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Solving Multiple Depot Vehicle Routing Problem (MDVRP) using Genetic Algorithm

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Abstract— **Vehicle Routing Problem is a NP-Hard classical complex combinatorial problem described as task of determining efficient and shortest delivery or pickup routes to service several customers scattered in different geographical regions with a fleet of vehicles with additional predefined constraints to satisfy real-life scenarios. Vehicle Routing Problem has wide applications in Logistics and Transportation with growing economic importance. In Solutions of Vehicle Routing Problem maintaining the defined restrictions is of high Interest. Exact solutions of Vehicle Routing Problem can't be obtained due requirement of high computation time. Due to Genetic Algorithm's stochastic characteristics and efficiency in solving combinatorial problems it is used to find true and approximate solutions of Vehicle Routing Problem. For constrained variants of Vehicle Routing Problem feasible space is smaller than whole search space and Genetic Algorithm finds a solution with high precision that doesn't violate any of the constraints.**

Keywords*— *Genetic Algorithms, Local Heuristics, Multiple Depot VRP, MBCRC Crossover, Inter-Depot Mutation.

I. INTRODUCTION

There are a lot of complex combinatorial NP Hard optimization problems which currently exists in modern world and we yet don't have fully optimized and applicable solutions for all variants of these problems. Obtaining an optimal solution to these problems can make way to an efficient and productive approach to real life everyday problems and can make production cost effective and eco-friendly.

Among these NP hard problems Vehicle Routing Problem i.e. VRP is a very popular combinatorial problem where several customers with demand of goods has to be satisfied with a given fleet of fixed capacity delivery vehicles based on generally one (multiple in some predefined constraints) storehouse i.e. depot. VRP is called an optimization problem due to the fact that the objective of the solution to be obtained should be to find most optimal path to serve the demands of clients in scattered locations with minimum possible cost in terms of either one or both number of required vehicles and travelled distance cost while maintaining the constraint that every customer demand must be met. In [1], VRP is mathematically expressed as a graph $G = (N, E)$ and a set of vehicles $V = \{1,2, \ldots, n\}$. N is number of nodes is in graph G i.e. $\{N = n_0, n_1, .., n_k\}$. Therefore, we can deduce $\frac{N}{\{n\}} = k$ customers are in requirement of service. Edge set $E = \{e_{ij}\}$ where $i \neq j, 0 \leq i, j \leq k$ and $D =$ Cost Matrix and identical capacity Q is also defined.

In recent years obtaining optimal solution of VRP has become very important because their application and usage in real world everyday problems most commonly and frequently faced by Logistics, Transportation and Distribution companies. Massive growth and heavily increased fame and demand of home delivery e-commerce service like Amazon, Aliexpress has motivated researchers to look into this problem rigorously. Logistics system integrated with Global Positioning System (GPS) can result in very effective solution for tasks and services like Postal service, Goods supply, Fuel transportation etc. It also help improve ecology and environment by resulting in less requirement of fuel thus reducing pollution. Another reason for its popularity is VRP is difficult and ideal NP hard problem whose solution provides ideal benchmarks for to test newly developed global optimization algorithms.

There exists Local search and heuristic method approaches for solving VRP which requires severely increased computation time given a large Dataset and require further data training. Metaheuristic technique can used to solve combinatorial problems like VRP whose solution computation time is huge using other local heuristics. One such very efficient and widely used metaheuristic approach is Genetic algorithm which is modeled on Darwin's evolution theory and mimics human evolution and breeding. Genetic algorithms are commonly used to heuristically solve and generate high-quality solutions to optimization and search problems such as traveling salesman problems (TSP), quadratic assignment problems, bin-packing problems etc.

The organization of the following part of this paper is as follows. Section II of this paper describes background of VRP and MDVRP. Proposed Genetic Algorithm model is shown in Section III. Section IV addresses our experimental evaluation and results. Section V provides the conclusion and finally Section VI finishes with possible future works.

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II. BACKGROUND

For obtaining optimal delivery path of gasoline delivery trucks the most elementary version of VRP was first introduced by authors Dantzig and Ramser in [2].By imposing various constraints on the traditional definition and objective set of Vehicle Routing Problem several variants of VRP can be defined. These variants of Vehicle Routing Problem are grouped with respect to their constraints. One constraint may be such as that it limits or expands the available number of depots, one may change the dimension of demand parameter and one may impose a visiting time range constraint which have to be maintained during the service of that customer. Usually real life situations are represented by these constraints. In [3], the authors introduce the different variants of Vehicle Routing Problem.

