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Effects of Introducing Similarity Measures into Artificial Bee Colony Approach for Optimization of Vehicle Routing Problem

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***Abstract*—**Vehicle Routing Problem (VRP) is a complex combinatorial optimization problem and it is quite difficult to find an optimal solution consisting of a set of routes for vehicles whose total cost is minimum. Evolutionary and swarm intelligent (SI) algorithms play a vital role in solving optimization problems. While the SI algorithms perform search, the diversity between the solutions they exploit is very important. This is because of the need to avoid early convergence and to get an appropriate balance between the exploration and exploitation. Therefore, it is important to check how far the solutions are diverse. In this paper, we measure the similarity between solutions, which ABC exploits while optimizing VRP. The similar solutions found are discarded at the end of the iteration and only unique solutions are passed on to the next iteration. The bees of discarded solutions become scouts and they start searching for new solutions. This process is continued and results show that the solution is optimized at lesser number of iterations but with the overhead of computing similarity in all the iterations. The problem instance from Solomon benchmarked dataset has been used for evaluating the presented methodology.

***Keywords*—**ABC algorithm, vehicle routing problem, optimization, Jaccard's similarity measure.

I. Introduction

VRP was introduced in Truck Dispatching by Dantzig and Ramser in 1956 as a generalization of Travelling Salesman Problem [1]. The problem is to find the optimal set of routes for the vehicles so as to minimize the total cost. Since its proposal, the problem has been widely explored for its optimization by using exact algorithms, approximate algorithms, heuristic, metaheuristic algorithms, Evolutionary Algorithms (EA) like Genetic Algorithm (GA) and SI algorithms like Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and ABC algorithm [2]-[9]. The reason for such a wide exploration is that the problem is highly related to real-time applications such as transportation, distribution and logistics. There are several variants of VRP, each imposing specific constraints on VRP. They are VRP with Time Windows (VRPTW), VRP with Soft Time Windows (VRPSTW), VRP with Hard Time Windows (VRPHTW), VRP with Homogeneous fleet, VRP with Heterogeneous fleet, Single Depot VRP, Multi Depot VRP, Capacitated VRP and Dynamic VRP [10].

Single Depot VRPSTW with homogeneous fleet is considered in this paper for the methodology. In single depot VRP, all the vehicles should start and finally reach at the same depot. VRPSTW means that the time window within which customers should be serviced can be violated by paying a penalty. Homogeneous fleet is that all vehicles have equal capacity and speed.

ABC algorithm is a SI, meta-heuristic search algorithm inspired by the foraging behavior of honey bee swarms [11]. This algorithm serves as a powerful optimization tool and has shown a competitive performance (and sometimes superior) compared to GA, PSO and ACO [12]-[14]. The ABC algorithm is also simple in concept and has only fewer control parameters [15]. With such remarkable features, ABC hybridized with neighborhood search had yielded good results for multi-objective optimization of VRPSTW (Bee_VRPSTW) [9].

The problem here is that, some of the solutions (vehicle routes), which the bees explore are similar and hence unnecessary time is wasted in exploiting the same sets of solutions by different sets of bees. To overcome this drawback, we have included similarity measure into ABC search to check for similar sets of solutions (non-unique) in the population of solutions (Enhanced ABC for optimization of VRP (EABC-VRP)). Jaccard's similarity measure has been used in ABC approach to VRP for finding the set of unique and non-unique solutions. Only the unique solutions and one member from each set of non-unique solutions are passed to the next iteration. The rest of the non-unique solutions are discarded and the corresponding bees become scouts, which search for new solutions.

In literature, similarity between solutions has been attempted for GA based optimization of VRP [16]-[18]. The similarity of solutions has been measured for GA search by using two metrics for similarity - Edit distance and Jaccard's similarity coefficient. It has been proved that, measuring the similarity and avoiding exploration of non-unique solutions has resulted in increased optimization [16]-[20].

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This paper is organized in 7 sections. Section II gives a brief note on VRP. The concept of ABC algorithm is explained in Section III. In Section IV, the previous works in the literature related to similarity measures for VRP are discussed. Section V gives the detailed description of the proposed EABC-VRP. Experiments and results are discussed in Section VI. Section VII concludes the paper.

