*1116*	*1097*	*1097*
8	A-n38-k5	874	907	874	874	*813*	*844*	*813*	*813*
9	A-n39-k5	881	918	877	877	*878*	*912*	877	877
10	A-n39-k6	997	997	991	991	*969*	*981*	*975*	*969*
11	A-n44-k6	1165	1229	1164	1164	*1056*	*1116*	*1056*	*1056*
12	A-n45-k6	1117	1141	1115	1115	*1073*	*1081*	*1075*	*1073*
13	A-n45-k7	1343	1386	1343	1343	1343	*1380*	1343	1343
14	A-n46-k7	1026	1085	1026	1026	*990*	*1033*	*990*	*990*
15	A-n48-k7	1152	1165	1152	1152	1152	1165	1152	1152
16	A-n53-k7	1174	1212	1174	1174	*1091*	*1132*	*1090*	*1090*
17	A-n54-k7	1361	1374	1366	1361	1361	1374	*1361*	1361
18	A-n55-k9	1201	1215	1201	1201	1201	1215	1201	1201
19	A-n60-k9	1556	1606	1553	1553	*1503*	*1528*	*1503*	*1503*
20	A-n61-k9	1219	1238	1219	1219	1219	1238	1219	1219
21	A-n62-k8	1533	1565	1532	1532	*1501*	*1532*	*1501*	*1501*
22	A-n63-k9	1826	1856	1823	1823	*1823*	*1852*	1823	1823
23	A-n63-k10	1551	1571	1551	1551	*1461*	*1478*	*1446*	*1446*
24	A-n64-k9	1598	1622	1598	1598	1598	1622	1598	1598
25	A-n65-k9	1382	1405	1380	1380	*1317*	*1339*	*1317*	*1317*
26	A-n69-k9	1254	1280	1254	1254	*1254*	*1280*	*1252*	*1252*
27	A-n80-k10	2139	2195	2137	2136	*2137*	2195	*2136*	2136
Average		1208.56	1236.74	1207.74	1207.52	1169.48	1195.33	1169.19	1168.63
Outperformance of variant Sweep over corresponding standard Sweep based method						19	19	19	17
Best count						21	0	24	27

ant Sweep outperformed its corresponding standard Sweep clustering. For a particular optimization method, if a variant Sweep is found better than standard Sweep, it placed as italic font. The route optimization with GA, ACO, PSM and VTPSO on variant Sweep outperformed corresponding standard Sweep in 19, 19, 19 and 17 cases out of 27 cases, respectively. It is notable that for a particular route optimization (e.g., GA), the outperformance of variant Sweep over standard Sweep is only for different starting angles in variant Sweep. On the other hand, GA, ACO, PSM and VTPSO achieved average CVRP cost of 1169.48, 1195.33, 1169.19 and 1168.63, respectively. Among variant Sweep based methods, PSM and VTPSO outperformed GA and ACO. Finally, CVRP solutions with VTPSO are found better than any other methods showing best outcomes (i.e., minimum CVRP costs) for all 27 problems.

Table 3 shows the comparison of CVRP costs for clustering with standard Sweep and variant Sweep on P-VRP benchmark problems. Bottom of the table shows summary of result presented for 24 problems. The result presented for variant Sweep is the best result from seven different starting angles. As like A-VRP problems, CVRP costs for variant Sweep are found better than or at least equal to standard Sweep for all 24 problems. The CVRP costs with variant Sweep are found better than standard Sweep in 17, 20, 17 and 17 cases out of 24 cases for GA, ACO, PSM and VTPSO, respectively. GA, ACO, PSM and VTPSO achieved average CVRP cost of 642.29, 653.46, 638.13 and 633.17, respectively. VTPSO and PSM showed minimum CVRP costs for all 24 problems and 20 cases, respectively. At a glance, CVRP costs with

Table 3. CVRP cost comparison for clustering with standard Sweep and variant Sweep on P-VRP benchmark problems

