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# A Nomadic Genetic Algorithm Approach with GMOUX Crossover for Multi Depot Vehicle Routing Problem

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***Abstract— In logistics and distribution management, the delivery of products from depot to customers is a practical, complex and challenging task as this involves simultaneous determination of the routes for several vehicles from multiple depots or single depot to service a set of customers who are distributed throughout the distribution area and return to the same or different depot. Better delivery decisions will lead to service more number of customers with better satisfaction in a reduced time period. This kind of classical distribution problem from a single centralized depot is generally formulated as the Vehicle Routing Problem (VRP). This paper focuses on the multi-depot Vehicle Routing Problem (MDVRP), a variant of classical Vehicle Routing Problem which deals with more than one depot. As the MDVRP is a NP-hard problem, this paper uses an improved Genetic algorithm approach called as Nomadic Genetic Algorithm to solve the MDVRP. The objective of Nomadic Genetic Algorithm (NGA) in this work is to minimize delivery cost in terms of total travel distance during distribution without violating the capacity constraints of the vehicle. In order to demonstrate the effectiveness of NGA, Cordeau's benchmark instances for MDVRP with different problem sizes are used to examine NGA's search and convergence performance. The results are evaluated in terms of total minimum distance travelled. Comparison of the experimental results with Genetic Algorithm and Genetic Clustering shows that the performance of NGA is better, encouraging and effective for solving the multi-depot vehicle routing problem.***

***Keywords— Logistics, one stage Ordered Routing, Multi Population GA, Nomadic GA, Migration***

## I. INTRODUCTION

The Vehicle Routing Problem was first introduced by Dantzig and Ramser in 1959 and it has been widely studied since beginning. VRP has been studied for several decades to find efficient vehicle routes in logistics and distribution field and it is a vast field of study among researchers. A very large number of research papers about various varieties of Vehicle Routing Problems indicate the practical and theoretical importance of this problem.

For any logistics service provider, limited commodities and transportation resources need highly complex planning and the increasing cost pressure through the strong competition between logistics service providers in market, make it essential to use some softwares or computer programs for the better planning of the distribution in cost effective way as well as better customer's satisfaction. It is very important for a firm to reduce its cost of delivery and increase its operational area by reducing the length of delivery routes or to reduce the number of vehicles for distribution with better services to its customers. In logistics management, the delivery of products from depot to customers is a practical and challenging task. Better delivery decisions like routing and scheduling will lead to service more number of customers in a shorter time. This kind of classical distribution problem from a single centralized depot is generally formulated as the Vehicle Routing Problem (VRP). This paper focuses on the multi-depot Vehicle Routing Problem (MDVRP), a variant of classical Vehicle Routing Problem which deals with more than one depot. As MDVRP is NP-hard, this paper uses an improved genetic algorithm approach called as Nomadic Genetic Algorithm to solve it. In case of large search space, Genetic Algorithm suffers with two major drawbacks: slow search speed and premature convergence. Nomadic Genetic Algorithm solves these problems very effectively up to some extent. NGA has already been used in solving different benchmark mathematical functions as well as to solve application problems like time tabling problem, multiple sequencing alignment problem, 0/1 knapsack problem [12]-[14]. In this paper, Cordeau's benchmark instance for MDVRP has been experimented. The results are evaluated in terms of optimal distance. Comparison of the experimental results with Genetic Algorithm and Genetic Clustering shows that the performance of NGA is better, encouraging and effective for solving the multi-depot vehicle routing problem.

The rest of the paper is organized as follows: Section II describes the related work. Section III describes NGA. Section IV describes the MDVRP with an example and the mathematical model. Section V describes the use of NGA for MDVRP. Section VI contains computational results and analysis. Section VII draws the conclusion along with future enhancements.

## II. LITERATURE REVIEW

This section deals with the related work in VRP which involves different optimization techniques and studies about different application problems solved by NGA. Heuristics, exact algorithms and meta-heuristics are some possible optimization methods to solve multi-depot VRPs. Surekha et al. found solution to multi-depot VRP using genetic algorithm. In this work assignment of customers to their corresponding depots are done based on Euclidean distance. Assignment of customers to several routes within depot was done using Clarke and Wright saving method followed by a scheduling phase to sequence each route and after this GA is used to optimize the routes [3]. A multilevel composite heuristic method for multi-depot VRP introduced by Salhi et al. used within depot reduction test and between depot reduction test to improve the performance of the proposed heuristic [2].

Lau et al. introduced GA with fuzzy logic to adjust the crossover and mutation rates after ten consecutive generations and considered simultaneous minimization of cost due to total travelling distance as well as total travelling time [1]. William et al. developed two hybrid genetic algorithms (HGAs) to solve MDVRP. In HGA1, the initial solutions are generated randomly while in HGA2, the Clarke and Wright saving method and nearest neighbour heuristic were used for initial solution generation. They also proposed one heuristic iterated swap procedure which was used to improve the solutions [4]. Shirafkan et. al proposed a suitable solution using refrigerating simulations hybrid algorithm and genetic algorithm for multi-depot multiple TSP for non fixed destination with time window and waiting penalty [5].

