International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-11, September 2019

Enhancement of Firefly Technique for Effective Optimization of Multi-Depot Vehicle Routing

R.Yesodha, T.Amudha

Abstract*: Vehicle Routing Problem (VRP) plays a significant role in today's demanding world, especially in Logistics, Disaster relief supplies or Emergency transportation, Courier services, ATM cash replenishment, School bus routing and so on and it acts as a central hub for distribution management. The objectives of the present research are to solve NP-Hard Multi-depot Vehicle Routing Problem (MDVRP) by using an enhanced firefly approach as well as to examine the efficiency of the proposed technique Cordeau benchmark dataset of MDVRP were used. The foremost principle of MDVRP is to optimize the cost of the solution, to minimize the overall vehicles, travelling distance and number of routes. MDVRP is constructed with two phase, assignment and routing. The firefly technique is enhanced by using inter depot, which is applied in assignment phase. In routing phase saving cost, intra and inter-route were used. The results were compared with Ant colony optimization (ACO), Genetic algorithm (GA), Intelligent water drops (IWD), Particle Swarm Optimization (PSO), Genetic cluster (GC), Genetic using Pareto Ranking (GAPR), Nomadic Genetic algorithm (NGA), and General Variable neighbourhood search (GVNS) algorithm. The solutions obtained in this research work found to be optimal for most of the benchmark instances.

Keywords*: Vehicle routing, Multi-Depot VRP, Firefly algorithm, Bio-Inspired computing.

I. INTRODUCTION

Bio-Inspired computation (BIC) is a subset of Nature-Inspired computing which focuses on societal performing and inspired from nature. Bio-inspired techniques is a modern optimization procedure which are arisen to solve complex problems which is applied in various research areas ranging from biomedical and data mining, computer science and technology, electronics, network security and robotics [14] etc. This technique targets to speed up the multi-objective and progress to expand the scope into tougher optimization areas. Bio-inspired metaheuristics procedures can be applied for solving various NP-hard problems [17] and its search process depends on balancing between two foremost mechanisms first, the exploration signifies the way of finding new outcomes in the search space second, exploitation denotes the use of existing information [8, 18].

VRP [8] is a combinatorial optimization problem originates from TSP or Arc routing problem. Combinatorial optimization is a subclass of optimization that is interrelated to operations research, and computational complexity model. TSP, Knapsack problem, scheduling problem, bin packing and assignment problem, and so on are some of the common problems involved in combinatorial optimization. There are numerous techniques employed to solve combinatorial problem during the last decades, but Bio-inspired techniques are found to be suitable and very effective [14]. Vehicle routing problem is an intersection of TSP and Bin packing problem along with a number of constraints than TSP [17]. Its ultimate aim is to reduce the travelling distance, vehicles used, number of routes and cost of the solutions in addition to satisfying the customer needs. The minimum distance toured by each vehicle without excluding any instruction is considered as a feasible solution. Better directing of transportation makes major profitable consequences for civic and private divisions. Numerous algorithmic strategies have been proposed for finding optimal solutions to solve vehicle routing problem especially MDVRP but there is still some room for improvement and further research works. Standard VRP constraints are as follows: [8, 14]

a. Every single customer is visited exactly once which is similar to TSP
b. Each vehicles will begin and terminate with the same depot
c. Every vehicle have equal capacity
d. Time factors are considered to serve the customers and to avoid the late penalties.

II. MULTI-DEPOT VEHICLE ROUTING PROBLEM

MDVRP problems [5] are classical VRP problem and the statement is similar as that of the standard VRP. In MDVRP, more than one depot is used and it is much complicated compared to single depot VRP. The primary part of the multi-depot VRP is to minimalize the distance and routes along with the available vehicles and to reduce the cost of the solutions. The objective functions of MDVRP are given below [5, 9, 10, 12, 11]

a. To minimize cost of the solution
b. To reduce travelling distance
c. To reduce the number of routes
d. To minimize overall vehicle
e. Demand fulfillment/customer satisfactions

The constraints involved in solving MDVRP are

a. Each customer should not be served more than once
b. Each tour starts from multiple depots which is located in different places
c. Vehicle availability should not be exceeded
d. Vehicle capacity should not exceed the capacity limit
e. Once visiting the allocated customers, every vehicle should proceed to its initiated depot.

Manuscript published on 30 September 2019.
*Correspondence Author(s)
Mrs. R.Yesodha, Department of Computer Applications, Bharathiar University, Tamilnadu, India,
Dr. T.Amudha, Department of Computer Applications, Bharathiar University, Tamilnadu, India,