II. VRP

VRP is an NP-hard and combinatorial optimization problem, hence it is a tedious and time consuming job to find an optimal solution for VRP [21]. VRP is defined as follows: Consider a number of vehicles and a set of inter-connected locations distributed geographically, called customer points where certain demand has to be met out. The customer location where a vehicle starts is called the depot. There are different travelling costs like travel time and distance between the customer points. The problem is to find a set of routes for the vehicles such that travel cost of each route is minimized, hence minimizing the overall travel cost. The number of routes is equal to the number of vehicles. A customer should be served only once and by only one vehicle, except the depot. The vehicles should start and end at their respective depot.

In the presented work, we have considered Soft Time Window version of Single Depot VRP, VRPSTW where a penalty is charged when the time window is violated, but violations are permitted. Also, the VRP has been optimized for a single objective of finding a set of routes for the vehicles so that the overall distance travelled is minimum.

The problem VRPSTW is formulated as [4], [9]:

Let G = (V, E) be a graph representing the set of vertices V and the set of connections or edges E that exist between them.

- V - Vertices are used to represent the customers and there are 'n+1' numbers of customers {v0,v1,v2, ….vn}.
- v0 - Starting Point or depot for all the vehicles.
- E - {e(i,j), $0 \le i, j \le n$}, the set of edges between the depot and a customer and between the customers
- T - set of vehicles ti, $1 \le i \le |T|$
- R - set of routes ri, $1 \le i \le |R|$. Each vehicle has only one route associated with it. Hence, |T| = |R|
- di - fixed demand at the customer point
- Tq - capacity of the vehicle
- Costi,j - Travel Cost associated with the edge (i,j) and it is usually a distance or time taken to reach from customer i to customer j.
- [ai, bi] - time window associated with the customer Ci, $0 \le i \le n$.
- [a0, b0] - time window of the depot
- Si - Service time of the customer Vi

III. ABC Algorithm

ABC algorithm is inspired by the foraging behavior of honey bees and it is characterized by three types of bees: Employed bees, onlooker bees and the scouts [11]. The beehive has equal population of employed bees and onlooker bees. The number of food sources is considered to be half the size of beehive population. Initially, the employed bees search for the food sources and once they have found, they return to the hive and perform a waggle dance. The waggle dance is in the form of figure eight, it conveys the information about the direction of the food sources and the quantity of nectar to the onlooker bees present in the hive. Food sources represent the valid solutions to the problem and the nectar content represents the quality of the solutions. The onlooker bees exploit the food sources based on the information received from the employed bees. Employed bees are responsible for exploration and onlooker bees are responsible for exploitation. Once the food sources pointed by the employed bees become exhausted, the corresponding employed bees become scouts. The scouts then go in search of new food sources. The search processes performed by the bees explore the optimal solutions and the proportion of nectar content influences the probability of selection of a particular food source by the onlooker bees [14], [22].

IV. Related Works

While finding optimal solutions to VRP by evolutionary and SI algorithms, there are high possibilities for some of the solutions to be similar to other solutions. In VRP, similarity between the solutions will consider the contents of routes of the solutions and not the sequence of routes [19]. When solutions are similar, there is less diversity between the solutions that are exploited; also time is wasted unnecessarily in exploiting the same solution (set of routes); some useful solutions are likely to be unexplored.

Similarity between solutions has been explored previously in GA and EA based optimization of VRP and in Decision Support systems. Some metrics to measure solution similarity have also been proposed and evaluated [16]-[20], [23]. The effects of similarity measures on GA based VRP optimization was investigated for single-objective, bi-objective and multi-objective cases of optimization; analysis of all these cases have been done by using two similarity measures namely the edit distance and Jaccard's similarity measure; it has been proved that GA yielded improved results in all these cases, when the similar solutions are discarded and only the unique solutions are passed on to the next generation. Also, a comparative analysis between the two similarity measures has been performed and it has been proved that, Jaccard's similarity measure suits better to VRP than Edit Distance [16]-[19].

Two other metrics for similarity measures have been proposed in Genetic local search based VRP by making use of some recombination operators. They are Similarity as common pairs of nodes and Similarity as common edges [19]. Another metric called as Tversky's similarity measure and an attribute based similarity function was proposed for VRP in VRP decision support system.