Chen et. al proposed a hybrid algorithm in which performance of genetic algorithm is improved using simulated annealing. In this hybrid algorithm, Metropolis acceptance rule of simulated annealing has been embedded in genetic algorithm. In this new solution is accepted with probability 1, if its fitness is improved, otherwise accepted with probability exp (- (f(s') – f (s0)/T), where s0 is current solution, s' is another solution in neighbourhood of s0 and T is temperature [6]. Nallusamy et al. proposed a solution for multiple vehicle routing using K-Means clustering algorithm and genetic algorithm. K-Means clustering algorithm has been used for easy clustering of the cities depending on the number of vehicles [7].

Soloman has described several popular route construction heuristics. Most important among those are the insertion heuristics [8]. Potvin et al. proposed a parallel construction heuristic for the VRPTW based on Soloman's insertion heuristic. In this parallel construction heuristic, several routes are first initialized with seed customers and to find the total number of initial routes, first soloman's insertion sequential algorithm is run. If the initial numbers of routes fail to produce a feasible solution, more routes are added as per need [9].

Lin has described edge exchange method to improve the solution of TSP. It is only applied to one route in current solution and often termed as k-exchange, where k is the number of edges involved in edge exchange and a route which cannot be improved more by k-exchange is termed as k-optimal [10]. Potvin has introduced a modification to the 2-Opt heuristic of [10], known as 2-Opt* exchange heuristic and it works on two different routes and tries to combine the two routes without changing the direction of routes [11].

Tan et al. has shown Ant Colony Optimization has the capability to tackle the CVRP with satisfactory solution quality and run time [17]. Chen et al. has proposed Max-Min ant colony algorithm and Adaptive ant colony algorithm to overcome the drawbacks of basic ant colony optimization algorithm [16]. Ombuki et. al. has solved the MDVRP with route length as well as capacity of vehicle both as constraints using GA and proposed an encoding of chromosomes which behaves as an intelligent route scheduler and adaptive mutation exchange for inter-depot [18].

## III. NOMADIC GENETIC ALGORITHM

Genetic algorithms are stochastic search algorithms based on the concept of genetics and natural evolution. Generally, the performance of GA is measured by the speed of the search as well as reliability of the search. Among the various forms of GA, Multi-population Genetic Algorithm (MGA) introduces better diversity in the population, speeds up the convergence and also simplifies the choice of migration parameter by allowing the multiple populations to evolve independently and migrate at intervals. The success of any MGA depends on the proper selection of the correct set of parameters like migration rate, migration interval, connection topology, etc.

NGA is an adaptive MGA having inherent migration capabilities with very simple and automatic selection mechanism for various migration parameters. NGA follows "Birds of the same feather flock together". In this individuals keep migrating from one group to another based on their fitness and hence the name "Nomadic GA". This helps in maintaining population diversity and gives equal opportunities to low fit individuals and gives better convergence than SGA. The individuals can migrate to any group which seems to be similar to its fitness. Migration can take place with adjacent as well as far-off sub-populations and it occurs whenever there is a change in fitness value of individuals in the sub-populations. Migration rate depends on the number of individuals which has shown improvement in their fitness and it remains uniform among the sub- populations.

In NGA, the entire initial population is divided into several groups of equal sizes based on the ranking of their fitness unlike GA, in which algorithms runs over whole initial population together. Now the basic GA steps like selection, crossover or mutation is carried out within each group. Offsprings produced may have different fitness values and migrate to other group which have near about similar fitness level. In this way, individuals keep on migrating from one group to other depending on their fitness. The algorithm is simple and robust, capable of solving any kind of problem that has a large search space. The pseudo code is given below:

### *A. Steps involved in NGA*

1. Generate initial population randomly (initialization)
2. Evaluate the fitness of each Individual (fitness evaluation)
3. Sort the Individuals according to their fitness values (ranking)
4. Division of ranked initial population into groups based on their fitness range
5. for each group do,

 

   a) select individuals from each group
   b) apply crossover/mutation operators
   c) evaluate the fitness of offspring
   d) add offspring to the same group
6. Combine all the groups into a single population
7. Sort the population based on their fitness values and trim to the size of the groups
8. Repeat the process from Step 5 to the required number of generations
9. Select the best (high fit) individual

## IV. MDVRP PROBLEM

To explain the MDVRP problem, an example with 2 depots (D1, D2) and 14 customers (1, 2, 3..., 14) is considered, which is shown in Fig. 1. The bracket with each of the customer node shows their demand in units ordered by each of them. In MDVRP, the co-ordinates of each depot and customer is already known. Hence the locations of each of them can be easily predetermined. Total number of customers and depots is known already. Each depot has multiple identical vehicles with fixed capacity. In this example, each vehicle can transport at most 20 units of products per route or trip, which is also shown in the brackets within the depots in the Fig. 1. Each depot is large enough to store the quantity of products ordered by the customers assigned to that particular depot. Each vehicle starting depot and finishing depot is same in this problem. Each customer is visited by any one vehicle exactly once. The various steps in solving the problem to get optimized solution involves are grouping, one stage ordered routing and optimization using NGA as shown in Fig. 2. In grouping, customers are grouped based on distance between customers and depots. In one stage ordered routing, original nearest insertion algorithm has been used with modification of handling vehicle capacity constraint to create feasible routes. In the example, customers 2, 3, 6, 7, 10, 11 are assigned to depot D1; 1, 4, 5, 8, 9, 12 are assigned to depot D2. The total demand of customers in a vehicle route cannot exceed the vehicle capacity.