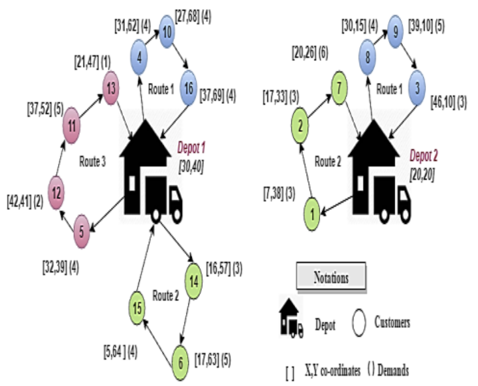

Fig. 1 Example of MDVRP using 2 depots

A. Problem Formulation of MDVRP

The problem formulation of MDVRP problem is as follows:

$$Minz = \sum_{i\in NI\cup NH} \sum_{j\in NI\cup NH} \sum_{h\in NH} ds_{ij} cs_{ij}\, x_{ij} \qquad (1)$$

$$\sum_{h\in H} \sum_{j\in I\cup H} x_{ijk} = 1 \quad i\in I \qquad (2)$$

$$\sum_{i\in I} d_i T y_{ik} \le VQ(K) \qquad (3)$$

$$\sum_{i\in I} \sum_{j\in H} Tx_{ijk} \le 1 \quad h\in H,\ v\in NV \qquad (4)$$

$$\sum_{i\in NI\cup NH} Tx_{ij} = \sum_{j\in NI\cup NH} Tx_{ijk} \le 1 \quad i\in I\cup NH,\ h\in NH \qquad (5)$$

Table 1 Notations and Descriptions of MDVRP

Notations	*Descriptions*
NI	Total customers
NH	Total depots
NV	Total vehicles
cs_{ij}, ds_{ij}	Cost, distance between i,j,
d_i	Customers demand
k , *VQ(k)*	Vehicles in the depots, capacity of the vehicle
Tx_{ijk}-1	if vehicle *k* finishes the task at customer *i*, then travels to *j*; 0 otherwise
Ty_{ik}	1, if vehicle k offers service i; 0 otherwise.

In the above equation (1) is to minimize the cost of the solution, eq. (2) denotes that every customer is allocated to individual route; eq. (3) is vehicle capacity constraints, equation (4) ensures that each customer is served once and in equation (5), vehicles should end with the initiated depots.

B. Applications of MDVRP

MDVRP has extensive possibility to resolve with the new era of Bio-inspired computing and in recent years only few Bio-inspired techniques were applied. Table 2 shows few algorithm and applications for MDVRP.

III. FIREFLY TECHNIQUE

Firefly technique is one of the swarm intelligence and a kind of stochastic bio-inspired metaheuristic that be able to apply for resolving NP-hard problems and societal existence of fireflies is not only committed for searching food and reproduction, but also to guard themselves from predators. These combined processes are closely related with the flashing light performance that functioned as the main biological basis for emerging the firefly algorithm. Fireflies can produce light inside the body where its flashes are unique patterns for an individual kind of firefly, and it is emitted through chemical procedure called bioluminescence and it is utilized to fascinate the mating partners for interaction [9, 13].

Table 2 BIC algorithms and applications for MDVRP

Problem	*Algorithms*	*Applications*
MDVRP	• ACO • PSO • Genetic • Memetic • Artificial Immune • Hybrid Mosquito host-seeking •	• Fast Food Supply • Garbage Disposal • Distribution of oil • Disaster/Emergency relief • Cash Distribution • Supply chain Management • Bus fleet scheduling • Grocery Distribution • Logistics & Transport of Biomass for Electricity Production

Firefly algorithm has two important benefits than other techniques firstly, it can mechanically subcategories its populace, where the native attractiveness is stronger compare to longer distance attraction and secondly, firefly technique can vastly pact with non-linear, multi-modal optimization problems efficiently and logically. Firefly technique is modest in proviso of intricacy and simple to implement and every time it is focused on attractiveness among every firefly in the group also this makes time consume for large optimization problems. The rules of Firefly algorithm is described in the following steps [8, 16, 17, 19].

1. Each firefly fascinates all fireflies (unisex) with its weaker flashes regardless of their gender
2. Next, attraction is proportionate to the brightness of the fireflies and it is inversely proportionate to the distances between the fireflies. For any two flashing fireflies, the weaker firefly would attract optimistic one
3. Further, attraction and brightness decrease as the distance among the fireflies increases. Finally, Fireflies will start moving randomly if no brighter one is found within the attractiveness limit.

In this work where α is set as 0.2, β as 1 and γ as 1, population of the firefly is set as 5 and generation as 500 with average of 30 runs. The formulation of firefly algorithm as follows: The light intensity of every firefly is expressed in the eq 6. The light intensity differs with distance monotonically and exponentially where LI_0 signifies new light intensity and it

Retrieval Number: J11320881019/19©BEIESP
DOI: 10.35940/ijitee.J1132.0981119
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-11, September 2019

$$LI(dr) = LI_0 e^{-\gamma dr^2} \quad (6)$$

can be inversed as $\frac{LI_0}{1+\gamma dr^2}$. γ signifies static light absorption and β_0 is the attractiveness. The attractiveness is a comparative quantity of the light and it can be any monotonically reducing function as in equation 7,

$$A\beta(dr) = \beta_0 e^{-\gamma dr^2} \quad (7)$$

and it is quicker to compute *1/ (1+dr²)* than an exponential function and if required it can be suitably substituted by $\frac{\beta_0}{1+\gamma dr^2}$. Distance among fireflies *i* and *j* at dx_i, dx_j is calculated by Euclidean distance [17].