Sl.	Problem	Clustering with standard Sweep				Clustering with variant Sweep			
		GA	ACO	PSM	VTPSO	GA	ACO	PSM	VTPSO
1	P-n16-k8	595	595	595	595	*553*	*557*	*553*	*553*
2	P-n19-k2	239	242	236	236	239	242	236	236
3	P-n20-k2	242	257	238	238	242	*249*	238	238
4	P-n21-k2	241	261	238	238	*211*	*217*	*211*	*211*
5	P-n22-k2	243	266	237	237	*219*	*228*	*217*	*216*
6	P-n22-k8	688	690	688	688	*649*	*649*	*649*	*649*
7	P-n23-k8	687	687	687	687	*634*	*636*	*634*	*634*
8	P-n40-k5	509	525	509	509	*474*	*482*	*474*	*474*
9	P-n45-k5	528	572	528	528	*524*	*537*	*523*	*523*
10	P-n50-k7	599	615	599	599	*579*	*600*	*579*	*579*
11	P-n50-k8	692	718	692	692	*677*	*704*	*677*	*677*
12	P-n50-k10	783	790	783	783	783	790	783	783
13	P-n51-k10	807	835	807	807	*802*	*822*	*802*	*802*
14	P-n55-k7	616	634	613	613	*593*	*624*	*593*	*593*
15	P-n55-k8	612	635	611	611	*585*	*613*	*585*	*585*
16	P-n55-k10	742	762	742	742	742	*759*	742	742
17	P-n55-k15	1133	1140	1133	1133	*1099*	*1108*	*1099*	*1099*
18	P-n60-k10	835	868	835	835	*830*	*863*	*830*	*830*
19	P-n60-k15	1092	1113	1092	1092	1092	1113	1092	1092
20	P-n65-k10	864	932	864	864	*837*	*893*	*837*	*837*
21	P-n70-k10	900	928	900	900	900	928	900	900
22	P-n76-k4	654	638	633	603	*651*	*635*	633	603
23	P-n76-k5	681	697	685	655	681	*673*	*671*	*649*
24	P-n101-k4	831	785	799	728	*819*	*761*	*757*	*691*
Average		658.88	674.38	656	650.54	642.29	653.46	638.13	633.17
Outperformance of variant Sweep over corresponding standard Sweep based method						17	20	17	17
Best count						17	1	20	24

VTPSO are found best among the methods and PSM is shown competitive to VTPSO.

To identify the proficiency of proposed variant Sweep (vSweep) based approach, its outcome have been compared with prominent CVRP methods. Among the selected methods, Hybrid Heuristic Approach [12], Sweep +Cluster Adjustment [9] and Sweep Nearest [20] are also used Sweep based clustering to assign nodes to different vehicles but followed different approaches for route generation of individual vehicles. Hybrid Heuristic Approach [12] is the most recent CVRP method which used nearest neighbor method for route optimization. Centroid-based 3-phase [9] method is also considered in result comparison because it also found an effective method to solve similar benchmark CVRPs. The method follows three different steps: cluster formation with centroid based approach from the farthest point, centroid based cluster adjustment and finally route generation using Lin-Kernighan heuristic method.

Table 4 and Table 5 compare outcome of vSweep based method with the selected exiting methods in solving A-VRP and P-VRP benchmark problems. Among the existing methods, outcomes of Sweep Nearest are not available for several cases which are marked with '-'. In the comparison, vSweep+VTPSO (i.e., VTPSO with variant Sweep) is considered as a proposed method since it outperformed others vSweep based methods. The presented results of vSweep+VTPSO are collected from Table 2 and Table 3. On the other hand, results of the existing methods are the reported results in corresponding papers. The best (i.e., minimum) CVRP cost among the five methods for a particular problem is marked as bold face type. Bottom of a table also shows pairwise win/draw/lose summary among the methods for better understanding. According to Table 4 for A-VRP benchmark problems, Centroid-based 3-phase is the overall best and Hybrid Heuristic Approach is the worst showing average CVRP costs 1134.67 and 1310.11, respectively. On the other hand, proposed vSweep+VTPSO is shown competitive to Centroid-based 3-phase showing average CVRP cost 1168.63. On the basis of best individual count, Sweep Nearest is the best showing minimum CVRP costs for 12 cases among its available results for 24 cases. The proposed method showed best CVRP solutions for five cases and outperformed Sweep Nearest for 8 cases out of 24 cases. More interesting, the proposed method outperformed Hybrid Heuristic Approach, Sweep +Cluster Adjustment and Centroid-based 3-phase for 27, 14 and 8 cases, respectively, out of 27 cases.