Jaccard's similarity measure has been adopted in the presented work to investigate the effects of removing similar solutions and retaining only the unique solutions over the iterations in ABC based optimization of VRP.

V. Enhanced ABC Algorithm for VRP Optimization with the Effect of Similarity (EABC-VRP)

ABC algorithm has been enhanced with an additional step of using Jaccard's similarity measure for VRP in the presented method (EABC-VRP). ABC based optimization of VRP (Bee_VRPSTW), Similarity measure computation and the proposed method are explained in this section:

A. An ABC Inspired Algorithm for VRPSTW(Bee_VRPSTW)

Multi-objective optimization of VRPSTW has been experimented with ABC algorithm and it has yielded good optimization results. ABC is hybridized with variable neighborhood search to enhance the local search space. i.e. The exploitation of employed and onlooker bees have been extended by performing neighborhood candidate selection. If better solutions are available in the neighborhood of the bees, compared to the solution they hold, then random swapping is performed to generate high quality solutions in the local search space. The solutions are swapped based on random permutation and the current information. This results in fast convergence of the algorithm as well as improved solutions. The steps of Bee_VRPSTW are outlined in Fig. 1.

1. Generate initial solution (food source)
2. Assign **Unique** initial solution to each of the employed bees
3. Determine neighborhood solutions (food sources)
4. Evaluate the Fitness
5. Assign solutions to employed bees and onlooker bees
6. Generate scout bees and assign new solutions to scout bees
7. Repeat the steps 1-6 for fixed number of iterations or until optimal solution is reached

Fig. 1 Steps of ABC inspired algorithm for VRPSTW(Bee_VRPSTW)

In Bees-VRPSTW, after generating initial solutions, they are assigned to employed bees and it is taken care, that the solutions are unique to ensure diversity. This is done only in the initial stage of assignment to the bees. However, the method employed for finding uniqueness has not been mentioned explicitly.

B. Computation of Jaccard's Similarity Measure

The solutions that the bees exploit are examined for similarity only at the end of each iteration of the onlooker bee phase. This is very important because, unnecessary time will be wasted in exploring the same sets of solutions and some better solutions available in the search space may not be explored at all. Jaccard's similarity measure has been used to find the sets of similar solutions among the population of bees' solutions [18].

Jaccard's similarity coefficient between two solutions to VRPTW is the ratio of the number of shared arcs to the number of total arcs used in both solutions. It is computed as follows:

Let $y_{ijk} = 1$ if arc (i,j) from vertex i to vertex j is used by any vehicle in solution R, and $y_{ijk} = 0$ otherwise. Then the similarity between solutions R and Q is:

$$\delta_{RQ} = \frac{\sum_{i=0}^{n}\sum_{j=0}^{n} y_{ijR} \cdot y_{ijQ}}{\sum_{i=0}^{n}\sum_{j=0}^{n} sign\,(y_{ijR}+y_{ijQ})} \tag{1}$$

In (1), the term in the sum of the numerator will be equal to 1 if arc (i,j) is used by both solutions, while the same in the denominator will be equal to1 if either solution uses it. Arcs (i, j) and (j, i) are considered to be different, even if their cost is the same. If solutions P and Q are the same then, $\delta_{RQ} = 1,$ and if they are two completely different solutions with no arc in common then, $\delta_{RQ} = 0$ [18].

This calculation of similarity measure using (1) has been adapted and used for the proposed method. For each employed bee, its similarity with all other solutions is calculated by using (1). If M is the total number of bees, then we will have (M-1) similarity values computed for each employed bee. i.e. the similarity of each bee with (M-1) bees and hence (M-1) similarity values.

Then, the Jaccard's Similarity coefficient for every employed bee is computed by the average of (M-1) similarity measure values that have been calculated. Jaccard's similarity coefficient is found by using (2) as:

$$\sigma_R = \frac{1}{M-1}\sum_{Q\epsilon \boldsymbol{P}\backslash\{R\}} \delta_{RQ} \tag{2}$$

where **P** represents the population of solutions and |**P**| =M.

The bees which have the same σ_R values as that of other bees are organized into separate groups and are stated as non-unique bees. Rest of the bees is termed to be unique bees.

