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Vehicle Route Optimisation Using Artificial Bees Colony Algorithm and Cuckoo Search Algorithm-A Comparative Study

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Abstract

One among the impacts of globalization of economy is the exponential growth in the exchange of goods between different parts of the world. Restriction in the availability of materials and transportation resources, complexity involved in planning and the cut throat competition between logistic service providers contributing to increased cost, calls for the use of computer aided systems for the planning of transports. In this regard, a prominent subtask is the operational and optimal planning of transportation vehicles. These optimization tasks are commonly referred to as vehicle routing problems or transportation problems. Swarm optimization Algorithms including Particle Swarm optimization, ant colony optimization, bee inspired algorithms and many more, have been identified as good methods to solve vehicle routing problems. This paper discusses the implementation of two swarm optimization algorithms viz. Artificial Bee Colony algorithm (ABC) and Cuckoo search algorithm. In addition, this paper focuses on enhancing the quality of results by opting for very large search spaces. The performance of the two algorithms are compared on the basis of a set of four benchmark functions.

General Terms—Vehicle Routing Problem, Artificial Bee Colony Algorithm, Cuckoo Search Algorithm

Keywords: Optimisation Algorithm, Artificial Bee Colony Algorithm, Cuckoo Search Algorithm, Swarm Intelligence

INTRODUCTION

Vehicle Routing Problem(VRP) is a generalized version of Travelling Salesman Problem(TSP). In VRP the vehicle will start from a depot, serve all the customers in transit network and come back to the depot. The only difference when compared to TSP is that in TSP there will be only one salesman who starts from a source node and visit all the cities and come back to the origin. In the case of VRP there will be multiple salesmen whose routes needs to be optimized. The objective of VRP is to find the minimum cost route. The cost can be time, distance or some other variable. There are different variations of vehicle routing problems viz. Capacitated Vehicle Routing Problem(CVRP), vehicle Routing Problem with Time Windows(VRPTW),Time Dependent Vehicle Routing Problem(TVRP),Vehicle Routing Problem with Heterogeneous Fleet(VRPHF).

The following subsections discusses the components and a few variants of VRP.

1) Vehicle Routing Problem Components

a) Depot

Depot is the starting and ending node in a transit network. Every trip will start and end in the depot. In most of the variants of vehicle routing problem only one depot will be there. However, there are cases in which there are more than one depot.

b) Customers

The main objective of vehicle routing problem is to serve customers. Customers are spread across the network.

c) Vehicles

Vehicles are used to traverse in the network. It will start from depot, serve all the customers and come back to the depot.

d) Routes

Vehicle routing problem is used to find the routes in a transit network. There will be different routes possible but only one route can provide optimum result.

2) Vehicle Routing problem variants

a) Capacitated Vehicle Routing Problem

Capacitated vehicle routing problem (CVRP) [1] is one of the most studied VRP. In this routing problem, along with other constraints we will also consider the capacity of vehicle. Customer’s demands are known in advance. The capacity of each vehicle will be the same and sum of customer’s demands must not exceed the vehicle’s capacity.

b) Vehicle Routing Problem with Time Windows

Vehicle Routing Problem with Time windows(VRPTW)[2] is a variant of capacitated vehicle routing problem. Each customer has a time window and customer has to be served during that time window.

c) Heterogeneous fleet Vehicle routing problem

In Heterogeneous Fleet Vehicle routing problem(HFVRP) [3] different vehicles with different capacities will be used. Since the capacity is different the cost will vary from one vehicle to the other.