A. Capacitated Vehicle Routing Problem (CVRP):

The available fleet of vehicle has capacity constraint imposed upon then that is whatever the customer demand parameter is a vehicle can't exceed a predefined capacity limitation. If capacity is exceeded to serve a customer new vehicle with a new route have to be assigned.

B. Vehicle Routing Problem with Time Windows (VRPTW):

The available fleet of vehicle has service time constraint imposed on them where k customers must be serviced within a predefined range of time. In [1], this time frame is described the writers as $S_i = [e_i, l_i]$ for customer i, where e_i start of time range to begin service and l_i the end time. Time frames can be single-sided too i.e. only the earliest time to start service is imposed as constraint.

C. Vehicle Routing Problem with Pickups and Deliveries (VRPPD):

In real life situations like soft drinks delivery an uncommon constraint is imposed on Vehicle Routing Problem where there is only a delivery demand but also a pickup demand define from each customer. So, item have to be brought back from customers to depot. In [4], Vehicle Routing Problem with Pickups and Deliveries (VRPPD) is described as an extension to the classical Vehicle Routing Problem (VRP).

D. Multiple Depot Vehicle Routing Problem (MDVRP):

A depot is the place where delivery service is initiated by loading the demanded items into the vehicle for delivering. In MDVRP there is a not a single depot for service initiation rather service can be initiated from a number depots. Real life scenarios where we face MDVRP are such as – Delivery of newspaper, Chemical product delivery etc. In [3], the authors mathematically expressed MDVRP as a graph $G = (V, A)$ where V is subdivided into $V_c = \{v_1, \dots, v_n\}$ and $V_d = \{v_{n+1}, \dots, v_{n+p}\}$ representing the set of customers and depots respectively. Set A denotes all possible edge costs between nodes and cost matrix C_{ij} is defined.

In [4], MDVRP is explained by the author using a derived term borderline customers. How MDVRP is a classical combinatorial NP-hard problem that is explained in [5]. The authors of [6], made two classification of MDVRP that is fixed MDVRP and Non-fixed MDVRP. An overview of the exact algorithms that can be applicable to MDVRP is given in [7] but these algorithms can perform calculation only on small datasets for MDVRP. There are some metaheuristic approaches that can obtain a decent solution in acceptable time frame. In these approaches the path to obtain exact optimal which demands severe computation time is entirely avoided. Such a metaheuristic approach Tabu search with diversification is described in [8] where as in [9] the authors implemented Genetic clustering approach to obtain efficient solution for MDVRP.

Although lot of researchers worked on solving Capacitated Vehicle Routing Problem (CVRP) using Genetic Algorithm approach and well documented approaches exist for the most elementary form of Vehicle Routing Problem the literature for solving MDVRP using GA approach is very limited. Our paper attempts to overcome this scarcity of effective Genetic Algorithm solution approaches for MDVRP.

III. PROPOSED METHODOLOGY

Genetic algorithms has the ability to obtain almost optimal in relatively comparable time frame due to their inherently adaptive characteristics. Genetic algorithms do that by relying on operators such as mutation, crossover and selection. A simple three-phased Genetic Algorithm approach for MDVRP is as follows –

1) First phase focuses on generating initial population by clustering genes i.e. customers into a service list assigned to a particular depot based on capacity of a depot and distance between depot and customer and makes use of a local heuristic algorithm to optimize the generated population

2) In second phase a GA is applied to formulate an optimized routes for servicing the customers leaving from each depot.

3) Finally, GA is applied again to build a network structure connecting all obtained routes.

A. Initial Population Creation

At first step from the given dataset that Genetic Algorithm is performed on each customer is pushed into the service list of nearest depot. As there is no capacity or service limitation imposed upon the depots following this strategy makes the best use of time. During this initial assignment,

i) Some customers are tagged as border genes of chromosome if they do not violate a predefined maximum distance for assignment limit. Mathematically we can determine if gene a is border gene using following formula

$$\frac{d_{ax} + d_{ay}}{\Sigma d_{ai}} \geq r$$

Where, r is a value between 0 and 1 and x and y are the closest and secondary closest depots to customer a.

ii) Rest of customers are non-border genes.

Then a modified efficient K-means Clustering algorithm is used on the generated depot service list so that optimal solution is found in limited or comparatively less recombined offsprings. In later stages when evolution process is performed, a mutation exchange strategy is followed which operates by re-assigning a border gene from there initially placed depot to their final placement to another depot to maintain genetic diversity.