$$dr_{ij} = \sqrt{(dx_i - dx_j)^2 + (dy_i - dy_j)^2} \quad (8)$$

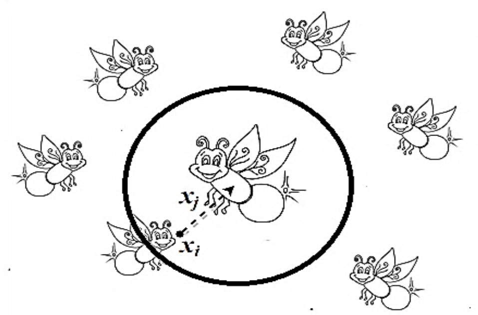

Fig. 2 Schematic of firefly's migration

$$x_i = x_i + \beta_0 e^{-\gamma dr^2 ij}(x_j - x_i) + \alpha * (rand - 0.5) \quad (9)$$

Equation (9) determines the firefly's movement [12, 19].

IV. ENHANCED FIREFLY TECHNIQUE TO SOLVE MDVRP

To construct MDVRP problem, assignment phase and routing phase are taken into account.

A. Assignment Phase

The assignment phase is performed by computing the distance matrix and customers are grouped to the nearby depots using equation 8. The main aim of the problem is to reduce the overall travelling distance as well as vehicles. In figure1, 2 depots namely depot1 and depot2, every customer is allotted to individual depot by using equation 8. During this stage, a few customers are recognized as marginal (borderline) cases, where customers are located approximately halfway between nearest and it's second nearest depots as mentioned in the fig.3. In this stage, inter-depot method allows for exchanging of customer from a depot to alternative depot which benefits to progress the outcomes.Inter-depot method permits a list of customers to re-assign from one depot to another depot which is named as swappable-customer list in which it comprises of marginal customers. Further, whichever depot is within a certain distance (Dis) from a given customer, that customer will be included into swappable-customer list. Every customer in this list accommodated with candidate list which is the customers set of probable depot assignments and list for a given distance (cu, depi) denotes the distance between the customer to the depot, and (minz) is the minimum distance from the customer

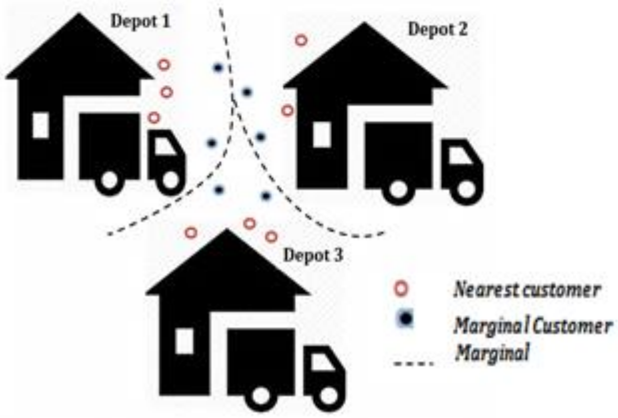

Fig. 3 Illustration of Marginal customers

to the nearest depot and bound is a stable value [3] which is given in equation 10.

$$\frac{distance(cu, dep_i) - minz}{minz} \le Bound \quad (10)$$

Then the customers are organized in descendent sequence and allocated to the vehicles with vehicle capacity constraints which are based on superior value of light intensity of the firefly. Further, the customers will be organized in arbitrary sequence and allotted to their relevant depots if there are no brighter ones found.

B. Routing Phase

Routing phase calculated by C&W procedure and improved by inter-route and intra-route method. In MDVRP routing phase, each customer should be visited exactly once along with vehicle capacity constraint, duration length constraints with customers' demand satisfaction. Clarke and Wright (C&W) in the year 1964 [12, 14, 7] proposed savings heuristic and it is the first algorithm that is used to solve VRP. By incorporating 2 routes, total means of transport, distance or cost of the solutions can be reduced. The steps adopted to calculate the saving cost method are as follows.

a. First, calculate the distance matrix.

b. Saving value between the customer *i* and *j* is calculated as equation (13) where $S_{ij,}$ should be non-negative, $C_{ij,}$ represents the distance among location *i* and *j*.

c. Finally, categorize the saving cost in descendent sequence and combine the route if the constraints fulfills.

The cost savings attained via connecting two routes into single route as shown in figure.4. In figure.4 (a) *i* and *j* customers are visited on distinct routes and alternate to this it is possible to visit the two customers on the similar route shown in figure 4 (b).