LITERATURE REVIEW

This section discusses a few relevant works in the area of vehicle routing problem. The authors [4] in their work proposes a modified version of ABC algorithm to improve the fitness of original ABC. In the proposed algorithm, the mechanism used by scout bees in replacing abandoned solution with new ones impacts the convergence speed. In the modified version of ABC scout bees memorizes the solutions that exceed the trial limit by maintaining a list of abandoned solutions. In the next step scout bees will select a random route from the best solution which contains a set of routes. In the VRPTW vehicles are allowed to arrive or leave the customers location during a particular time window. Thus this variant of VRP imposes a time window on the vehicles that are used to serve the customers. One major concern of the original version of ABC is that a new solution is created randomly when the existing solutions cannot be improved. The randomly created solution will make the bees to explore the area blindly to find the optimal solution which makes it difficult to find the optimal solution. The scout bees select a random solution from the abandoned list based on the roulette wheel selection. Bees select a new solution randomly from the list of best solutions and replace it with newly generated solution. Penna et al. [5] proposed an iterated Local Search(ILS) metaheuristic algorithm for solving heterogeneous fleet vehicle routing problem. ILS uses a variable neighborhood descent procedure with a random neighborhood ordering in the local search space. Yianmakou et al. [6] suggested an ant colony algorithm for the multi compartment vehicle routing problem. This paper demonstrates the application of Ant Colony Optimization (ACO) algorithm to solve the CVRP which is applied in the collection of recycling waste from houses. In this algorithm. Particular transit network households are treated as nodes. ACO algorithm has two different phases called route construction and the pheromone update. In the first phase the ants randomly choose a node as starting node and at each node the ants apply probabilistic random proportional to decide which node to go next. The ACO algorithm is extended by making an ant to keep a record of the amount of waste collected during its tour. Whenever the ant is not able to proceed to the next node it will be redirected to the depot. Yue-Jia Gong [7] proposed a discrete particle swarm optimization algorithm for optimizing the vehicle routing problem with time windows. A set based PSO is proposed to solve this problem. SPSO treats the VRPTW, discrete search space as an arc set of the complete graph. Habibch Nazif and L.S Lee [8] formulated a genetic algorithm for solving capacitated vehicle routing problem. CVRP is defined by using same capacity vehicles according to the demand of customers. The proposed genetic algorithm uses an optimized crossover operator for solving the CVRP. Baldacci et al.[9] discusses recent development in the field of exact algorithms on vehicle routing problem. The paper does a survey of exact algorithms for CVRP and VRPTW. Comparison of different versions of exact algorithms are discussed in this work. The extended version of exact method is used to solve CVRP and VRPTW by means of various improvements in existing algorithm. Szeto et al.[10] discusses the implementation of ABC algorithm for solving the capacitated vehicle routing problem. The extended version of ABC made improvements to the solution quality of original version of ABC. In this version the condition altered is that if the best solution X1 found by all onlookers with the food source ‘i’ is better than the food source Xj ,then X1 will replace the food source Xj based on following two criteria. 1) Xj has not been improved for the largest number of iterations among all existing food sources. 2) Xj is worse than X1. Dusan Teodrovic and Milo Nikoli [11] proposed Artificial Bee Colony (ABC) algorithm for solving the problem of traffic network design. When designing the transit network we try to maximize the number of satisfied customers. The proposed method first generated the initial feasible solution space in the neighborhood of the solution and attempts to improve the solution found so far. The modification is performed through forward pass within single iteration. Santillan et al. [12] proposed cuckoo search algorithm via Levy flights for the capacitated vehicle routing problem. The cuckoo search algorithm was performed with the help of Levy flights with the 2-opt and double bridge operations and for each run 500 iterations are performed. Initial solution is generated randomly and vehicle is picked arbitrarily, with the assumption that vehicle is able to serve the customer with least demand. Otherwise algorithm loops until vehicle with required capacity is selected. Next, an unassigned customer is randomly chosen and added to the route. If the customer does not meet the constraints algorithm moves to the next possible combination. Otherwise, customer will be removed from the pool of unsigned customers. The vehicle’s capacity will be updated after this step. Liyang Xiao et al.[13] proposes a method of adapting the CS-Ouaarab to solve the CVRP. The main idea of this work was to extend CS-Ouaarab to solve the CVRP. Levy flights specialize the search areas for CS-Ouaarab and hence CS-Ouaarab can find good solutions using local search. In cuckoo search algorithm, probability of trapping in local optima is very less since levy flights provide displacement zones instead of solutions. Hongqiang Zheng[14] proposed Cuckoo search algorithm for solving vehicle routing problem. The Cuckoo Search algorithm prepare a suitable representation of candidate solution for finding the solution of a particular problem. Each individual (tour) in the case of VRP, for instance, is recorded via the path representation of the tour, that is, via the specific sequence of the nodes. In order to represent the solution an integer string of length n is used. Each nest in the string represents customers and the order of sequence represents the order of visiting these customers.