C. Enhanced ABC for VRPSTW(EABC-VRP)

In the proposed work, ABC algorithm for optimization of VRP has been enhanced by introducing Jaccard's similarity measure to find out similar solutions that are exploited. While the bees perform search process, there are high possibilities for the bees to explore and exploit sets of similar solutions. This is because we start the search process by assigning random initial solutions to the employed bees and some bees may be assigned the same solutions as other bees. So, the bees which hold the same solution as other bees are identified using Jaccard's similarity measure as explained in Section V *B*. The steps of EABC-VRP method are given in Fig. 2.

The main difference between Bee_VRPSTW and EABC-VRP is in finding the non-unique solutions. In Bee_VRPSTW, the solutions are checked for uniqueness in the initial stage of assigning random solutions to the bees. However, the method of finding unique solutions has not been mentioned explicitly. But in the proposed method, solutions are checked for uniqueness at the end of every iteration by means of measuring Jaccard's similarity coeffecient.

In EABC-VRP method, the problem solving starts with the same steps 1-5 (except uniqueness checking) of Bee_VRPSTW. Then, attempt for finding non-unique solution is performed by measuring Jaccard's similarity coefficient (σ_R) as explained in Section V *B*.

Step 1 :**Do initialization**
(1.1) Setup input parameters (number of employed bee, onlooker bee and iterations).
(1.2) Generate random initial solutions
Step 2 :**For each employed Bee**,
(2.1) Assign an initial solution (food source)
(2.2) Perform two-step tweaking on current solution (local search) which aims to produce a higher quality neighboring solution as follows:
(2.2.1) Select two routes and one customer from each the routes randomly and swap the customers between these two routes.
(2.2.2) Select a single route randomly and replace a block of customers within that route by random permutation of the customers.
(2.3) Evaluate the fitness of current and neighborhood solution and record the best one
(2.4) Move the employed bee to neighboring solution only if it is improved over current one. Therefore, always a better solution is kept within the local space.
Step 3 :**For the onlooker bees,**
(3.1) Collect fitness information from employed bees
(3.2) choose a solution depending on the fitness and change the status to employed
(3.2) Repeat Steps 2.2 to 2.4.
Step 4 : **Similarity Measure**
(**4.1)**Compute the similarity population value for every employed bee at the end of every iteration
(4.2) Find the Non-Unique Bees and discard the solutions pointed by them
(4.3) The associated employed bees becomes a scouts.
(4.4) Carry over the Unique Bees to the next iteration
Step 5 :**For the scout bee,**
(5.1) Explore randomly within the total search space to produce a new solution and scout bee becomes an employed bee.
Step 6: Repeat Steps 1 to 5 for m number of Iterations and n number of Runs.

Fig. 2 ABC Algorithm for VRP with similarity effect (EABC-VRP)

The bees which have same σ_R values are organized into separate groups. The other bees are said to be unique bees with distinct solutions. Now, single bees from each of the groups along with the unique bees are passed on to the next iteration for further exploitation. The solutions which the other bees point are discarded and these bees are considered as scouts. The scouts will be assigned new solutions, the same way initial solutions are assigned.

The search process is continued and solutions are checked for similarity at the end of the iterations. Only unique solutions are retained and non-unique solutions are discarded at every iteration. Hence, the solutions explored are highly unique and diverse.

VI. Experiments and Results

Preliminary experiments have been conducted to prove the effectiveness of the proposed method. Both Bee_VRPSTW and the EABC-VRP have been implemented in Java JDK1.5 using Eclipse (Luna).

A. Dataset Used

Computations were done using the benchmarked problem instance R101 taken from Solomon Dataset for VRPTW [24]. The problem instance R101 has 101 customers and 200 as vehicle capacity. But for the proposed method, only 51 customers and the same vehicle capacity of 200 has been considered. The details of the Problem instance are presented in Table I.

B. Experimental Setup

ABC with similarity measures has been implemented for VRPSTW with the specifications given in Section II. The objective is to find the optimal set of routes for the vehicles so that the total travel cost is minimum. Hence, the problem we have considered is a single objective VRP. Travel cost is the distance or time taken to reach between two customers.

