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EODVGA: An Enhanced ODV Based Genetic Algorithm for Multi-Depot Vehicle Routing Problem

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Abstract

Multi-Depot Vehicle Routing Problem (MDVRP) is a familiar combinative optimization problem that simultaneously determines the direction for different vehicles from over one depot to a collection of consumers. Researchers have suggested variety of meta-heuristic and heuristic algorithms to elucidate MDVRP, but none of the existing technique has improved the fitness of the solution at the time of initial population generation. This motivates to propose an enhanced ODV based population initialization for Genetic Algorithm (GA) to solve MDVRP effectively. The Ordered Distance Vector (ODV) based population seeding method is a current and effective population initialization method for Genetic Algorithm to produce an early population with quality, individual diversity and randomness. In the proposed model, the customers are first grouped based on distance to their nearest depots and then routes are scheduled and optimized using enhanced ODV based GA. The experiments are performed based on different types of instances of Cordeau. From the experimental results, it is very clear that the proposed technique outperforms the existing techniques in terms of convergence rate, error rate and convergence diversity

Keywords: Multi-Depot Vehicle Routing Problem (MDVRP), Ordered Distance Vector (ODV), Genetic Algorithm (GA)

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1. Introduction

Dantzig and Ramser [1] in 1959 introduced the Vehicle Routing Problem (VRP) which was derived from the traveling salesman problem. It is one of the most challenging optimization problems. Based on a particular depot, the routes are determined by VRP for a set of vehicles. Subsequently around ten to twelve variants are introduced in VRP such as Open vehicle Routing Problem (OVRP), Capacitated Vehicle Routing Problem (CVRP), Period vehicle routing problem (PVRP), Split delivery vehicle routing problem (SDVRP), Time Dependent Vehicle Routing Problem with Time Windows (TDVRPTW), Vehicle Routing Problem with Time Windows (VRPTW), Vehicle Routing Problem with Pickup and Delivery (VRPPD), and Multi-Depot Vehicle Routing Problem (MDVRP) and also many other variants are there. Our research focuses on one of the most important variant – multi depot VRP (MDVRP). MDVRP is a classical vehicle routing problem. In last few years researchers are very much interested in these variants and in solving it using methods such as heuristic and meta-heuristic techniques.

In 1969, Tillman studied Multi-Depot Vehicle Routing Problem (MDVRP) which is a main variant in VRP. It is a well-known combinatorial optimization problem to simultaneously determine the routes for fleet of vehicles from over one depot to serve the customers. Without violating the capacity of vehicle and serving all the customers, the fleet of vehicles has to return to same depot. Fig.1 illustrates the multi-depot VRP, it has 3 depots and 14 customer and optimal routes for the customers are shown. More number of depots and group of vehicles are assigned to each depot, and the customers nearest to the depot are clustered within that depot. At first customers and depot are clustered then Multi depot VRP is solved. The goal of MDVRP is to reduce the entire cost of the collective routes for collection of vehicles. Cost is closely related with distance thus the objective is to reduce the full distance travelled by vehicle fleet.