B. Optimization using Intuitive Route Creator

In other variants of VRP a chromosome contains singular route but in MDVRP chromosome defines several routes in correct servicing order. To achieve this our proposed the GA is integrated with a route creator that creates the routes following predefined constraints. Route creator starts adding genes in chromosome by maintaining their service list. It keeps adding customers until any of predefined capacity constraint Q_i for max_distance for a route constraint. If any constraint is violated then it creates a new route under that exact depot. Then, for optimization the end gene of service list I_{R_i} is considered as the first gene of service list $I_{R_{i+1}}$and two new routes i.e. is obtained as $F_{R_i}$and $F_{R_{i+1}}$. Then feasibility is calculated using –

$$C\left(I_{R_i}\right) + C\left(I_{R_{i+1}}\right) < C\left(F_{R_i}\right) + C(F_{R_{i+1}})$$

So each chromosome in MDVRP initial population has several optimized routes based on a particular depot that contains customers in their service order.

C. Fitness Evaluation

After creation and optimization of initial population we have to evaluate the fitness value of the chromosomes. The fitness evaluation is done by two very popular existing evaluation methods known as weighted-sum fitness function and Pareto ranking technique.

i) Using weighted-sum fitness function fitness $F(r_1)$ of an individual r_1 is returned as –

$$F(r_1) = \alpha \,.\, |\, V \,| + \beta \,.\, \sum V_d$$
$$V_d = \sum_{i,j \in N} C_{ij}$$

α and β are weights assigned to vehicle quantity and total travelled distance. In this fitness function Fitness is evaluated as a single score.

ii) Pareto ranking fitness function has often been used for multi-objective optimization problem (MOP) applications of genetic algorithms [10]. Our GA integrated Pareto ranking scheme within fitness evaluation process. As a result raw fitness scores are changed by Pareto ranks. Using Pareto ranking we obtained the optimal solutions both in terms of distance travelled and number of vehicles and accommodating the user's choice optimizing any single parameter or maintaining a balance between both of them.

D. Selection

After evaluating fitness of every chromosome in initial population we must reproduce new population by mating the most feasible chromosomes. New generation is formulated Tournament selection strategy combined with elite retaining model. In Tournament selection strategy several random chromosomes are selected thus making a tournament set. Fitness values obtained from members in the tournament set are rescaled in such a way that total sum is 1.

$$\frac{F(x_i)}{\sum_1^t F(x_i)}$$

Where, t = number of chromosomes in the tournament set. The probability of choosing a chromosome for selection is as strong as its fitness value. In our GA, chromosome which is fittest survives but pushed into competition against the obtained fittest chromosome in the later generation.

E. Crossover

Crossover operator can't produce new characteristics. Modified Best Cost Route Crossover (MBCRC) operator was used which in our proposed GA. Steps of MBCRC is given below-
i) A random customer i is selected as the first customer.
ii) A local search for customer i is performed two parent chromosomes and immediate predecessors and successors is identified, tagged as neighbors.
iii) Closest feasible customer j identified by performing Best cost evaluation among the not visited customers is selected as the next customer in offspring until none found.
iv) Repeated for all customers.

F. Mutation

As Crossover operator can't introduce new and unique characteristics to avoid getting stuck in local maxima we had to accommodate several mutation operator in our proposed GA to pave the path to global maxima. To add new characteristics these mutation operators initiates little intuitive alterations which Crossover is unable perform. To break free from local minima mutation operator exchanged swap of genes not only within a single depot but also within several depot known as Inter-Depot Mutation. During Initial population generation a group of customers who are reassignable to non-parent depots is created called swap list. Each customer in this swap list contains a candidate list which is set of possible depot assignments. Using following formula we determine if Inter Depot Mutation can be performed on a customer -

$$\frac{dist(x_i - d_i) - near}{near} \leq \beta$$

$dist(x_i - d_i) =$ Euclidean distance between customer x to currently calculating depot d_i.
$near$ = Distance between x its closest depot.

Different steps of Genetic Algorithm for solving MDVRP is shown in Fig. 1.