### *A. Mathematical Model Of MDVRP*

The MDVRP is formulated with the objective of adding customers on each vehicle route in such a way that total demand of customers in that route cannot exceed vehicle capacity. The demands of each customer are known in advance. It is assumed that all the vehicles have the same capacity and each vehicle starts its travel from a depot and upon completion of service to customers, it has to return to that same depot. The notation used in the MDVRP and the mathematical model is as follows:

*Notations Used:*

U : set of customers / client / city.
S : set of depot.
U0 : set of customers and depot; $U0 = \{U \cup S\}$.
K : set of all vehicle routes.

*Indices Used:*

s : depot index.
u, v: node index.
k : vehicle route index.

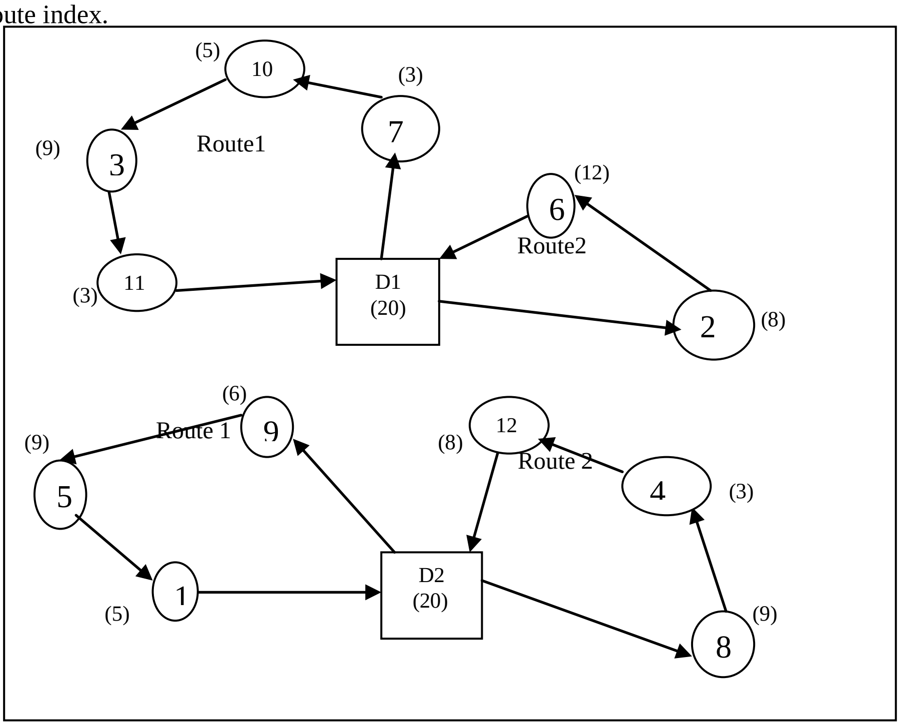


**Fig. 1: An example of MDVRP with 2 depots and 14 customers**


**Fig. 2: Stages involved in MDVRP**

*Parameters:*

n : no of vehicles.

$C_{suv}$ : Cost or distance associated between nodes u and v ; (u, v) ∈ U0, if u = v , $C_{suv} = 0$.

$d_u$ : Demand of customer u, u∈ U.

$Q_k$ : Capacity of vehicle route k, k∈ K.

Ws : maximum throughput at depots.

*Nature of decision variable:*

$X^k_{suv}$ = 1, if u precedes v on vehicle route k for particular u, v ∈ U0.
= 0, otherwise.

$Z_{su}$ = 1, if customer u allotted to depot s, u ∈ U.
= 0, otherwise.

$Y^k_{u/v}$ = Sequence no (start from 0) of nodes u or v in the route k, u, v ∈ U0.

*Objective function:*

The objective function is to minimize the total distance travelled by all vehicles given by equation:

$$\text{Min} \left(\sum_{k\epsilon K} \sum_{s\epsilon S} \sum_{v,u\in U_o} C_{suv}\ x_{suv}\right) \quad (1)$$

*Capacity constraints for a set of vehicles:*

$$\sum_{u\in U} du \sum_{v,u\in U0} \sum_{k\in K} xsuv \quad (2)$$

*Capacity constraints for the depots:*

$$\sum du\, Z_{su} \leq Ws \quad (3)$$

*Each vehicle start and end at the same depot:*

*Start node:*

$$X^k_{suv} = 1,\ s \in S\ ,\ u = s, v \in U, k \in K \quad (4)$$

*End node:*

$$X^k_{suv} = 1:\ s \in S\ , v = s, u \in U, k \in K \quad (5)$$

*Vehicle must travel in a fixed sequence*:

$$X^k_{suv}\ (Y^k_u{+}1\ - Y^k_u\ ) = 0 \quad (6)$$

*Depot must be always first and last vertex of any route:*

In any particular k

$Y^k_s$ = 0 for start and end route. (7)

*Integrity constants*

$$X^k_{suv}\ \in \{0,1\} \forall\ s \in S\ (u, v)\ \in\ U0 \quad (8)$$

$$Z_{su}\ \in \{0,1\}\ ,\ \forall\, u \in U, k \in K \quad (9)$$

$Y^k_u$ or v ∈ N ∀ u or U ∈ U0, ∀ k ∈ K , N is set of natural no (10)

## V. MDVRP SOLUTION USING NGA

Nomadic Genetic Algorithms (NGA) is based on a parallel search mechanism, which makes it more efficient than other classical optimization techniques such as GA. Due to GA's high potential for global optimization; this has received great attention in solving multi-depot vehicle routing problems using various variants of GA. The basic idea of NGA is similar to GA which is to maintain a population of candidate solutions that evolves under selective pressure. The NGA can also avoid getting trapped in a local optimum by tuning the genetic operators, crossover, migration and mutation.