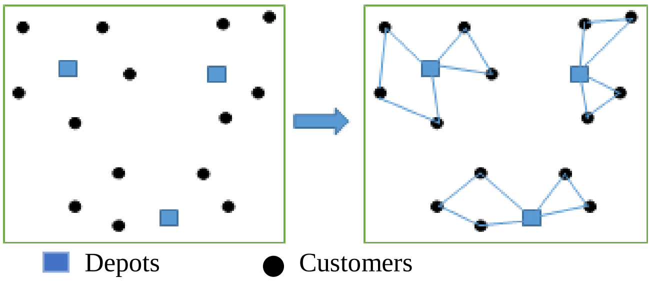

Figure 1. Multi-Depot Vehicle Routing Problem

2. Related Work

Genetic Algorithm (GA) is one of the methods of Meta-heuristic algorithm. Meta-heuristic algorithm finds solutions in less computational time for routing problems. Variable Neighbourhood Search Algorithm for the Multi Depot Heterogeneous Vehicle Routing Problem with Time Windows is one of the variants of heuristic and meta-heuristic methods presented by Yingcheng Xu et al.,[2]. Multi-Phase Meta-Heuristic for Multi-Depots Vehicle Routing Problem uses extremal optimization (EO) for re-adjusting the solutions. For every cluster it implements the Shuffled Frog Leaping Algorithm (SFLA). It was proposed by Jianping Luo, Xia Li et al., [3]. For solving min–max Multi-Depot Vehicle Routing Problem K. Venkata Narasimha et al., [4] proposed Ant colony optimization technique. Modular heuristic algorithm to solve Fleet-sizing for multi-depot and periodic vehicle routing problem was proposed by Alireza Rahimi Vahed., [5]. Under capacity and route length constraint for solving multi-depot vehicle routing problem C. Contardo, R. Martinelli et al., [6] proposed variable fixing, column-and-cut generation. For solving large-scale multi-depot vehicle routing problem W. Tu et al., [7] proposed Bi-level Voronoi diagram-based metaheuristic. There are various methods namely Tabu search [8, 9], Simulated annealing [10, 11], Genetic approach [12], Ant colony optimization [13, 14, 20], Particle swarm optimization [15, 16].

Genetic Algorithm (GA) takes less computation time and results in reasonable and optimal solutions when compared with further meta-heuristic algorithms. Because of these things still Genetic Algorithm (GA) is used for solving NP hard problems [21, 22], Vehicle routing problem, Travelling salesman person problem. Still today there exists no solution for determining how Genetic Algorithm influences the process of searching upcoming variants, different aspects setting and operator of GA. Ordered Distance Vector (ODV) [17] is a recent population seeding and effective population initialization method for Genetic Algorithm.

3. Ordered Distance Vector (ODV) Based Genetic Algorithm

Genetic algorithm (GAs) is a seeking procedure used to discover sufficient results for optimization. It has been ended up being effective at seeking ideal arrangement among a substantial and complex examination space in a versatile way. The need of it is to locate the best arrangement in the substantial search space which is the gathering of every doable arrangement among which the coveted arrangement re-sides. The Ordered Distance Vector (ODV) based population seeding system is a successful population initialization strategy for GA to produce an underlying population with irregularity, quality and individual assorted variety. It has three sorts of population initialization strategies; they are Vari-begin with Variable diversity (VV), Equi-begin with Variable diversity (EV), Vari-begin with Equal diversity (VE). In our proposed work Equi-begin with Variable diversity (EV) is used to solve MDVRP.

3.1. ODV based EV technique

The effective population initialization technique is used to initialize the initial population in Genetic Algorithm. Since the starting city is fixed in our work, we are using EV (Equi-begin with Variable diversity) based ODV (Ordered Distance Vector) population seeding technique which is built on the ODV Matrix (ODVM).

Ordered Distance Vector (ODV): ODV based population seeding system produces an arrangement of change of ‘n’ cities utilizing the Ordered Distance Vector matrix. In every permutation, the categorization of the cities is picked in such a way where the sum of distance among the cities is close least. By the permutation of C cities, the distance is computed and based on it the cities are sorted here. The ODV C_x of is as appeared in the Equation and the condition for the distance between the city and the following cities are given.

$$(C_x) = (C \qquad) \text{, Then}$$

$$d(C \quad) \qquad (C_{x,y+1}) \leq (C_{x,y+2}) \ldots \qquad (C \qquad)$$

Where $d(C \qquad)$ distance between the and

Ordered Division Matrix (ODM) : For every city, the ODV creates relating least distance cities in arranged request and rank the cities on the basis of distance, at that point it will be moved to the ODM (Ordered Division Matrix) that is given by $n(n-1)$ matrix as given.

$$\begin{bmatrix} \end{bmatrix}$$

$$\begin{bmatrix} 1(y) & 1(y\ \ 1) & 1(y\ \ 2) & 1(n\ \ 1) \\ 2(y) & 2(y\ \ 1) & 2(y\ \ 2) & 2(n\ \ 1) \\ C_{n(y)} & n(y\ \ 1) & n(y\ \ 2) & n(n\ \ ) \end{bmatrix}$$

Equi-begin and Vari-diversity (EV)

Equi-begin (E): The starting city of the each individual is always same here. So C_1 remains stable for all the individuals in the population. In VRP the starting city of the individuals is fixed (depot) so here this method is applied.