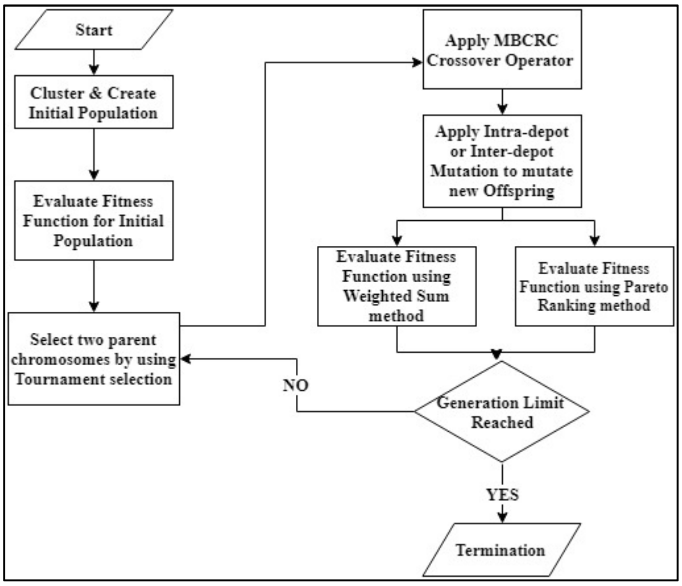


Fig. 1. Flow Chart of MDVRP

IV. EXPERIMENTAL EVALUATION

The required information page that takes the required parameters as input. Typical Genetic Algorithm inputs are Number of Customers, Generation Limit, Crossover Probability and Mutation Probability. Locations of customers and depots are also asked of the user in the format of ('Location Name', 'Latitude', 'Longitude'). This UI is shown by Fig. 2.

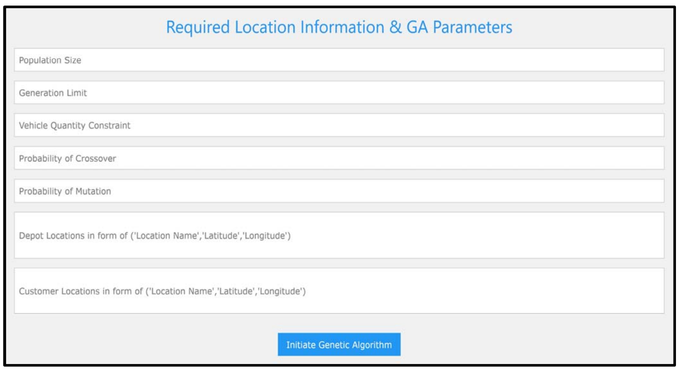
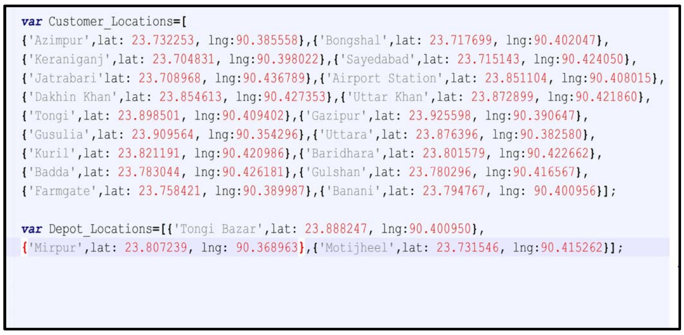


Fig. 2. Required information page

Then implementation of derived Dataset upon which GA was performed on is shown by Fig. 3. The Location is initialized in the code with two JavaScript variables "Customer_Locations" and "Depot_Locations".



```
var Customer_Locations=[
{'Azimpur',lat: 23.732253, lng:90.385558},{'Bongshal',lat: 23.717699, lng:90.402047},
{'Keraniganj',lat: 23.704831, lng:90.398022},{'Sayedabad',lat: 23.715143, lng:90.424050},
{'Jatrabari'lat: 23.708968, lng:90.436789},{'Airport Station',lat: 23.851104, lng:90.408015},
{'Dakhin Khan',lat: 23.854613, lng:90.427353},{'Uttar Khan',lat: 23.872899, lng:90.421860},
{'Tongi',lat: 23.898501, lng:90.409402},{'Gazipur',lat: 23.925598, lng:90.390647},
{'Gusulia',lat: 23.909564, lng:90.354296},{'Uttara',lat: 23.876396, lng:90.382580},
{'Kuril',lat: 23.821191, lng:90.420986},{'Baridhara',lat: 23.801579, lng:90.422662},
{'Badda',lat: 23.783044, lng:90.426181},{'Gulshan',lat: 23.780296, lng:90.416567},
{'Farmgate',lat: 23.758421, lng:90.389987},{'Banani',lat: 23.794767, lng: 90.400956}];

var Depot_Locations=[{'Tongi Bazar',lat: 23.888247, lng:90.400950},
{'Mirpur',lat: 23.807239, lng: 90.368963},{'Motijheel',lat: 23.731546, lng:90.415262}];
```

Fig. 3. Dataset Implementation

After initializing the given locations in variables those are plotted in Google Map using "function initMap" and "google.maps.Marker".