The proposed method is evaluated by performing computations on Solomon's problem instance R101. The geographical locations of the customers are given in terms of x and y coordinates as shown in Table I. The distances between the customers are computed with this information. We have considered a single depot VRP and homogeneous fleet. Here Customer 1 is considered as depot and all vehicles are assumed to have equal speed and capacity. Also, we have neglected the service time which means, the vehicle is assumed to start at the same time, it reaches a particular customer i.e. arrival and the departure times are the same. The ready time and due date in Table I represents the time window of the customers. Since the problem is VRPSTW, time window violations are allowed. If the time window is violated, then penalty is levied on the travel cost of the vehicle.

Both early and late penalties are included. They are calculated as:

- Early penalty: If a vehicle reaches a customer early before its ready time, the vehicles waiting time will be calculated and will be added to the vehicle's travel cost.
- Late Penalty: If a vehicle reaches a customer late after its due time, the vehicle's late time will be calculated and will be added to the vehicle's travel cost.

We have considered equal number of employed bees and onlooker bees. It is set as 100.

TABLE I
SOLOMON'S PROBLEM INSTANCE FOR VRP – R101

Cust No.	XCoord.	YCoord.	Demand	Ready Time	Due Date	Service Time
1	35.00	0.00	0.00	230.00	0	10
2	41.00	49.00	10.00	161.00	171.00	10
3	35.00	17.00	7.00	50.00	60.00	10
4	55.00	45.00	13.00	116.00	126.00	10
5	55.00	20.00	19.00	149.00	159.00	10
6	15.00	30.00	26.00	34.00	44.00	10
7	25.00	30.00	3.00	99.00	109.00	10
8	20.00	50.00	5.00	81.00	91.00	10
9	10.00	43.00	9.00	95.00	105.00	10
10	55.00	60.00	16.00	97.00	107.00	10
11	30.00	60.00	16.00	124.00	134.00	10
12	20.00	65.00	12.00	67.00	77.00	10
13	50.00	35.00	19.00	63.00	73.00	10
14	30.00	25.00	23.00	159.00	169.00	10
15	15.00	10.00	20.00	32.00	42.00	10
16	30.00	5.00	8.00	61.00	71.00	10
17	10.00	20.00	19.00	75.00	85.00	10
18	5.00	30.00	2.00	157.00	167.00	10
19	20.00	40.00	12.00	87.00	97.00	10
20	15.00	60.00	17.00	76.00	86.00	10
21	45.00	65.00	9.00	126.00	136.00	10
22	45.00	20.00	11.00	62.00	72.00	10
23	45.00	10.00	18.00	97.00	107.00	10
24	55.00	5.00	29.00	68.00	78.00	10
25	65.00	35.00	3.00	153.00	163.00	10
26	65.00	20.00	6.00	172.00	182.00	10
27	45.00	30.00	17.00	132.00	142.00	10
28	35.00	40.00	16.00	37.00	47.00	10
29	41.00	37.00	16.00	39.00	49.00	10
30	64.00	42.00	9.00	63.00	73.00	10
31	40.00	60.00	21.00	71.00	81.00	10
32	31.00	52.00	27.00	50.00	60.00	10
33	35.00	69.00	23.00	141.00	151.00	10
34	53.00	52.00	11.00	37.00	47.00	10
35	65.00	55.00	14.00	117.00	127.00	10
36	63.00	65.00	8.00	143.00	153.00	10
37	2.00	60.00	5.00	41.00	51.00	10
38	20.00	20.00	8.00	134.00	144.00	10
39	5.00	5.00	16.00	83.00	93.00	10
40	60.00	12.00	31.00	44.00	54.00	10
41	40.00	25.00	9.00	85.00	95.00	10
42	42.00	7.00	5.00	97.00	107.00	10
43	24.00	12.00	5.00	31.00	41.00	10
44	23.00	3.00	7.00	132.00	142.00	10
45	11.00	14.00	18.00	69.00	79.00	10
46	6.00	38.00	16.00	32.00	42.00	10
47	2.00	48.00	1.00	117.00	127.00	10
48	8.00	56.00	27.00	51.00	61.00	10
49	13.00	52.00	36.00	165.00	175.00	10
50	6.00	68.00	30.00	108.00	118.00	10
51	47.00	47.00	13.00	124.00	134.00	10