Variable diversity (V): The succeeding city in the individual is added based on the value, is a selected integer whose range is within value. The city in the position of value is progressed to the succeeding city location of the individual.

The population is generated using Equi-begin with Variable diversity (EV), the starting city of each individual is fixed and based on the b_{ax} value and the succeeding city of the individual is chosen and added. The individuals in the population have high permutation of cities and the time complexity can be reduced. During initialization the number of maximum individuals in the population is as given,

$$(\mathrm{tot}(P_{ODM})) = ba^{(n-1)}$$

Where $\mathrm{tot}(P\quad)$ total amount of individuals in the population,

$-$ best adjacent value and n $-$ total cities.

EV method generates the initial population as given,

$$\begin{bmatrix} (C_1) & (C_2) & (C_3) & (C_n) \\ (C_1) & (C_2) & (C_3) & (C_n) \\ & & & \\ (C_1) & (C_2) & (C_3) & (C_n) \end{bmatrix}$$

4. Proposed System

4.1 ODV based EV for MDVRP

The Ordered Distance Vector (ODV) Equi-begin and variable diversity (EV) population seeding technique based on GA is proposed to solve MDVRP. The proposed algorithm consists of two stages first; an Order Distance Matrix (ODM) will be generated from the Distance Matrix (DM) and followed by generation of the initial population based on the ODM. The second stage of the technique can be performed by EV, VE and VV depending on the type of population seeding technique to be chosen. In our proposal we are using Equi-begin with Variable diversity (EV) technique. The algorithm for MDVRP using ODV based EV techniques as shown below.

Algorithm for MDVRP using ODV- EV

Step1: Initialization of no_cities, gen, pop_size, Q, max_gen, len, ba
Step2: Iterating Step1 to 6 until S
Step3: Assign the distance matrix into temp. Distance matrix
Step 4: Iterating Step 5 to 7 until i ≤
Step 5: Customer with minimum distance from Sth customer is identified and moved to ODM
{ }
Step 6: The customer with min distance has changed as maximum
{ } { }
Step 7: Incrementing i
Step 8: Completed current customer and iterating for next customer S ←
Step 9: Initialization the initial customer in
Step10: Iterate step 19 to 20 until S
Step 11: Iterate through Step 18 until le
Step 12: Initialize the initial customer and total demand

Step 13: Random number is generated (∞), based on best adjacent (ba) value
Step 14: Obtaining the next customer from ODM using current customer

Step 15: Checking next customer belongs to individuals

Step 16: Obtaining the demand of the customer and then added to total demand

Step 17: Iterate Step 18 until total demand is less than are equal to Q

Else goto Step 11
Step 18: Incrementing the length of individual and initializing the next customers to the individuals

Step 19: Move the current individual of the population

Step 20: Increment the size
Step 21: End

The above shown algorithm is ODV- EV technique for MDVRP. The flow of algorithm is, first the Initialization is done for number of cities, generation, capacity, best adjacent and population size. Then distance matrix is assigned to temporary distance matrix then distance vector matrix is created by using temporary distance matrix. Customer with minimum distance from size of customer is identified and moved to ODM. The minimum distance customer is visited and then random ba value is generated, using that best adjacent (ba) value the next customer is visited, these process is done for until the service is done for all the customers.

5. Experimentation and Result Analysis

The enhanced ODV EV population initialization technique based genetic algorithm is implemented in MATLAB 2011b. The experiments are performed different types of Cordeau's Instances (p01, p02, p03, p04, po7, p15, p18, pr05, pr06, pr10) obtained from (http://neo.lcc.uma.es/vrp/vrp-instances). The significance of the proposed techniques is examined by the performance factors such as Convergence rate, Error rate and Convergence diversity.