*A. Chromosome Representation*

The chromosomes are encoded using path representation in the MDVRP, where each gene corresponds to customers. This representation contains depot also as marker to distinguish different routes. All corresponding customers to any particular depot appear in the order, in which they are visited in different routes. In the example shown in Fig. 1, there are 12 customers designated with numbers 1-12. In the figure, path representation for depot D1 is (D1, 7, 10, 3, 11, D1, 2, 6, D1), hence two routes are needed by the vehicles to serve all the customers associated with depot D1. In the MDVRP with n depots, the chromosome representation consists of n links, where each link corresponds to each depot and contains all routes in that depot. The initial feasible solutions to start the optimization process are produced in two basic steps: Grouping and One stage Ordered routing.

*B. Grouping*

The objective of the MDVRP is to minimize the total delivery distance and hence cost. In this customers are assigned to their nearest depots. Grouping of customers to depot is done based on the rule given below:

- If Dist ($c_i$, D1) < Dist ($c_i$, D2), then customer $c_i$, is assigned to depot D1
- If Dist ($c_i$, D1) > Dist ($c_i$,D2), then customer $c_i$, is assigned to depot D2
- If Dist ($c_i$, D1)= Dist ($c_i$,D2), then customer $c_i$, is assigned to any depot randomly between D1 and D2

In the above cases, $\mathrm{Dist}(c_i, m) = \sqrt{(x_{ci} - x_m)^2 + (y_{ci} - y_m)^2}$

The above equation represents the distance between customer $c_i$ and depot m.

*C. One stage Ordered Routing*

This basically uses the nearest insertion algorithm, which starts with any random customer among all the customers. The delivery sequence is chosen such that the next customer is closest to the depot and also previously added customers in the route. The current node is added in the current route at that place which will result in minimum total distance travelled by the vehicle.

The modification made in original nearest insertion algorithm is to make the algorithm to handle the route construction without violating the capacity constraint of vehicle and instead of starting with random customer, start with customer which is closest to the depot. This process of selecting nodes and addition of nodes in the route is repeated until all the unselected nodes are traversed without violating the vehicle capacity constraint. In one route the total demand of customers must not exceed the total capacity of the vehicle. This stage results with a set of a feasible solution in terms of one or more route. A feasible solution of the MDVRP example problem (Fig. 1) is given in Fig. 3.

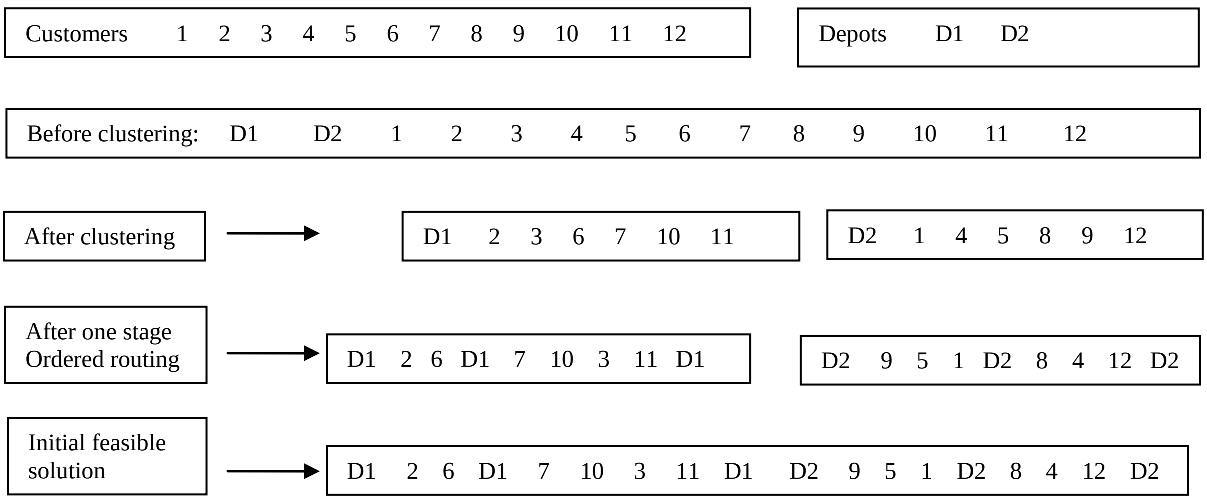


**Fig. 3: Chromosome representation of various stages**

*D. Fitness Evaluation*

The delivery of goods at each depot to customers starts at the same time. Depending on the total route length, vehicle will take different time in serving all the customers in the route. For the longest route the serving time for that route is maximum. So minimizing this maximum time is the fitness function in this work. Hence time taken in servicing the longest route among all depots is the minimum time required to deliver all products to all customers clustered with all depots. Let $\mathrm{Dist}_t$ be the total delivery time required by a depot k and let min ($\mathrm{Dist}_t$) represents the fitness function.