C. Results and Analysis

The steps of the proposed method EABC-VRP summarized in Fig. 2 are executed on Solomon's benchmark instance R101, with the settings specified in Section VI *B*. Random solutions are assigned to employed bees, neighbourhood solutions are generated, they are evaluated for fitness and then assigned to employed and onlooker bees. Then, Jaccard's similarity coefficient is calculated to find out unique and non-unique solutions as explained in Section V *B*. Only the bees with unique solutions and one candidate bee from each set of similar solutions are passed on to the next generation. The other bees with similar solutions are discarded and they become scouts. Scouts are then assigned with new solutions using step 1 of Fig. 2, they become employed bees and join the other bees in the next iteration. The same process is repeated and optimal solution to VRP is obtained as a set of routes for vehicles with minimized travel cost. The results obtained are presented in Tables II and III. Table II presents the results obtained for Bee_VRPSTW on the Problem instance R101 (Table I) and the execution results of EABC-VRP on R101 are given in Table III.

Both Bee_VRPSTW and EABC-VRP were executed for 200 iterations and 5 runs. Computation results were recorded at the end of certain iterations and runs as specified in Tables II and III. The counts of unique and non-unique bees are presented in the tables. It can be seen that unique bees (solutions) are higher in the proposed method, which proves the exploration of diverse solutions. This is given as a pictorial representation in Fig. 3. Maximum Fitness Evaluation (MFE) in both tables is a counter that represents the total number of solutions generated by the algorithm including the solutions that were discarded. This counter is increased whenever a new bee or a neighbourhood solution, an onlooker or a scout solution is generated. This count is larger for Bee_VRPSTW compared to EABC-VRP. This is because in the first method, solutions which have no improvement over the last 10 iterations are discarded whereas in the later, similar solutions are removed in the earlier stage itself. Best costs in the tables represent the solution of the best bee added with the penalty cost of the particular iterations. The comparison between the best costs of both the Bee_VRPSTW and the proposed EABC-VRP through various iterations of runs 1, 2 and 5 is three- dimensionally presented in Fig. 4. It could be inferred from Fig. 4 that, the best costs of proposed method were initially greater than Bee_VRPSTW, but towards end in the 5th run, the best costs computed at the end of all iterations of the proposed method had considerably been less compared to Bee_VRPSTW. It can also be inferred from Fig. 4 that, best cost that is obtained in each run takes less number of iterations for the presented method compared to the existing method.

Maximum Cost represents the highest cost solution among the solutions at the end of iterations and Medium Cost represents the average of the solution costs. Computing time represents the execution time of the algorithms in seconds. This is insignificantly higher for the proposed method as it involves with more time for computing similarity measure.

WB represents the percentage of Window Breaks occurred during execution of the solutions and Penalty cost represent the extra cost that was charged either because of early or late penalty.

TABLE II
RESULTS OF BEE_VRPSTW THROUGH VARIOUS RUNS OF THE ALGORITHM

Runs	Iterations	No. of Unique Bees	No. of non-unique bees	MFE	Best Cost	WB (%)	Cost Max	Cost Med	Penalty Cost	Computing Time (Secs)
	20	21	79	10893	1926	6	3614	2506	102	5.606
	40	14	86	21965	1718	10	3369	2464	3	7.549
	60	21	79	32865	1625	16	3235	2387	52	9.398
	80	25	75	43814	1662	8	3252	2409	28	11.632
1	100	20	80	54947	1688	8	3290	2334	39	13.672
	120	20	80	65896	1704	10	3085	2323	51	15.926
	140	21	79	76907	1733	20	3096	2330	115	17.001
	160	22	78	87867	1600	6	3411	2330	10	19.813
	180	27	73	98903	1728	14	3534	2315	22	21.477
	200	24	76	108859	1738	10	2870	2212	10	22.194
	20	22	78	21895	1699	4	3101	2457	21	7.35
	40	21	79	43915	1850	12	3939	2414	10	11.904
	60	27	73	66106	1872	0	3210	2347	108	15.79
	80	23	77	87918	1850	16	3932	2305	184	19.017
2	100	29	71	109968	1697	2	2969	2283	0	23.248
	120	23	77	131997	1798	20	3438	2278	42	27.439
	140	32	68	153518	1754	0	3195	2218	34	30.545
	160	33	67	176697	1676	22	3405	2242	91	35.049
	180	28	72	197855	1767	0	2823	2183	56	37.527
	200	25	75	219323	1709	10	2748	2161	74	40.375
	20	22	78	54777	1650	4	3045	2295	8	13.502
	40	27	73	110214	1822	22	3019	2227	42	23.103
	60	29	71	164772	1492	4	2852	2178	10	31.863
	80	21	79	220160	1792	26	2760	2141	181	41.997
5	100	34	66	275162	1751	0	2857	2165	113	51.56
	120	34	66	327873	1778	2	3347	2150	9	61.352
	140	32	68	384674	1626	14	2722	2127	25	71.142
	160	32	68	438625	1653	12	4730	2155	0	77.833
	180	31	69	495911	1735	30	2816	2152	92	90.354
	200	29	71	549992	1516	2	2862	2063	93	100.423