Relevant works reviewed in the above paragraphs, discusses the implementation of various Swarm intelligence algorithms to solve Vehicle Routing problem. These works are mainly concentrating on a particular algorithm and discusses how it can solve the vehicle routing problem. This research paper focuses on carrying out a comparative study of ABC algorithm and Cuckoo Search algorithm from the perspective of arriving at an optimal solution to a vehicle routing problem.

TECHNIQUES TO SOLVE VRP

There are many techniques to solve VRP. This research work focuses on implementing two swarm optimization techniques and identifying which algorithm can provide better solution. The algorithms discussed in this paper find the maximum value of a given function in a search space. For example, with respect to ABC algorithm we can say that these algorithms find the food source with the maximum amount of food. In accordance with the objective of the algorithms we use the word ‘fitness’ or ‘f value’ for the value of the function. Few benchmark functions are considered to analyse and compare the performance of both the algorithms.

1) Artificial Bee Colony Algorithm(ABC)

The Artificial Bee Colony (ABC) [15] algorithm is a swarm intelligence algorithm inspired by the foraging behavior of bees. This algorithm was introduced by Karaboga for solving different optimisation problems.

In ABC algorithm, the colony consists of three types of bees: employed bees, onlooker bees and scout bees. Working of each of these bees are different and are as follows: Onlooker bees who are associated with a food source make decisions based on the dancing of employed bees. Scout bees are responsible for searching food source. Both onlookers and scouts are also called unemployed bees. In the initialization phase scout bees will search and find the food sources. Thereafter, the food sources are exploited by employed bees and onlooker bees. This exploitation will cause the food source to become exhausted. Whenever the food is exhausted, the employed bees that are associated with that particular food source will become scout bees and search for food source. In ABC algorithm, each food source represents solutions of the problem and nectar amount represents fitness of the solution. Number of food sources and number of employed bees will be same since each bee can produce one and only one solution.

a) Algorithm Logic

In the initialization phase the various parameters such as population size which includes the number of employed and onlooker bees, number of iterations etc. are defined.

A variable ‘i’ is declared to iterate through the loop. In the first phase which is employed bee phase, the loop variable will vary from 1 to the number of employed bees. The result of this phase will be a random solution. In the second phase which is onlooker bee phase another variable is declared to iterate through the loop. In this phase the solution will be found based on the roulette wheel selection and a random neighborhood structure will be selected. If the solution is found better than the solution that is already there then the new one will be taken and the old one will be abandoned. In the next phase which is scout bee phase, scout bees find the abandoned food sources and replace it with the new food sources

b) Pseudo code for ABC algorithm

Initialize the population and calculate initial fitness value, f(sol)

Set the best solution;

Set number of iterations and population size;

set iteration=0;

do while(iteration not equal to number of iterations)

for i=1: employed bees number

Select random solution

end for for i=1: number of onlooker bees sol* select solution from population based on Roulette wheel selection if(f(sol) < f(sol*))

sol*=sol;

end if

end for

solbest=best

Scout bees replace the abandoned food source with new food source

Iteration++

end do

2) Cuckoo Search Algorithm

Cuckoo Search [16] is an optimization algorithm developed by Xin She Yang and Suash Deb in 2009. It was inspired by the nature of brood parasitism of some cuckoo species. Cuckoos will lay their eggs in nest of other birds. If the host bird finds that the eggs in the nest are not their own they will abandon the eggs and nest and build a new nest.

a) Pseudo code for Cuckoo Search Algorithm

Begin

Objective function f(x), x=(x1,x2,...xd)^T

Initialize the population and host nest

While (t not equal to MaxGeneration) or (Stop criterion)

Select a cuckoo randomly and evaluate its fitness Fi;

Select a nest j randomly

if(Fi not equal to Fj)

replace j by the new solution

end

Abandon worse nest and build new ones

Keep best solution

end while

The algorithms discussed in this paper find the maximum value of a given function in a search space. For example with respect to ABC algorithm we can say that these algorithms find the food source with the maximum amount of food.In accordance with the objective of the algorithms we use the word ’fitness’ or ’f value’ for the value of the function.