Since, transport outlays are specified, the savings that outcome from driving the route in figure 4 (b) instead of the two routes in figure 4 (a) can be computed [14]. Representing transport outlay among locations *i* and *j* as c_{ij}, the total transport outlay T_a in figure 4 (a) signifies

Retrieval Number: J11320881019/19©BEIESP
DOI: 10.35940/ijitee.J1132.0981119
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

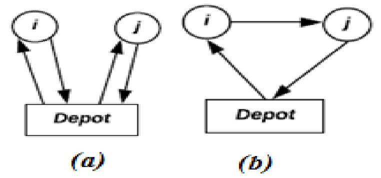

Fig 4 Illustration of C&W procedure

$$T_a = C_{depot\ i} + C_{i\ depot} + C_{depot\ j} + C_{j\ depot} \quad (11)$$

Similarly, transportation cost T_b in fig.5 (b) is

$$T_b = C_{depot\ i} + C_{ij} + C_{j\ depot} \quad (12)$$

By merging two routes the resultant S_{ij} savings can be attained where,

$$S_{ij} = C_{depot\ i} + C_{depot\ j} - C_{ij} \quad (13)$$

The results achieved by C&W technique enhanced by applying inter-routing and intra-routing in sequence to progress the solution quality. Exchanging customers in the similar route in the depot is called intra-route progression. For example, a random customer is eliminated from its current location and added into the best possible location within the same route as illustrated in figure 5 where --→ denotes arcs deleted and → denotes arcs created.

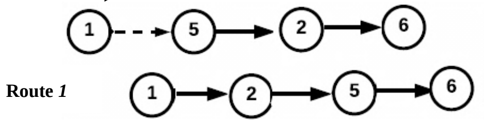

Fig. 5 Single Move (Intra-route operator)

In Intra-route two-opt operator, in each step two ends are eliminated and two new ends are reconstructed in the similar route, and this process occurs until no further improvement can be done or until a feasible move is found without violating the given condition and this kind of enhancements is purely reliant on the selection of customers and its distance in order to get possible solution [1].

Exchanging customers from single route to alternative route in the depot is said to be inter-route progression. In inter-routing more than one route is involved, a customer is removed from single route further inserted into alternative route. In sequence to reduce the distances the removed customer is added in finest location as shown in figure 6 (a) and similarly two

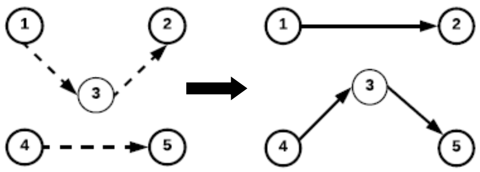

Fig. 6 (a) Single Move (inter-route operator)

customers can be eliminated from two dissimilar routes, and every eliminated customer is added in the other route as shown in figure 6 (b). In Inter route two opt operator; single end/edge is eliminated from two dissimilar routes then relinks the first node of the end with a second node of the second end/edge and compute the distance travelled by individual vehicle and total cost of the solutions. By using improvement operators as explained above if current result is found superior than the recent best; keep the current result as finest solution.

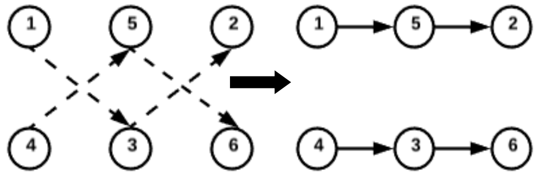

Fig. 6 (b) 1-1 interchange (inter-route operator)

The routing process is considered when the route duration and vehicle capacity conditions are not violated while appending the customer to the present route and it is sustained till every customer has been allotted exactly to single route and when a route is initiated if a customer is inconsistent to the exceeding constraints that could not be inserted to current route due to satisfy the objective needs. The proposed technique was tested using Cordeau benchmark dataset of MDVRP problem and the outcomes were compared with ACO [16], PSO [4], GA[3], GVNS[15], GC[3], IWD[2], NGA [6], GAPR[3] algorithm. The results obtained by using enhanced firefly algorithm are compared with the metaheuristics and heuristic algorithms and by testing them on MDVRP instances ranging from class I to class II instances.

V. RESULTS AND DISCUSSION

The performance of enhanced firefly algorithm in solving Cordeau benchmark instances of MDVRP problem is analyzed. In class I cases, the total customer varies from 50–100, vehicle capacity from 60-200. In the Class II cases, the total customer varies from160–360 whereas vehicle capacity ranges from 60-500. The experimental results executed for 30 runs. Table 4 and 5 shows the result of enhanced firefly technique and includes the total vehicles available, vehicle capacity, demands, vehicle utilization as well as capacity utilization percentage and gap percentage for class I and class II instances. The gap percentage, vehicle and capacity utilization are calculated as follows

$$Gap\ \% = \frac{FFO-BK}{BK} * 100 \quad (12)$$

$$Vehicle\ Utilization\ \% = \frac{AO}{MO} * 100 \quad (13)$$

$$Capacity\ Utilization\ \% = \frac{TD}{VU*VC} * 100 \quad (14)$$

FFO is the best optimum distance achieved by enhanced firefly technique, BK is the best known, AO stands for actual output and MO means maximum output. In capacity utilization the term TD refers total demand, VU refers vehicle used and VC refers vehicle capacity.