The comparative results presented in Table 5 identified the proposed vSweep+VTPSO is the best for P-VRP benchmark problems. The proposed method is shown the best for 12 cases out of 24 cases and achieved average cost of 633.17. The proposed method outperformed Hybrid Heuristic Approach, Centroid-based 3-phase, Sweep +Cluster Adjustment on 23, 15 and 15 cases, respectively, out of 24 cases. On the other hand, results for Sweep Nearest are available for only 10 problems and the proposed method outperformed it for six cases. Between two exiting Sweep based methods, Hybrid Heuris-

Table 4. CVRP cost comparison with existing methods on A-VRP benchmark problems

Sl.	Problem	Hybrid heuristic [12]	Centroid-based 3-phase [9]	Sweep + cluster adjustment [9]	Sweep nearest [20]	vSweep + VTPSO
1	A-n32-k5	1012	881	872	**853**	882
2	A-n33-k5	847	728	788	702	**698**
3	A-n33-k6	919	770	829	767	**751**
4	A-n34-k5	933	812	852	803	**785**
5	A-n36-k5	1126	**814**	884	840	881
6	A-n37-k5	876	756	**734**	797	739
7	A-n37-k6	1180	1027	1050	**966**	1097
8	A-n38-k5	920	819	874	**801**	813
9	A-n39-k5	1147	**864**	971	886	877
10	A-n39-k6	1065	**881**	966	-	969
11	A-n44-k6	1356	1037	1092	**1020**	1056
12	A-n45-k6	1210	1040	1043	**991**	1073
13	A-n45-k7	1361	1288	1281	**1235**	1343
14	A-n46-k7	1071	992	1013	1022	**990**
15	A-n48-k7	1292	1145	**1143**	1181	1152
16	A-n53-k7	1261	1117	1116	-	**1090**
17	A-n54-k7	1414	**1209**	1320	-	1361
18	A-n55-k9	1317	1155	1192	**1134**	1201
19	A-n60-k9	1733	**1430**	1574	1446	1503
20	A-n61-k9	1285	1201	1184	**1158**	1219
21	A-n62-k8	1604	1470	1559	**1392**	1501
22	A-n63-k9	2001	1766	1823	**1763**	1823
23	A-n63-k10	1542	**1405**	1523	1475	1446
24	A-n64-k9	1821	1587	1597	**1586**	1598
25	A-n65-k9	1429	**1276**	1351	1299	1317
26	A-n69-k9	1333	1283	1254	**1225**	1252
27	A-n80-k10	2318	**1883**	2014	1896	2136
	Average	1310.11	1134.67	1181.44	1134.92	1168.63
	Best/worst	0/27	8/0	2/0	12/0	5/0
				Pairwise win/draw/lose summary		
	Hybrid heuristic	-	27/0/0	27/0/0	24/0/0	27/0/0
	Centroid-based 3-phase		-	7/0/20	15/0/9	8/0/19
	Sweep + cluster adjust.			-	21/0/3	14/1/12
	Sweep nearest				-	8/0/16

Table 5. CVRP cost comparison with existing methods on P-VRP benchmark problems

Sl.	Problem	Hybrid heuristic [12]	Centroid-based 3-phase [9]	Sweep + cluster adjustment [9]	Sweep nearest [20]	vSweep + VTPSO
1	P-n16-k8	546	497	568	**463**	553
2	P-n19-k2	253	256	**236**	264	**236**
3	P-n20-k2	267	240	238	**217**	238
4	P-n21-k2	288	240	238	**211**	**211**
5	P-n22-k2	274	245	237	219	**216**
6	P-n22-k8	667	672	687	721	**649**
7	P-n23-k8	743	703	645	**558**	634
8	P-n40-k5	563	505	499	516	**474**
9	P-n45-k5	662	533	525	-	**523**
10	P-n50-k7	647	583	585	-	**579**
11	P-n50-k8	721	**669**	675	-	677
12	P-n50-k10	808	**740**	779	-	783
13	P-n51-k10	857	**779**	806	-	802
14	P-n55-k7	679	610	611	-	**593**
15	P-n55-k8	690	654	601	-	**585**
16	P-n55-k10	832	749	763	-	**742**
17	P-n55-k15	1180	**1022**	1056	-	1099
18	P-n60-k10	896	**786**	823	-	830
19	P-n60-k15	1159	**1006**	1086	-	1092
20	P-n65-k10	964	**836**	856	-	837
21	P-n70-k10	989	**891**	902	-	900
22	P-n76-k4	753	685	**603**	690	**603**
23	P-n76-k5	671	737	**647**	-	649
24	P-n101-k4	891	698	702	789	**691**
	Average	708.33	639.00	640.33	464.80	633.17
	Best/Worst	0/20	9/2	4/2	4/0	12/0
			Pairwise win/draw/lose summary			
	Hybrid heuristic	-	21/0/3	22/0/2	8/0/2	23/0/1
	Centroid-based 3-phase		-	10/0/14	5/0/5	15/0/9
	Sweep + cluster adjust.		-	-	5/0/5	15/3/6
	Sweep nearest				-	6/1/3

tic Approach outperformed proposed method only for P-n16-k8 that is very small sized problem and Sweep+ Cluster Adjustmentis found better than proposed method for only six cases. Finally, outcomes of vSweep+VTPSO identified the proficiency of variant Sweep in clustering and VTPSO in route optimizing.