D'JONG'S TEST FUNCTIONS

D'jong's functions are test functions which used to test the optimization algorithms. The ABC algorithm and Cuckoo Search algorithms can be used to maximise the objective function and the results of these algorithms are tested using D'jong's functions to achieve optimal solution. Following are the functions which are called D'jong's functions: Sphere, Rastrigin, Griewank, Rosenborck.Along with the D'jong's functions two more functions called Ackley and Schaffer is used in this experiment. Fig.1, Fig.2, Fig.3,Fig.4,Fig.5,Fig.6 shows a sample of the test data used for each the following test functions against which we tested the algorithm to attain the optimal result

1)Sphere Function

Sphere function is one test function which used to test the objective function. It consists of a single variable. The general definition of sphere function is f(X1,X2,...Xn) =

$$f(x) = \sum_{i=1}^{n} x_i^2 \qquad (1)$$

where 'n' is the number of sample values and Xi's are samples. Value for x will be in the range [-5.12,5.12]

Fields	Position
1	[1.0168,–0.0294,1.0497,–0.8995,–0.0839]
2	[0.0078,1.0036,–0.8373,0.1090,1.0374]
3	[0.8255,–0.9844,–0.9754,–0.0451,–0.8554]
4	[–0.0288,0.9584,1.9704,0.9265,–0.9843]
5	[–0.1311,–0.9783,0.0343,–1.0430,–0.0114]
6	[–0.9882,0.9770,0.0574,1.0144,–0.0893]
7	[0.9565,–0.0447,0.0746,–1.0121,0.0130]
8	[–0.0919,–0.8931,0.0250,–0.0412,0.0222]
9	[–1.9669,–0.0296,–0.9707,1.9257,–0.1641]
10	[0.9976,0.0924,–0.1043,–0.0531,1.1691]

Figure 1: Sphere function test data.

2) Griewank function

Griewank has many local minima which are regularly distributed. The general definition of the function is f(X1,X2,...Xn) =

$$f(x) = \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + \sum_{i=1}^{n} \frac{x_i^2}{4000} + 1 \qquad (2)$$

where 'n' is the number of sample values and Xi's are samples. Value for x will be in the range [-600,600].

Fields	Position
1	[–1.0472,–0.0168,0.0701,–2.1937e–04,1.0749]
2	[–0.9880,1.8733,–0.9756,–1.0120,–0.9512]
3	[–0.9599,–1.1613,–1.0710,1.1078,–1.0095]
4	[0.0269,1.0859,1.0339,0.0239,0.7359]
5	[0.9480,–0.0303,1.0514,–1.9829,–0.0980]
6	[0.0369,–0.9598,0.0569,0.9678,–0.9566]
7	[–0.9826,0.9787,–0.9645,–0.9487,0.0530]
8	[–0.1740,–0.0355,–0.2691,0.9923,–0.0123]
9	[–0.0379,1.0036,–3.0721,–0.0756,–1.0299]
10	[1.9768,0.9145,–0.9631,–0.9858,–0.0337]

Figure 2: Griewanks function test data.

3) Rastrigin Function

Rastrigin is a multimodal test function. The general definition of Rastrigin is f(X1,X2,..Xn) =

$$f(x) = n * 10 + \sum_{i=1}^{n} (x_i^2 \quad 10\cos(2\pi x_i)) \qquad (3)$$

where n is the number of sample values and Xi's are samples. Value for x will be in the range[-5.12,5.12]

Fields	Position
1	[0.9392,–0.0260,–0.0505,0.0254,–0.0394]
2	[1.0622,0.9281,1.9837,0.0017,–0.0617]
3	[–0.0230,0.1146,0.0193,1.0548,0.9713]
4	[–0.0281,1.0070,0.0742,–1.0065,0.1454]
5	[1.0674,–0.0308,0.0021,0.0235,–0.0292]
6	[0.1127,0.0049,–0.0183,–1.0617,0.0456]
7	[–0.0263,–1.0593,0.9836,–0.0220,0.0371]
8	[–0.0482,0.0216,–0.0469,0.9954,–0.0336]
9	[0.9595,1.0402,–0.1869,–0.0199,0.0679]
10	[0.9353,–1.0553,–0.9100,0.0227,0.9530]

Figure 3:.Rastrigin function test data.