Convergence rate: Convergence rate of an individual of a population set is defined as the percentage of fitness value obtained by the individual according to the optimal fitness value given below,

e (%)

Error rate: Error rate of an individual of a population set is defined as the percentage of difference between fitness obtained by the individual and optimal fitness value given below,

Convergence diversity: The convergence diversity of the population is the difference between the convergence best rate and convergence error rate. This factor shows that diversity among the individuals in the population. It is calculated by the below shown equation.

(%)

5.1 Result analysis

The result analysis of the proposed enhanced ODV EV technique is described in this section and comparison of ODV with other state of the art methods. The proposed enhanced ODV- EV based Genetic Algorithm is compared with other state of the art methods [18, 5, 19]. There are three performance factors used to examine the significance of the proposed techniques and they are Convergence rate, Error Rate and Convergence Diversity.

Convergence Rate

Convergence rate is commonly used for technical analysis. It indicates the series of convergence between the various instances. Different types of Cordeau's Instances (p01, p02, p03, p04, po7, p09, p10, p11, p12, p16, p17, p19, p10, pr10) are taken. For convergence rate (%) consider the Table 1 and Table 2. The proposed ODV technique system has high convergence for more number of instances. This shows ODV EV technique is best when comparing to other state of the art methods. The fig.2 shows the performance of different technique w.r.t best convergence rate and fig.3 shows the performance of different technique w.r.t worst convergence rate.

In the forthcoming table I refers to the Instance, S refers to SFLA-PLEONS, M refers to MHA, T refers to Tabu Search, O refers to ODV EV

Table 1. Experimental results w.r.t Best Convergence rate (%)

SL. NO	I	S	M	T	O
1	p01	100	99.473	99.232	100
2	p02	100	98.918	98.699	99.997
3	p03	100	99.374	98.875	100
4	p04	100	99.439	99.148	99.156
5	p07	100	100	99.725	100
6	p09	99.743	99.511	98.846	99.974
7	p10	99.831	99.735	99.477	99.945
8	P11	99.858	99.721	99.379	100
9	p12	100	99.195	99.006	100
10	P13	99.918	99.379	98.995	99.996
11	P14	99.666	99.369	98.779	99.691
12	P16	99.727	99.610	99.288	99.920
13	P17	99.962	99.622	98.766	99.884
14	P19	98.0938	97.691	96.131	99.815
15	P20	99.902	99.580	98.988	99.925
16	pr10	100	99.638	99.364	99.959

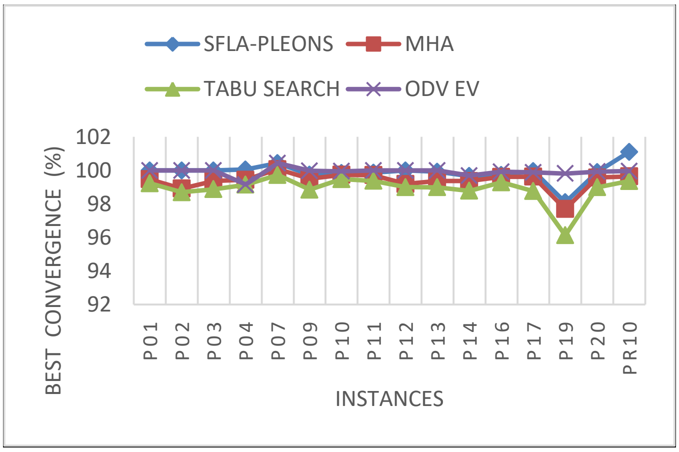

Figure 2. Performance of different technique w.r.t

Best Convergence rate (%)

Table 2. Experimental results w.r.t Worst Convergence rate (%)