Retrieval Number: J11320881019/19©BEIESP
DOI: 10.35940/ijitee.J1132.0981119
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

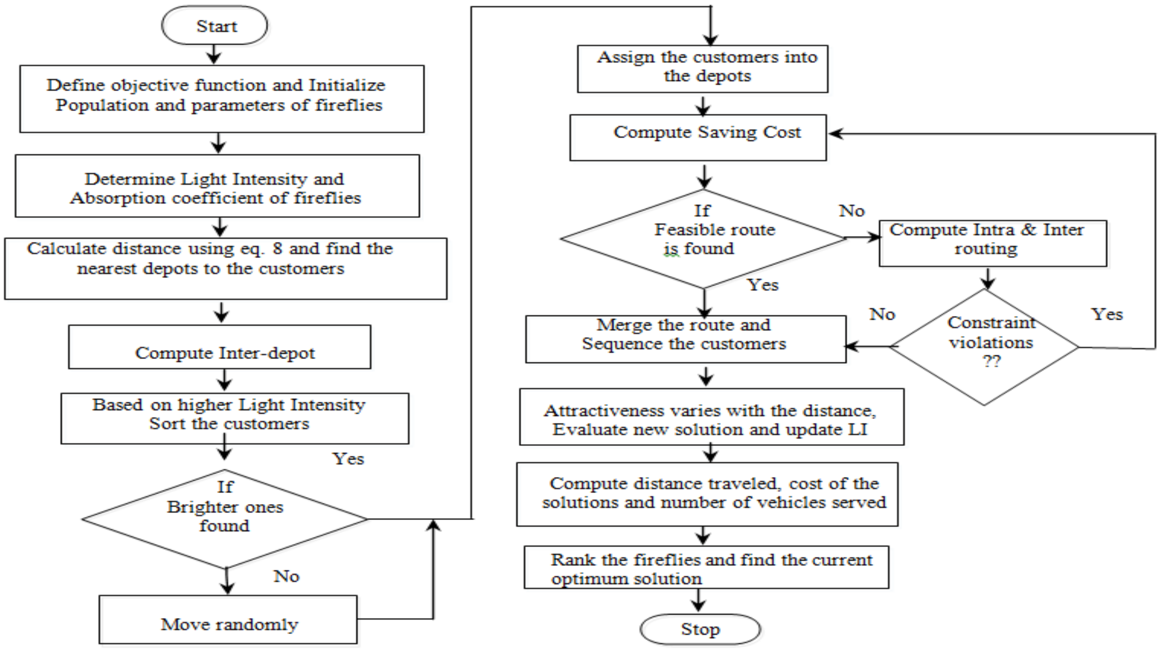

Fig.7 Flowchart of solving MDVRP using Enhanced Firefly Technique

Table 3 Classification of Cordeau benchmark instances

Instance	No. of Customers	No. of Depots	Vehicle Capacity	Total Demand	Durations	Optimal Results		GAP %	Utilization %	
						Best known	nhanced Firefly echnique		Vehicle	Capacity
P08	249	2	500	12106	310	4437.68	4440.98	0.07	89	97
P09	249	3	500	12106	310	3900.22	3901.34	0.03	72	93
P10	249	4	500	12106	310	3663.02	3676.04	0.36	81	93
P11	249	5	500	12106	310	3554.18	3560.42	0.18	87	93
P15	160	4	60	864	∞	2505.42	2528.52	0.92	80	90
P16	160	4	60	864	200	2572.23	2586.34	0.55	80	90
P17	160	4	60	864	180	2709.09	2709.09	0.00	80	90
P18	240	6	60	1296	∞	3702.85	3727.05	0.65	77	94
P19	240	6	60	1296	200	3827.06	3838.72	0.31	80	90
P20	240	6	60	1296	180	4058.07	4058.07	0.00	80	90
P22	360	9	60	1944	200	5702.16	5801.17	1.74	80	90
P23	360	9	60	1944	180	6095.46	6141.19	0.75	82	88

Table 4 Results of Enhanced Firefly Algorithm for Class I instances

Class Name	Instance Name	Complexity	Customer range	Vehicle capacity
Class I	P01, P02, P03, P04, P05, P06, P07, P12, P13, P14	Less	50-100	60-200
Class II	P08, P09, P10, P11, P15, P16, P17, P18, P19, P20, P22, P23	High	160-360	60-500

Retrieval Number: J11320881019/19©BEIESP
DOI: 10.35940/ijitee.J1132.0981119
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