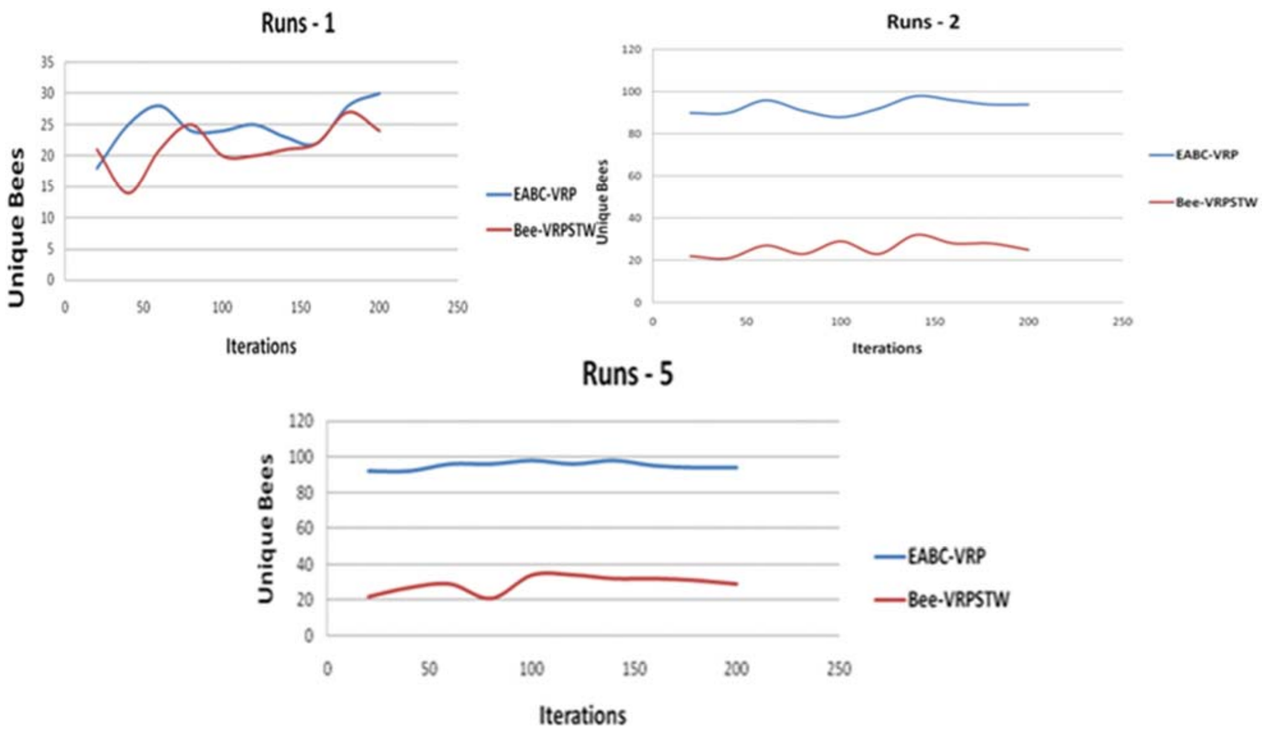

Fig. 3 Comparison of Number of Unique Bees obtained through Runs of the Algorithms Bees-VRPSTW and EABC-VRP