3.4 Experimental Analysis

The results presented in Table 2 and Table 3 are for fixed population and iteration in the TSP optimization technique; and therefore it is required to investigate variation effect of population and iteration on CVRP cost. The effect of population size on route optimizing has been investigated for A-n53-k7 problem with vSweep clustering for $\theta_s = 180°$. Population size was varied from 5 to 100 for GA, PSM and VTPSO. On the other hand, the number of ants in ACO was equal to the number of nodes in a cluster; therefore varied cluster to cluster. Figure 5 shows CVRP cost for population variation for fixed 100 iteration for fair comparison. The number of clusters (i.e., vehicles) were 7. From the figure it is observed that CVRP cost is invariant for ACO because population variation was not employed for it. On the other hand, GA is most sensitive with population size: CVRP cost through GA was very bad with respect to others at small population size (e.g., 5) and was competitive at larger population size. From the figure it also observed that PSM and VTPSO (the recent SI methods) are better than

ACO and GA in population variation. At a glance VTPSO is shown to outperform any other method for any population size and PSM is competitive to VTPSO.

Figure 6 shows CVRP cost varying iteration from 10 to 200 while population size was fixed at 50 for GA, PSM and VTPSO. Similar to previous experiments, the number of ants in ACO was equal to the number of nodes in a cluster while iteration varied from 10 to 200. From the figure it is observed that CVRP cost was high at small iteration (e.g., 10) and improved with iteration, in general. However, GA is shown very worse than others for small number of iteration. It is also observed from the figure that PSM and VTPSO are better than ACO and GA in iteration variation.

4. Conclusions

CVRP is a popular combinatorial optimization problem and interest grows in recent years to solve it in best possible ways. A popular way of solving CVRP is cluster the nodes according to vehicles using Sweep algorithm first and then generate route for each vehicle with TSP algorithm. In general, Sweep cluster construction starts from the node having lowest polar angle. This study considers a variant of Sweep which takes starting angle as a user defined parameter and produces different clusters for a given problem. Different optimization techniques such as GA, ACO, PSM and VTPSO are applied to generate optimal routes of individual clusters. The experimental results on the benchmark problems revealed that different starting angle have positive effect on Sweep clustering and VTPSO is better than other optimization methods to solve CVRP. Finally, VTPSO with variant Sweep is identified as a prominent CVRP solving method when compared with related existing methods.

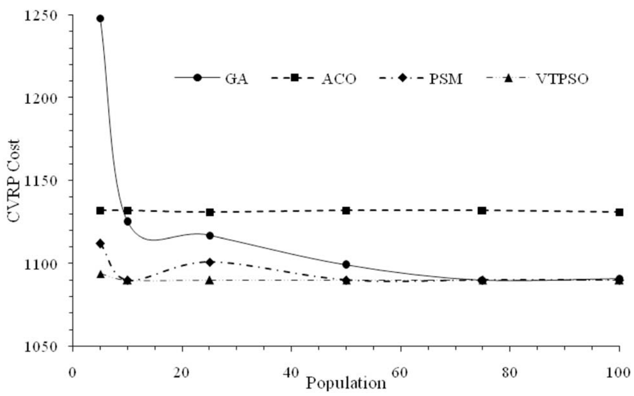


Figure 5. Effect of population size on CVRP cost for A-n53-k7 with vSweep clustering for $\theta_s = 180°$.

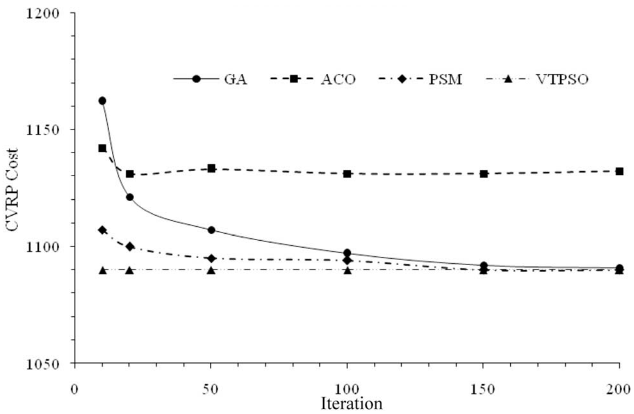


Figure 6. Effect of iteration on CVRP cost for A-n53-k7 with vSweep clustering for $\theta_s = 180°$.

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