$$\mathrm{Min}\ (\mathrm{Dist}_t = \sum_{S=1}^{S_{max}} [\sum_{k=1}^{r_m} d[c(t_c\ ), c(0)] + \sum_{j=1}^{t_c} c(j-1), (j)]\ ) \qquad (11)$$

Where d(u,v) = [[( $x_u$- $x_v$)2 + ( $y_u$- $y_v$)2] ½ ⁄ V ] is servicing time of a vehicle from point a to b. V is the speed of the vehicle. Here V is equal for each vehicle, c(j) is the location of the jth customer, c(0) is the location of the starting depot in any route r, $t_c$ is the number of customers in any route r, $r_m$ is the number of routes in depot k. $s_{max}$ is the total number of depot.

*E. Selection*

Since NGA is used, the selection of individuals is based on grouping the individuals based on the fitness range and then applying tournament selection within groups. The speciality of NGA is that even low fit individuals are not thrown off with the assumption that they will improve the fitness in the subsequent generations.

 

*F. Proposed Grouped Mix Ordered & Uniform Crossover Operator (GMOUX)*

Crossover is a genetic operator used to exchange genetic properties in the form of genes between parent chromosomes to produce offspring and has a great influence in the continuous exploration of the search space. This has been attracting researchers since its existence and still it is a very broad area of research in GA to improve its performance. Crossover is controlled by a crossover rate pc. A new Grouped mix crossover strategy (GMOUX) is used by NGA to solve MDVRP by mixing two existing crossover operator: Ordered crossover and Uniform crossover. Pseudo code for proposed crossover is given below.

*Pseudo Code for MOUX*

```
for each sub-group in NGA do,
    a)   if (group no. % 2 = 0)
              -  select parents P1 and P2 from group
              -  apply ordered crossover and produce offsprings O1 and O2
              -  produce offspring O1 and O2
         else
              -apply Uniform crossover
              -produce offspring O1 and O2
```

*G. Modified Insertion Mutation*

This is used to bring diversity in the population by avoiding NGA to get stuck in local optima. In MDVRP, a chromosome is a combination of various routes and each route has one or more customers as gene. A modified insertion mutation is proposed here.

*Pseudo Code for Modified Insertion Mutation*

for chromosome O do

1. Select any node g randomly in O
2. remove g from O
3. re-insert it in to location in O such that this should not break any existing feasible route into two routes
4. if there exist no feasible insertion then add g in a new route with single customer.

*H. Constraint Handling*

After applying genetic operators, it may possible that some solutions become infeasible and may violate some constraint which is already discussed in the mathematical model in section V. By using the chromosome representation discussed above, all constraints are easily satisfied, but it is must be verified whether all solutions after genetic operations satisfy the capacity constraint for a vehicle (2) or not. If there is any violation in (2), some penalty is added in the fitness value which depends on degree of violation of constraints.

Penalty = Absolute difference of RHS and LHS of constraint

## VI. RESULT ANALYSIS

In this section, a computational study is carried out on the Cordeau's benchmark MDVRP instances (p01-p10) to show the effectiveness of NGA through simulations. The parameters used in this simulation for NGA are tabulated in table 1. The detailed specification of benchmark is given graphically in figure 7.

TABLE 1: PARAMETERS OF NGA

| Parameter | Value/Type |
|---|---|
| Population Size | 75 |
| Total Generations | 1000 |
| Crossover Probability | 0.80 |
| Mutation Probability | 0.02 |
| Elitism | 2 |

The best values for calculated objective value, difference of best known objective value and calculated objective value, average of both objective values and standard deviation of both objective values among the 10 simulation runs were recorded for each of the 10 benchmark instances and listed in the Table 2. In Table 2, the difference between the best known solutions and best calculated objective values recorded by NGA in terms of percentage, is calculated by $Dp = ( Bc – Bo / Bo ) \times 100\ \%$

Where Dp is the difference in terms of percentage between the best known objective and best calculated objective obtained by NGA. Bc is the best calculated objective by NGA. Bo is the best known objective. Calculated objective value found by NGA does not outperform any best known objective, but for p02 it was found equal. In the coming discussion, it is shown that NGA out performs results obtained by genetic algorithm [3] [18] and genetic clustering [19]. It is found that it can reach to the best known objectives in case of instances p01, p05, p06, p10 and in the remaining cases it is not too far from the best known objectives. No worse result recorded for any instances.