Here, we used custom marker to distinguish between Depots and Customers. In Fig. 4. Marker with blue icons indicates depots and marker with green icons indicates customers or service locations.

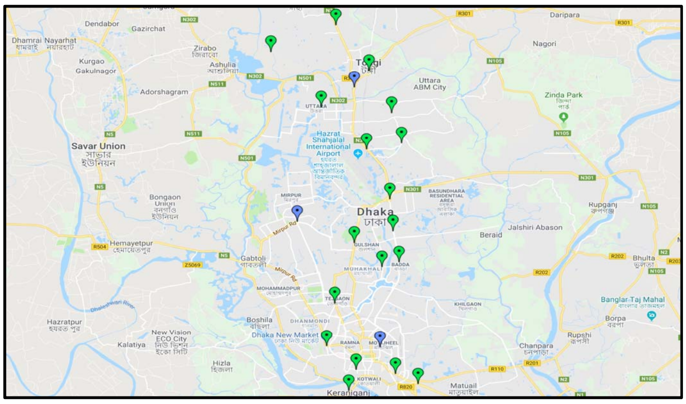


Fig. 4. Locations are shown in Google Map

Fig. 5. shows a output page which displays the optimal routes for each depot with travel cost for both weighted-sum scoring and Pareto ranking. Required time for Process Execution and button shows the optimal routes in Google Map is also shown.

Here we get two shortest Euclidean Distance. That's because we calculate the fitness function of the produced generations using both-Weighted sum fitness scoring, Pareto Ranking Algorithm.

If there are alternate paths with similar costs that is also shown in calculation. The alternate paths are shown in Google map too.

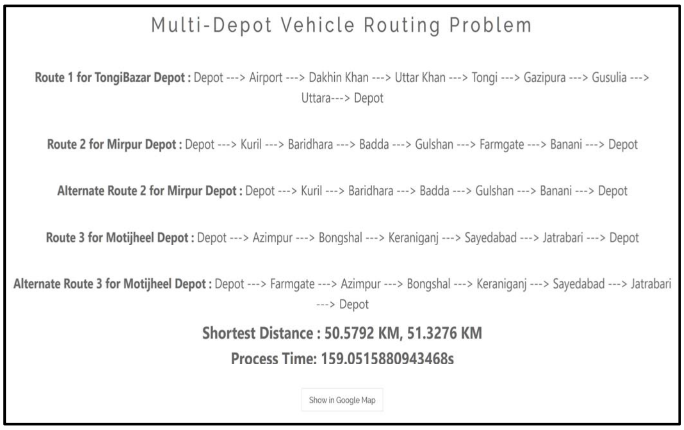


Fig. 5: MDVRP output

If Show in Google Map Button is clicked a UI like Fig. 6. will pop up which shows the obtained most feasible paths in google map. Marker and polylines are used to show the routes centric to different depots. The routes of different depots are shown using different colors for better visualization.

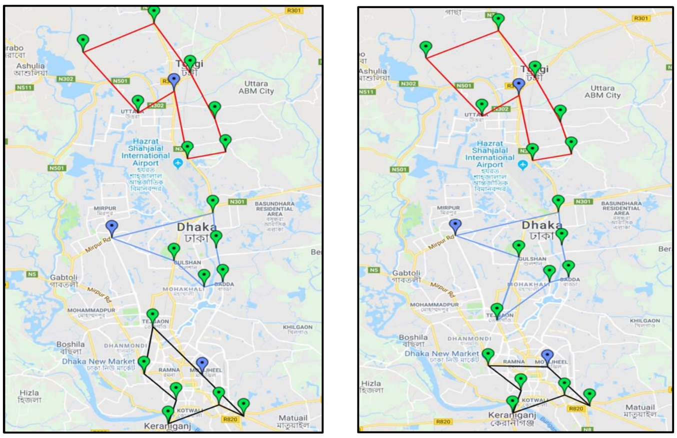


Fig. 6. Google Map UI to show obtained routes

We compared our proposed GA approach with GenClust Genetic algorithm approach implemented in [9] as shown in Fig. 7.