SL. NO	I	S	M	T	O
1	p01	99.531	99.089	97.810	99.531
2	p02	98.445	98.800	94.560	98.445
3	p03	98.248	97.765	96.158	98.248
4	p04	97.003	98.121	98.606	97.003
5	p07	99.599	99.390	99.068	99.599
6	p09	99.746	98.558	98.248	99.746
7	p10	99.809	99.131	99.120	99.833
8	P11	99.830	99.014	98.724	99.914
9	p12	99.996	98.765	98.444	99.997
10	P13	99.765	94.270	97.695	99.919
11	P14	99.624	97.966	97.439	99.616
12	P16	99.693	100.466	98.446	99.884
13	P17	99.874	97.951	97.262	99.629
14	P19	98.013	96.862	95.495	99.787
15	P20	99.725	99.398	98.468	99.900
16	pr10	100	99.411	98.733	99.888

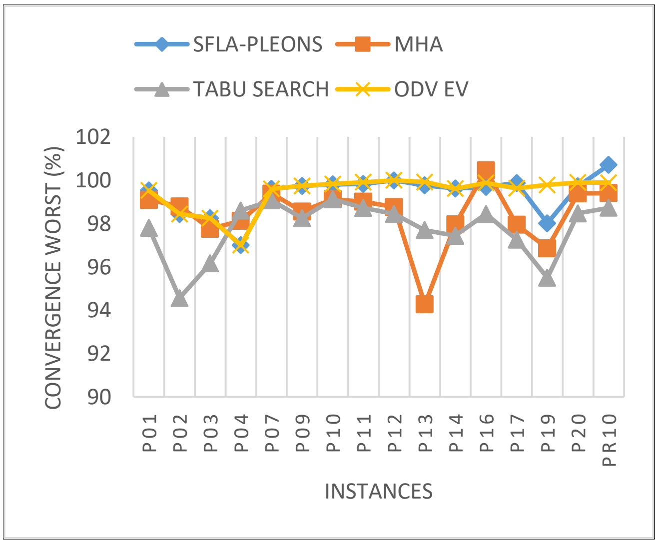

Figure 3. Performance of different technique w.r.t Worst Convergence rate (%)

Error Rate

Different types of Cordeau's Instances are chooses, now the instances are evaluated for the proposed technique and compared with the existing techniques. As per the computational results, the error rate for the ODV- EV technique is less when compare to state of art methods. This is shown in Table 3.

Table 3. Experimental results w.r.t Error rate (%)

SL. NO	I	S	M	T	O
1	p01	0	0.526	0.767	0
2	p02	0	1.081	1.300	0.002
3	p03	0	0.625	1.124	0
4	p04	-0.054	0.560	0.851	0.843
5	p07	-0.440	-0.073	0.274	-0.440
6	p09	0.256	0.488	1.153	0.025
7	p10	0.168	0.264	0.522	0.054
8	P11	0.141	0.278	0.620	0
9	p12	0	0.804	0.993	0
10	P13	0.0811	0.620	1.004	0.003
11	P14	0.333	0.630	1.220	0.308
12	P16	0.272	0.389	0.711	0.079
13	P17	0.037	0.377	1.233	0.115
14	P19	1.906	2.308	3.868	0.184
15	P20	0.097	0.419	1.011	0.074
16	pr10	-1.104	0.361	0.635	0.040

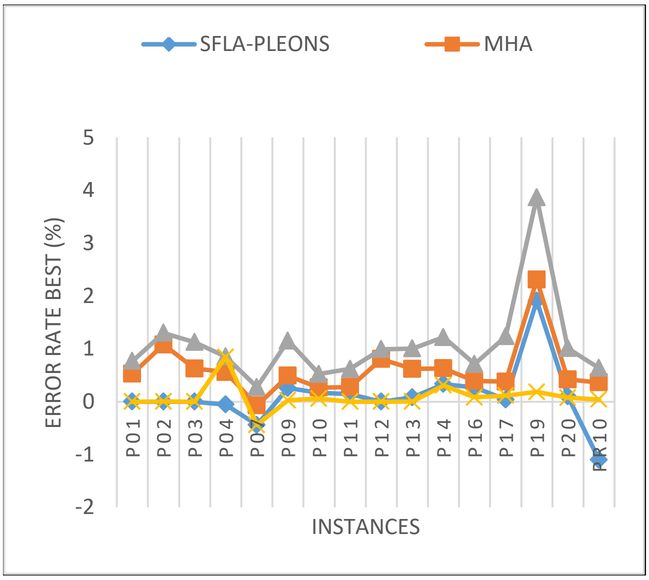

Figure 4. Performance of different techniques w.r.t Error rate (%)