 

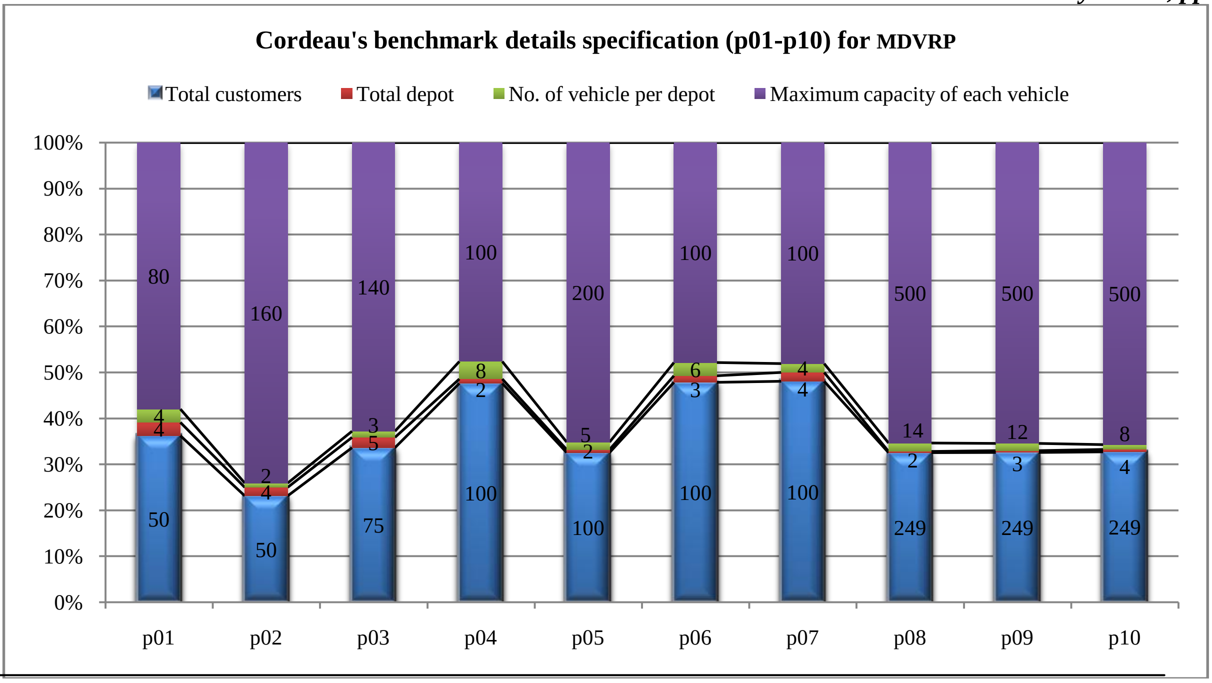


**Fig. 4: Benchmark Details**

TABLE 2: COMPUTATIONAL RESULTS FOR BENCHMARK INSTANCES USING NGA

| Benchmark Instance name | Best Known Solution (minimum Distance) | Best Known Calculated Objective (minimum Distance) | Computational Time (in sec .) | Difference Between best known and best calculated objective ( $D_p$) | Average of objective values | Standard deviation of objective values |
|---|---|---|---|---|---|---|
| P01 | 576.87 | 580.85 | 18.63 | 0.69 | 578.86 | 2.81 |
| P02 | 473.53 | 473.53 | 20.02 | 0 | 473.53 | 0 |
| P03 | 641.19 | 680.2 | 35.42 | 6.08 | 660.69 | 27.58 |
| P04 | 1001.59 | 1010.25 | 46.86 | 0.86 | 1005.92 | 6.12 |
| P05 | 750.03 | 753.36 | 53.67 | 0.44 | 751.03 | 2.35 |
| P06 | 876.5 | 878.88 | 49.04 | 0.27 | 877.69 | 1.68 |
| P07 | 885.8 | 893.6 | 52.52 | 0.88 | 889.7 | 5.51 |
| P08 | 4420.94 | 4453.86 | 153.27 | 0.74 | 4453.86 | 23.28 |
| P09 | 3900.22 | 3950.28 | 172.76 | 1.28 | 3925.25 | 35.4 |
| P10 | 3663.02 | 3668.87 | 188.37 | 0.16 | 3665.96 | 4.14 |