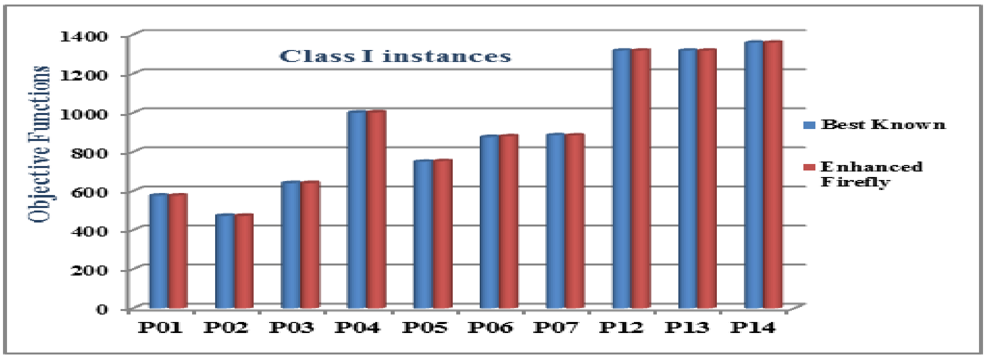

Fig. 8 Results of Enhanced Firefly Algorithm for Class I instances

Table 5 Results of Enhanced Firefly Algorithm for Class II instance

Instance	No. of Customers	No. of Depots	Vehicle capacity	Total Demand	Duration	Optimal Results		GAP %	Utilization %	
						Best known	Enhanced Firefly Technique		Vehicle	Capacity
P01	50	4	80	777	∞	576.87	576.87	0.00	69	88
P02	50	2	160	777	∞	473.53	473.54	0.00	63	97
P03	75	5	140	1364	∞	641.19	641.19	0.00	73	89
P04	100	2	100	1458	∞	1001.59	1002.84	0.12	94	97
P05	100	2	200	1458	∞	750.03	753.62	0.48	100	91
P06	100	3	100	1458	∞	876.50	884.52	0.92	89	91
P07	100	4	100	1458	∞	885.80	885.80	0.00	100	91
P12	80	2	60	432	∞	1318.95	1318.95	0.00	80	90
P13	80	2	60	432	200	1318.95	1318.95	0.00	80	90
P14	80	2	60	432	180	1360.12	1360.12	0.00	80	90

Table 6 Comparative results for Class I instances

stance	Best known	Enhanced Firefly	ACO	PSO	GA	GVNS	IWD	NGA	GC	GAPR
P01	576.87	576.87	607.66	576.86	622.18	582.34	576.87	580.85	591.73	600.63
P02	473.53	473.54	493.34	484.28	480.04	473.87	473.53	473.53	463.15	480.04
P03	641.19	641.19	670.82	645.16	706.88	641.19	643.58	680.2	694.49	683.15
P04	1001.59	1002.84	1021.36	1001.49	1024.78	1008.66	1006.19	1010.25	1062.38	1034.59
P05	750.03	753.62	750.72	750.26	785.15	752.97	754.84	753.36	754.84	778.01
P06	876.50	884.52	902.91	876.50	908.88	878.02	879.71	878.88	976.02	916.71
P07	885.80	885.86	907.55	887.11	918.05	890.46	885.82	893.6	976.48	922.83
P12	1318.95	1318.95	1318.95	1318.95	1318.95	1318.95	1324.34	-	1421.94	1318.95
P13	1318.95	1318.95	1318.95	1318.95	1318.95	-	1324.05	-	1318.95	1318.95
P14	1360.12	1360.12	1365.69	1365.68	1365.69	-	1369.38	-	1360.12	1365.69

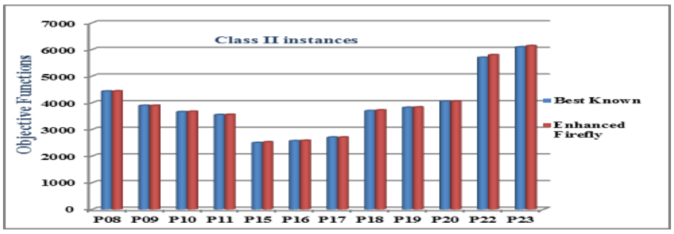

Fig. 9 Results of Enhanced Firefly Algorithm for Class II instances

Retrieval Number: J11320881019/19©BEIESP
DOI: 10.35940/ijitee.J1132.0981119
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