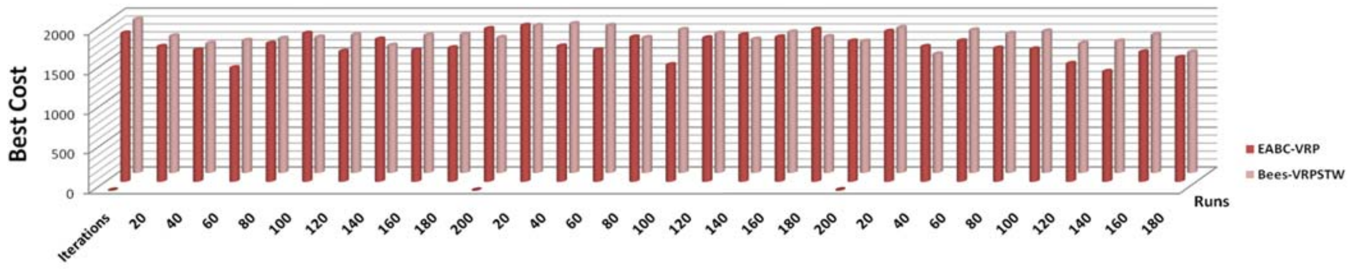

Fig. 4 Comparison of Best Cost obtained through Runs of the Algorithms Bees-VRPSTW and EABC-VRP

TABLE III
EXECUTION RESULTS OF EABC-VRP THROUGH VARIOUS RUNS OF THE ALGORITHM

Runs	Iterations	No. of Unique Bees	No. of Non-Unique bees	MFE	Best Cost	WB (%)	Cost max	Cost med	Penalty Cost	Computing Time (Secs)
1	20	18	82	10952	1865	8	3324	2618	54	7.906
	40	25	75	21894	1697	10	3182	2493	11	9.466
	60	28	72	32947	1655	0	3338	2407	3	11.057
	80	24	76	43879	1429	0	3062	2304	0	13.29
	100	24	76	55099	1736	8	3072	2350	10	15.387
	120	25	75	66147	1863	24	2999	2339	0	17.501
	140	23	77	77158	1635	14	3066	2385	11	19.516
	160	22	78	87945	1789	0	3004	2271	45	21.582
	180	28	72	98419	1651	10	2932	2229	14	22.387
	200	30	70	109884	1680	8	3146	2261	18	25.641
2	20	90	10	21853	1921	4	4070	2583	17	15.024
	40	90	10	43521	1962	8	4142	2430	111	18.456
	60	96	4	65844	1702	30	3340	2458	0	22.504
	80	91	9	88159	1654	0	3145	2342	64	25.007
	100	88	12	109494	1815	0	4630	2324	47	29.326
	120	92	8	131995	1467	12	3170	2285	0	33.404
	140	98	2	153348	1806	0	2877	2271	101	38.153
	160	96	4	175430	1844	6	3036	2265	119	41.242
	180	94	6	198361	1817	12	3139	2264	175	45.907
	200	94	6	219829	1914	0	2975	2239	103	49.776
5	20	92	8	54675	1764	0	3425	2535	10	20.272
	40	92	8	109896	1887	12	3311	2418	266	30.037
	60	96	4	165091	1696	10	3025	2312	9	39.758
	80	96	4	219261	1767	4	3086	2351	0	49.569
	100	98	2	274247	1676	8	3628	2327	32	59.109
	120	96	4	329424	1665	0	3069	2265	0	69.505
	140	98	2	383301	1482	4	3142	2194	0	81.121
	160	95	5	441296	1382	14	2862	2247	0	90.597
	180	94	6	493021	1628	2	3451	2279	21	95.78
	200	94	6	549503	1559	0	3083	2180	69	104.531

VII. CONCLUSION

ABC algorithm is a powerful optimization tool and has yielded good results for optimization of VRP (Bee_VRPSTW). When bees are assigned with random initial solutions and the search proceeds for optimization, there are possibilities of exploring the same sets of solutions unnecessarily; some good solutions might not be explored at all. To overcome this problem, we have introduced Jaccard's Similarity measure for ABC algorithm in the proposed EABC-VRP for single objective optimization of VRPSTW. The similarity measure computed at the end of iterations, has resulted in enhancement of exploration of the solution space and retaining unique diverse solutions discarding the non-unique ones. Also, optimal solution is obtained at comparatively lesser number of iterations and travel cost. Hence, similarity measure computation is proved to be effective for optimization of VRP using SI algorithms.

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