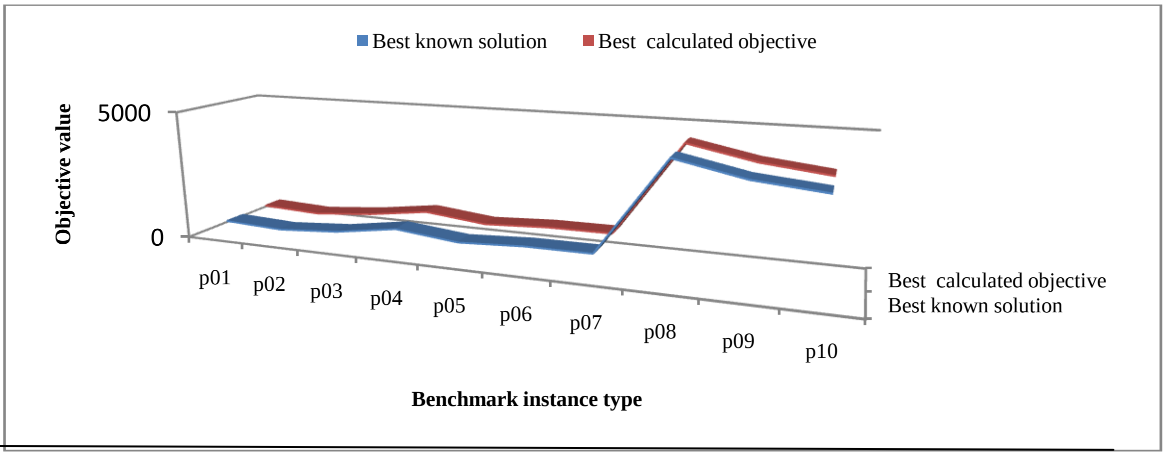


**Fig. 5: 3D Line graph for best known calculated objective and best known solution for behaviour analysis of NGA**

The maximum difference found is 50.06 in best known and recorded objective is in the case of p09. Dp ranges between 0 to 1.28. The averages of objective values obtained by NGA in all cases are near to the best known objective except p09. The standard deviations of objective values found are not bigger and generally below 7 except p03, p08, p09. These simulation results were found motivating and confirm the fact that NGA can provide better search and convergence to optimum. Search performance of NGA is also found comparable and acceptable here. The computational time of NGA increases with the increase in problem size, which is obvious and maximum computational time found is 3 minutes 9 seconds for p10, which is considerable. In Fig. 5, it is clearly visible that line for best known objective and best calculated objective are moving together for all instances and almost parallel. This graph also suggests that NGA can be a better choice to solve the MDVRP as it is giving almost very near value to best known objective and with incorporating some modification in NGA, it may give better results.

*A. Comparative analysis between Genetic Algorithm [3], Genetic Clustering [19], Genetic Algorithm [18] and NGA*

TABLE 3: COMPARATIVE ANALYSIS BETWEEN GC [19], GA [18], NGA

| Benchmark instance | Genetic Clustering [19] | Genetic Algorithm [18] | Nomadic Genetic Algorithm |
|---|---|---|---|
| P01 | 591.73 | 622.18 | 580.85 |
| P02 | 463.15 | 480.04 | 473.53 |
| P03 | 694.49 | 706.88 | 680.2 |
| P04 | 1062.38 | 1024.78 | 1010.25 |
| P05 | 754.84 | 785.15 | 753.36 |
| P06 | 976.02 | 908.88 | 878.88 |
| P07 | 976.48 | 918.05 | 893.6 |
| P08 | 4812.52 | 4690.18 | 4453.86 |
| P09 | 4284.62 | 4240.08 | 3950.28 |
| P10 | 4291.45 | 3984.78 | 3668.87 |

TABLE 4: COMPARATIVE ANALYSIS BETWEEN GA [3], NGA

| Benchmark instance | Genetic Algorithm [3] | Nomadic Genetic Algorithm |
|---|---|---|
| P01 | 598.45 | 580.85 |
| P02 | 478.65 | 473.53 |
| P03 | 699.23 | 680.2 |
| P04 | 1011.36 | 1010.25 |
| P06 | 882.48 | 878.88 |

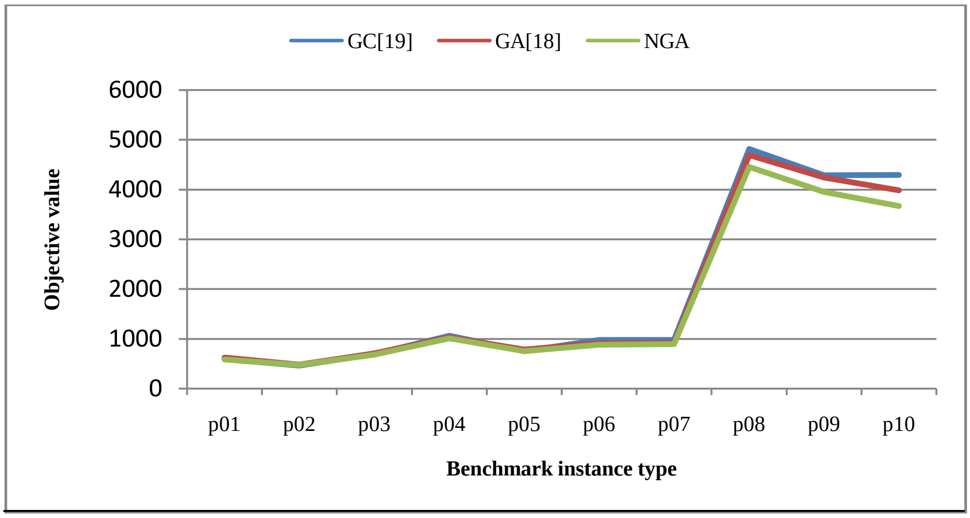


**Fig. 6: Comparison of objective values obtained using GA[18], GC[19], NGA**

The results given by NGA on MDVRP Cordeau's benchmark instances p01- p10 has been compared in Table 3 with already existing best objective values given by GA[18], GC [19] in terms of minimum total distance as objective. NGA has outperformed all those existing best objectives in case of GA [18]. When compared with genetic clustering [19], NGA was found better for all except p02. This shows that NGA can provide better search method for solution space exploration as well as convergence for smaller as well as larger problem size. In Table 3, results of GA [3] has been compared with the results of NGA for p01, p02, p03, p04, p06. GA [3] results are better than GA [18], but NGA results were found best among these. In Fig. 6, graph for NGA is always lower than GA [18] and GC [19]. This shows that NGA performance is better than GA for all instances taken for consideration and it is capable to yield better solution than GA for smaller as well as larger problem size.