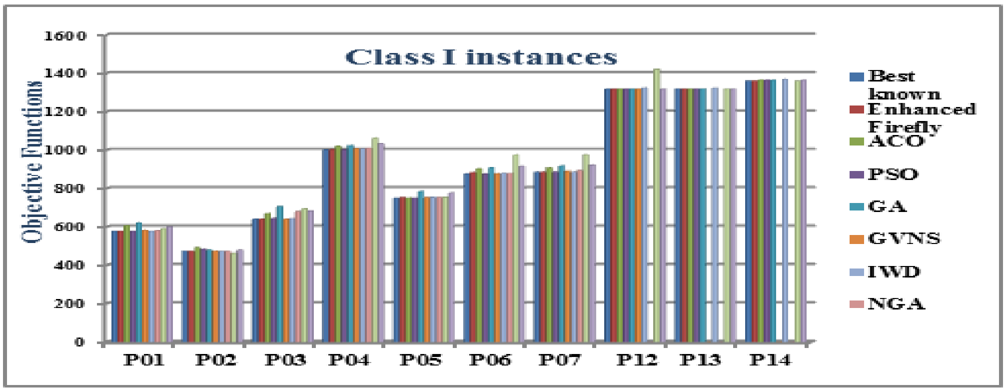

Fig. 10 Class I comparative results

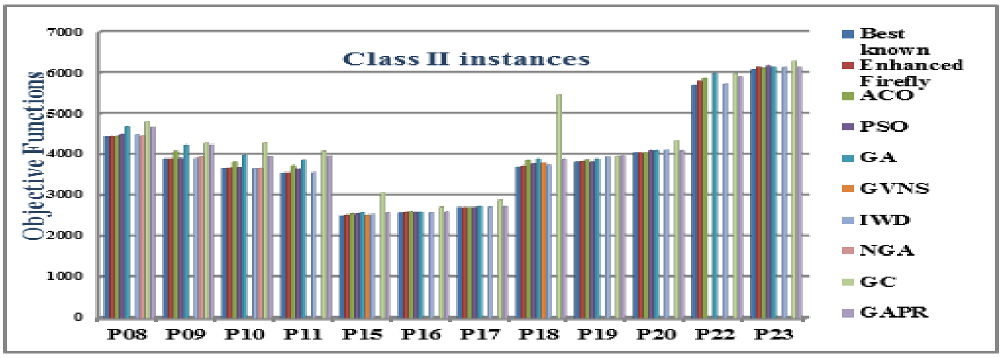

Fig. 11 Class II comparative results

VI. SUMMARY AND FUTURE WORK

Table 7 Comparative results for Class II instances

Instances	Best known	Enhanced Firefly	ACO	PSO	GA	GVNS	IWD	NGA	GC	GAPR
P08	4437.68	4440.98	4449.65	4500.15	4690.18	-	4492.39	4453.86	4812.52	4672.56
P09	3900.22	3901.34	4085.51	3913	4240.08	-	3910.62	3950.28	4284.62	4243.74
P10	3663.02	3676.04	3825.73	3693.4	3984.78	-	3663.29	3668.87	4291.45	3953.24
P11	3554.18	3560.42	3732.36	3648.95	3880.65	-	3565.17	-	4092.68	3962.17
P15	2505.42	2528.52	2554.12	2551.45	2579.25	2525.85	2539.25	-	3059.15	2579.25
P16	2572.23	2586.34	2606.22	2587.87	2587.87	-	2580.91	-	2719.98	2596.83
P17	2709.09	2709.09	2709.09	2708.99	2731.37	-	2721.28	-	2894.69	2731.37
P18	3702.85	3727.05	3871.01	3781.04	3903.85	3796.04	3743.12	-	5462.9	3897.22
P19	3827.06	3838.72	3884.81	3827.06	3900.61	-	3946.61	-	3956.61	3972.80
P20	4058.07	4058.07	4058.07	4097.06	4097.06	-	4109.06	-	4344.81	4097.06
P22	5702.16	5801.17	5873.41	5772..23	5984.87	-	5736.01	-	5985.32	5913.59
P23	6095.46	6141.19	6124.67	6183.13	6145.58	-	6134.91	-	6288.04	6145.58

In the last two decades, metaheuristics has evolved as the utmost encouraging path of research for the VRP variants, especially Bio-inspired metaheuristics. The current research

has focused on MDVRP problem which plays a vital role in day-to-day life especially in commercial activities. The proposed enhanced firefly technique is found to be potentially suitable and effective in solving MDVRP for most of the Cordeau benchmark instances. The MDVRP instances are classified into class I, II cases. In class I cases P01, P02, P03, P07, P12, P13, P14 obtained optimal solution whereas P04, P05 and P06 achieved near optimal solution. In the class II instances the enhanced firefly technique achieved optimum and near optimum results for most of the cases.

Instance P08, P11, P15, P16, P18 and P20 achieves better solution compared to other well-known algorithms. The

proposed technique has achieved the optimality in cost of the solutions, distance, number of vehicles and demand satisfactions and moreover none of the customers are omitted. The gap percentage occurred less than 1% to the BK solutions except instance P22. Table 6 and 7 show the comparative results for class I and class II instances. The outcomes of enhanced firefly technique were very promising and it is competent and effective in problem solving and this technique could effectively be utilized to the other combinatorial optimization as well. In forthcoming work, planned to widen MDVRP by tackling variants with further conditions and this research work is intensive towards applying enhanced firefly technique for real time scenario and it has been planned to work towards uncertainty and dynamic aspects of VRP variants. In future some of the best performing methods are intended to be applied for VRP variants to evaluate their problem solving effectiveness. The gap percentage of the

enhanced firefly technique can be decreased by using various approaches and capacity and vehicle utilization can be improved further.

Retrieval Number: J11320881019/19©BEIESP
DOI: 10.35940/ijitee.J1132.0981119
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