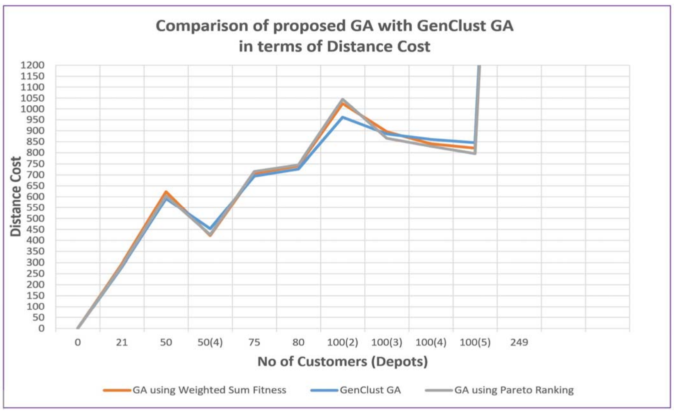


Fig. 7. Distance Cost Comparison

We compare obtained results using both weighted-sum fitness and Pareto ranking. During Comparison we limited CPU speed and RAM to match the specification that GenClust GA was performed in. Due to the adaptive nature of GA it cannot provide same output every time so we ran our genetic algorithm on each dataset ten times and then took the average value.

We can see our proposed GA is competitive with GenClust GA and improves upon the solution quality especially in reducing travel cost in a number of instances. The proposed GA finds more efficient solution than GenClust in 7 out of 10 datasets and constraints where we performed comparison. Fig. 8. shows CPU time comparison with GenClust GA which shows that in larger population size sets the computation time is increased rapidly.

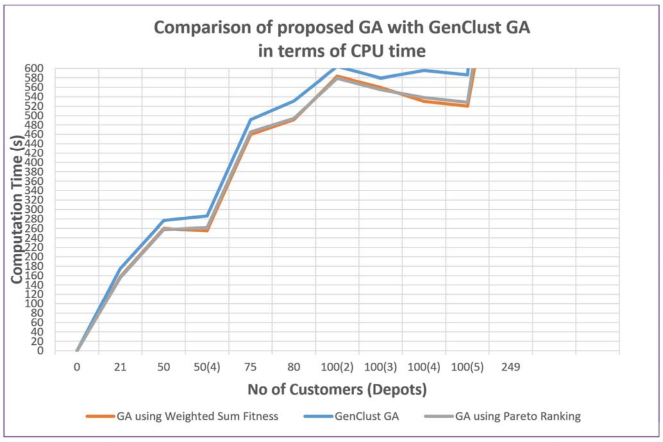


Fig. 8. Process Execution time Comparison

As GenClust only uses only geometric shaped initial clustering algorithm these shapes doesn't cover all areas. So, Missing customers has to be searched and manually inserted in random places and feasibility has to be calculated again as a result computation time increases. GenClust also uses weighted sum fitness evaluation which evaluates only in terms of a unified score. But less vehicle or less travelled distance this preference should be upto the user. So, we used Pareto Ranking along with weighted sum which allows MOP.

In [11], the authors implemented a Genetic algorithm approach with a intuitive crossover method and also added some custom insertion heuristic to obtain a faster approach. But this implementation was only done for CVRP. The authors in [12] compared different formulations of the multi-depot fleet size and mix vehicle routing problem (MDFSMVRP). This problem extends the multi-depot vehicle routing problem and the fleet size and mix vehicle routing problem. They performed their experiments on a commonly used set of instances in the MDFSMVRP literature. Thus, we were unable to compare their results.

V. CONCLUSION

Primary focus of this work is to find efficient solutions for Multiple Depot vehicle routing problem within acceptable time frame. We compared our proposed GA approach with GenClust approach which is the best bio inspired solution approach for MDVRP. After numerous analysis we concluded that GAs has an upper hand for obtaining solutions to NP-hard problems. Further considering the obtained results and CPU times and comparing them with other best known existing solutions for Multiple Depot vehicle routing problem it can be stated that, GA based proposed approach is efficient and performs well.

VI. FUTURE WORK

GA studied in this paper has performs better than existing Bio inspired and non-GA techniques. We can extend this work to Multiple Depot Vehicle Routing Problem with Time Windows (MDVRPTW) and Vehicle Routing Problem Pickup and Delivery (VRPPD) to see its performance against the existing GA's for those variants of VRP. Future work also includes better tuning of GA parameters and taking heterogeneous capacity vehicles into consideration for developing GA based approach for MDVRP. Also GA approach can almost never find more efficient solutions for exact methods of obtaining solutions. This should be investigated further,

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