## VII. CONCLUSION & FUTURE WORK

A highly complex planning is required to route and schedule vehicles in logistics and distribution management, and due to this reason vehicle routing is in main line for research among researchers since its inception.

A variant of VRP, MDVRP has been studied in this paper. NGA with one stage ordered routing is suggested in this paper. A number of Cordeau's benchmark instances are used to test the search and convergence capability of NGA for MDVRP. The result given by NGA is compared with the results given by GA [3], GA [18] and GC [19]. It was found that NGA is better and has outperformed GA and GC almost completely. Computational time recorded for NGA was also found satisfactory.

In future, there is still scope for improvement in this work as the result given by NGA was neither better nor equal to the best known results for any of the instances. But the result is motivating as in maximum cases it's very near to best known values. This work can be integrated with more real world constraints as well as more objectives like time constraint and delivery time. New constraint handling methods as well as operators like gene silencing operator after modification can be incorporated with this work, which may result in better objective values and computational time.

## REFERENCES


[1] H. C. W. Lau, T. M. Chan, W. T. Tsui and W. K. Pang, "Application of genetic Algorithms to solve the multidepot vehicle routing problem" IEEE transactions on automation science and engineering, vol. 7, No. 2, April 2010.

[2] S. Salhi and M. Sari, "A multi-level composite heuristic for the multi-depot vehicle fleet mix problem" European Journal of Operational Research, vol. 103, no. 1, pp. 95-112, Nov. 1997.

[3] Surekha P and Dr. S. Sumathi, "Solution to multi-depot vehicle routing problem using genetic algorithms" World Applied Programming, vol. (1), No (3), August 2011. 118-131.

[4] William Ho, George T. S. Ho, Ping Ji and Henry C.W. Lau, "A hybrid genetic algorithm for the multi-depot vehicle routing problem" Engineering Applications of Artificial Intelligence 21 (2008) 548-557

[5] Mohammad Taher Shirafkan, H. Seidgar, J. Rezaian-zeidi and N. Javadian, "Using a hybrid simulated annealing and genetic algorithms for non fixed destination multi-depot multiple travelling salesman problem with time window and waiting penalty" The Journal of Mathematics and Computer Science Vol. 4, No. 3, (2012) 428-435.

[6] Peiyou Chen and Xinming Xu "A hybrid algorithm for multi-depot vehicle routing problem" Service Operations and logistics, and Informatics 2008. IEEE International conference, Vol. 2, 2008, 2031-2034

[7] R. Nallusamy, K. Duraiswamy, R. Dhanalaksmi and P. Parthiban, " Optimization of multiple vehicle routing problems using approximation algorithms" International Journal of Engineering Science and Technology, Vol. 1(3), 2009,129-135

[8] M. M. Soloman, "Algorithms for the vehicle routing and scheduling problems with time window constraints" Operations Research, Vol. 35 (1987), pp.254-265

[9] J. Y. Potvin and J. M. Rousseau , "A parallel route building algorithm for the vehicle routing and scheduling problem with time windows" European Journal of Operational Research, Vol. 66 ( 1993), pp. 331-340

[10] S. Lin, "Computer solutions of the Travelling Salesman Problem ", Bell Systems Technical Journals, Vol. 44 (1965), pp. 2245-2269

[11] J. Y. Potvin and J. M. Rousseau, "An exchange heuristic for routing problems with time windows", Journal of the Operational Research Society, Vol. 46 (1995), pp. 1433-1446.

[12] S. Siva Sathya, S. Kuppuswami and K. Syam Babu, "Nomadic genetic algorithm for multiple sequence alignment (MSANGA)", International Journal of Adaptive and innovative systems" , Vol. 1 , 1/2009, pp. 44-59

[13] S. Siva Sathya and S. Kuppuswami, "Analysing the migration effects in nomadic genetic algorithm", International Journal of Adaptive and innovative systems" , Vol. 1, no. 2, 2010, pp. 158-170

[14] S. Siva Sathya, and M. V. Radhika, " Convergence of nomadic genetic algorithm on benchmark mathematical functions" Applied Soft Computing , 13 (5), 05/2013, 2759-2766

[15] S. Siva Sathya, S. Kuppuswami and Vivek Ranjan, "Analyzing the impact of population and group size in nomadic genetic algorithm" International Journal of Recent Trends in Engineering, Vol. 1, no. 1, 5/2009

[16] Changmin CHEN, Weicheng XIE, Songsong FAN, Lingling LI, Xue Zhang and Chao HUANG, "The logistics vehicle routing optimization method and implementation based on Ant Colony algorithm" Journal of Computational Information Systems, 8: 20 (2012), 8439-8446

[17] Tan, W. F., L. S. Lee, Z. A. Majid and H. V. Seow, "Ant colony optimization for capacitated vehicle routing problem", Journal of Computer Science, 8 (6), 2012, 846-852

[18] B. Ombuki-Berman and F. Hanshar, "Using genetic algorithms for multi-depot vehicle routing", Bio-Inspired Algorithms for the Vehicle Routing Problem - studies in Computational Intelligence, vol. 161, 2009, 77-99

[19] S. R. Thangiah and S. Salhi, "Genetic clustering: an adaptive heuristic for the multidepot vehicle routing problem", Applied Artificial Intelligence, vol. 15, pp. 361-383, 2001.


 