Convergence Diversity

ODV EV technique produces low convergence when compare to other existing techniques. Hence our proposed technique is proven to be efficient. To overcome the pre-mature convergence problem convergence diversity is an important factor which illustrates the different range between the individuals. This shown in Table 6.5 and ODV- EV is efficient as per computational results.

Table 4. Experiment results w.r.t Convergence Diversity (%)

SL. NO	I	S	M	T	O
1	p01	0.468	0.383	1.421	0.468
2	p02	1.554	0.118	4.139	1.552
3	p03	1.751	1.609	2.716	1.751
4	p04	3.051	1.317	0.542	2.152
5	p07	0.841	0.682	0.657	0.841
6	p09	-0.002	0.953	0.598	0.228
7	p10	0.021	0.604	0.356	0.111
8	P11	0.028	0.707	0.654	0.085
9	p12	0.003	0.429	0.561	0.002
10	P13	0.153	5.108	1.299	0.077
11	P14	0.042	1.403	1.339	0.074
12	P16	0.034	-0.507	0.842	0.036
13	P17	0.088	1.670	1.504	0.255
14	P19	0.080	0.828	0.635	0.028
15	P20	0.176	0.181	0.519	0.024
16	pr10	0.391	0.227	0.631	0.071

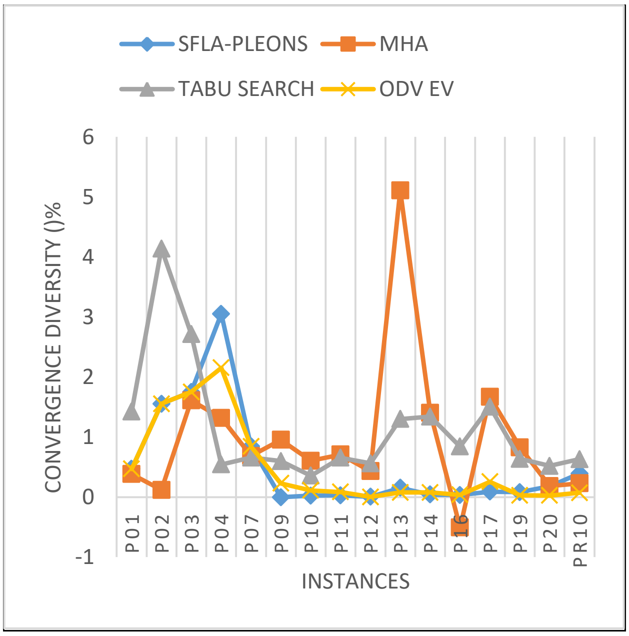

Figure 5. Performance of different techniques w.r.t Convergence diversity (%)

6. Conclusion and Future Work

Enhanced Ordered Distance Vector (ODV) based Genetic Algorithm (GA) is proposed to solve Multi-Depot Vehicle Routing Problem (MDVRP). For generating an initial population with individual diversity, randomness and quality, the ODV based population seeding technique is an active and recent population initialization method for GA and ODV based GA improves the fitness of the solution at the time of population initialization itself. The performance of the proposed technique is compared with state of the art methods and the experimental analysis is done through based performance factors such as convergence rate, error rate and convergence diversity. The values obtain from various instances shows that our proposed ODV EV population seeding technique based genetic algorithm solves MDVRP effectively than other methods. In future these ODV EV work can be extended to solve the others variants of vehicle routing problem in efficient manner.

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