4)Rosenborck Function

Rosenborck function is another test function which used to test the objective function. It consists of a single variable. The general definition of sphere function is f(X1,X2, ...Xn)

$$f(x) = \sum_{i=1}^{n \quad 1} 100\,(x_{i+1} \quad x_i^2)^2 + (x_i \quad 1)^2 \qquad (4)$$

Value of x will be in the range [-2.048, 2.048]

Fields	Position
1	[0.0880,−0.0164,−0.0215,0.0345,1.0521]
2	[0.0611,−0.9694,−1.1450,−0.0204,0.9727]
3	[0.1194,−1.0470,−0.9588,−0.0535,−1.0334]
4	[2.0580,−0.9903,−1.9667,−1.9537,−2.0761]
5	[0.0226,0.0672,0.0043,0.1515,0.0379]
6	[1.0798,0.0466,−1.0080,−0.0824,−0.0033]
7	[1.0468,−0.1230,−0.9288,0.0283,−2.0094]
8	[−0.9932,−0.9906,−2.0602e−04,0.9348,0.8737]
9	[−1.1385,0.8287,−0.0893,−1.9976,0.1396]
10	[−1.1059,0.0086,−1.9379,−0.0026,1.9311]

Figure 4: Rosenborck function test data.

5) Schaffer Function

Schaffer is a multimodal test function. The general definition of Schaffer is f(X1,X2,..Xn) =

$$f(\mathbf{x}) = 0.5 + \frac{\sin^2(x_1^2 - x_2^2) - 0.5}{[1 + 0.001(x_1^2 + x_2^2)]^2} \tag{5}$$

where n is the number of sample values and Xi's are samples. Value for x will be in the range[-100,100]

Fields	Position
1	[2.3965e−07,−1.0345e−07,1.4497e+27,−3.7218e+29,−2.6710e+27]
2	[−1.0313e−07,1.4919e−07,2.4343e+26,2.0760e+29,2.4330e+27]
3	[1.0294e−08,−9.3314e−08,2.2267e+27,1.5822e+28,3.4242e+26]
4	[−4.0701e−09,−1.3112e−07,−2.5217e+26,8.3132e+25,2.1040e+26]
5	[−4.6843e−08,7.4602e−08,−5.4195e+26,3.1905e+28,2.7475e+26]
6	[8.3592e−08,1.7551e−07,−5.5916e+26,−7.8250e+28,1.0737e+28]
7	[−1.3582e−08,−2.0437e−07,−1.7432e+26,1.4951e+29,2.2116e+26]
8	[−5.5275e−08,2.9266e−07,−2.3371e+26,−5.9422e+27,1.1660e+27]
9	[−5.7486e−08,−2.4375e−07,3.8446e+26,4.3547e+27,2.0370e+27]
10	[6.1875e−08,−1.2672e−07,−2.8334e+26,−6.0920e+28,−3.0953e+26]

Figure 5: Schaffer function test data.

6)Ackley Function

Schaffer is a multimodal test function. The general definition of Schaffer is f(X1,X2,..Xn) =

$$f(\mathbf{x}) = -a \exp\left(-b\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - \exp\left(\frac{1}{d}\sum_{i=1}^{d}\cos(cx_i)\right) + a + \exp(1) \tag{6}$$

where n is the number of sample values and Xi's are samples. Value for x will be in the range [-32.768, 32.768]

Fields	Position
1	[−1.0029e−13,2.4014e−12,6.5306e−15,−3.5037e−12,−4.6667e−13]
2	[2.8421e−13,1.7553e−15,−7.2174e−14,1.0621e−14,−3.1231e−13]
3	[1.5528e−12,−2.4456e−12,2.2380e−12,1.9725e−12,−2.9801e−12]
4	[1.7709e−12,7.2324e−13,2.3994e−12,−2.9829e−12,−9.0719e−13]
5	[5.0301e−13,−2.4785e−12,−1.8639e−12,−4.0400e−13,1.9850e−12]
6	[−6.6271e−13,−4.8942e−12,1.6941e−12,−4.3318e−12,3.4479e−13]
7	[3.8431e−12,−3.4511e−12,−1.6101e−12,2.5752e−12,−1.7166e−12]
8	[1.0723e−12,9.6614e−12,8.9506e−12,2.0111e−13,−1.2746e−11]
9	[−7.5587e−13,1.7854e−13,1.7306e−12,−1.6248e−13,−2.2142e−12]
10	[6.5080e−12,−2.9208e−13,6.0764e−12,−8.7232e−13,−6.6765e−14]

Figure 6:Ackley function test data.

IMPLEMENTATION

The parameters of the algorithms under study are assigned values according to the requirements of the algorithms. Various parameters of ABC algorithm are colony size, value of limit L, number of iterations etc.

ABC algorithm and Cuckoo Search algorithm are compared by varying the population size. Both the algorithms obtained are compared to understand whether, a variation in population size or the increase in search space, contributes towards the optimality of the result. In this experiment, the number of iterations are fixed to be 200 and experiment is repeated by changing the population size. The data for testing the functions are generated randomly using the matrix generation functions available in Matlab_R2016a.The data that we have generated is different for each of the functions because of the fact that the upper and lower values of each of these functions are different and these values are considered while generating the matrix. Each value in the newly generated matrix corresponds to locations for exploration to be considered by the algorithms under study. After each iteration, we will get a route and cost associated with traversing through the locations. These cost is improved on further iterations and at the end of 200th iteration minimum cost for that particular data will be generated. The experiment is conducted for each of the D'Jong's functions and is repeated by changing the population size. For each population size the experiment is repeated 10 times and the average value of cost for exploring the locations is taken.

TEST RESULTS

The expriment is repeated with population sizes of 100,200,300,400 and 500 for each of the given test functions. Results are taken for ABC and cuckoo search algorithms. Table 1. shows test results obtained.

RESULT ANALYSIS

In this experiment tests are conducted by changing the population size and repeated for different test functions for both the algorithms. The implementation results reveal that when we using ABC algorithm there is an improvement in the results with an increase in the population size. This is because When the population is high there will be more space for exploration and for finding the food source. Thus, in the case of ABC creating more search space leads to an increase in the probability of getting the better results. In the case of Cuckoo search algorithm, increasing the population size, does not enhance the results. In all the cases, the experimental results show that ABC is producing better results than Cuckoo Search Algorithm.

Table 1: Test Results

Function	Population Size	Average Cost	
		ABC	Cuckoo Search
Sphere	100	1.6409E-20	0.31164
	200	3.6227E-21	0.26424
	300	1.0146E-21	0.19767
	400	1.1414E-21	0.27583
	500	4.9341E-22	0.27913
Rastrigin	100	1.1898	42.8305
	200	0.40314	43.9878
	300	0.1675	42.0256
	400	0.1599	42.3429
	500	0.18428	41.3028
Griewank	100	1.0813	0.11035
	200	0.61185	0.14322
	300	0.59878	0.098803
	400	0.32831	0.10166
	500	0.17311	0.11915
Rosenborcks	100	1.5249	40.7049
	200	1.0128	32.93
	300	0.6538	31.007
	400	0.40883	37.774
	500	0.200088	38.6059
Schaffer	100	2.2204e-16	0.2463
	200	1.2204e-16	0.3264
	300	1.1021-16	0.2256
	400	1.00102-17	0.22654
	500	2.2025-18	0.6547
Ackley	100	1.014e-11	0.3372
	200	4.4276e-12	0.24243
	300	1.5783e-12	0.43544
	400	2.4665e-12	0.2173
	500	2.6406e-12	0.5678

CONCLUSION

In this paper two different swarm optimization techniques are applied to find the optimal routes pertaining to vehicle routing problems. Experiment is conducted for both the algorithms by changing the population size. The results are tested using D'jong's test functions for achieving optimal results. The test results prove that , in the case of ABC algorithm, there is an improvement in the results as the population size increases. However, in the case of Cuckoo Search algorithm there is not much difference in the cost by changing the population size. A comparison of the results produced by both the algorithms, reveals that, as the population size or the search space increases, ABC algorithm gives better performance than Cuckoo Search algorithm.

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