REFERENCES

1. A.Layeb, M.Ammi, S.Chikhi. 2013. A GRASP Algorithm Based on New Randomized Heuristic for Vehicle Routing Problem. Journal of Computing and Information Technology. Vol.1, pp: 35–46. (doi:10.2498/cit.1002085).
2. AE.Ezugwu, F.Akutsah, MO.Olusanya, AO.Adewumi. 2018 March. Enhanced intelligent water drops algorithm for multi-depot vehicle routing problem. PLoS ONE. Vol.13 (3), pp: 1-32. (doi:10.1371/journal.pone.0193751).
3. B. Ombuki-Berman, Hanshar F.T. 2008 September. Using Genetic Algorithms for Multi-depot Vehicle Routing. In: Pereira F.B., Tavares J. (eds) Bio-inspired Algorithms for the Vehicle Routing Problem, Studies in Computational Intelligence. Vol.161, pp: 77-99. (doi:10.1007/978-3-540-85152-3_4).
4. B.Yao, B.Yu, P.Hu, J.Gao, M.Zhang. 2016 July. An improved particle swarm optimization for carton heterogeneous vehicle routing problem with a collection depot. Ann Oper Res. Vol. 242(2), pp: 303–320.
5. Benoit Crevier, Jean-FrançoisCordeau, Gilbert Laporte. 2007 January. The multi-depot vehicle routing problem with inter-depot routes. European Journal of Operational Research. Vol.176, pp.756-773. (doi:10.1016/j.ejor.2005.08.015)
6. C.Prasad. 2014 May. A Nomadic Genetic Algorithm Approach with GMOUX Crossover for Multi Depot Vehicle Routing Problem. International Journal of Advanced Research in Computer Science and Software Engineering. Vol. 4(5), pp: 1-9.
7. C.Prins. 2009. A GRASP × Evolutionary Local Search Hybrid for the Vehicle Routing Problem. In: Pereira F.B., Tavares J. (eds) Bio-inspired Algorithms for the Vehicle Routing Problem. Vol.161, pp:35-53. (doi:10.1007/978-3-540-85152-3_2).
8. Iztok Fister, Iztok Fister, Xin-She Yang, Janez Brest. 2013 December. A comprehensive review of firefly algorithms. Swarm and Evolutionary Computation. Vol.13, pp.34-46. (doi:10.1016/j.swevo.2013.06.001)
9. Jacques Renaud, Gilbert Laporte, Fayez F. Boctor. 1996 March. A tabu search heuristic for the multi-depot vehicle routing problem, Computers & Operations Research, Vol.23(3), pp.229-235. (doi:10.1016/0305-0548(95)O0026-P).
10. Jairo R. Montoya-Torres, Julián López Franco, Santiago Nieto Isaza, Heriberto Felizzola Jiménez, Nilson Herazo-Padilla. 2015 January. A literature review on the vehicle routing problem with multiple depots. Computers & Industrial Engineering. vol.79, pp.115-129. (doi:10.1016/j.cie.2014.10.029).
11. M.Filipec, D.Skrlec, S.Krajcar. 1997 October. Darwin meets computers: new approach to multiple depot capacitated vehicle routing problem. IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation. Vol.1, pp. 421 - 426. (doi: 10.1109/ICSMC.1997.625786).
12. Nikhil, Amandeep Sharma, Navdeep Minhas, Arshdeep Singh. 2019 July. A Modified Winding Function Theory and Firefly Algorithm based Optimization for Diagnosis of Eccentricity in Induction Motors. International Journal of Innovative Technology and Exploring Engineering. Vol.8(9), pp:2869-2876.
13. R.Yesodha, Amudha.T. 2019 May. An Improved Firefly Algorithm for Capacitated Vehicle Routing Optimization. Amity International Conference on Artificial Intelligence (AICAI), Dubai, United Arab Emirates. IEEE. Publisher. pp. 163-169. (doi: 10.1109/AICAI.2019.8701269)
14. R.Yesodha, T.Amudha. 2015 October. A Study on Bio-Inspired Metaheuristics for Solving Vehicle Routing Problem. Indian Journal of Science and Technology. Vol.8 (25), pp. 85-93. (doi:10.17485/ijst/2015/v8i25/80042)
15. Sinaide Nunes Bezerra,Sérgio Ricardo de Souza,Marcone Jamilson Freitas Souza. 2018 April. A GVNS Algorithm for Solving the Multi-Depot Vehicle Routing Problem. Electronic Notes in Discrete Mathematics. Vol.66, pp: 167-174. (doi:10.1016/j.endm.2018.03.022).
16. Siva Krishna Reddy, Pothula Sujatha, Prasad Koti. 2019 July. Firefly Algorithm based Map Reduce for Large-Scale Data Clustering. International Journal of Innovative Technology and Exploring Engineering. Vol.8(9), pp:1505-1511.
17. T.Ralphs, L.Kopman, W.Pulleyblank, L.E Trotter. 2003 January. On the capacitated vehicle routing problem. Math. Program, Ser. B, Vol. 94(2-3), pp. 343-359. (doi:10.1007/s10107-002-0323-0).
18. Xin-She Yang, Xing shi He. 2013 August. Firefly Algorithm: Recent Advances and Applications. Int. J. Swarm Intelligence. Vol.1 (1), pp. 36--50. (doi:10.1504/IJSI.2013.055801).
19. Yudong Zhang, Lenan Wu, and Shuihua Wang. 2013 January. Solving Two-Dimensional HP Model by Firefly Algorithm and Simplified Energy Function. Mathematical Problems in Engineering. pp: 1-9. (doi:10.1155/2013/398141).

AUTHORS PROFILE

Mrs. R.Yesodha pursing her Ph.D. at Bharathiar University in the field of Biologically Inspired computing and she has awarded Master of Philosophy in computer science from Bharathiar University in 2013. Her research area interests include Bio-inspired Computing, Optimization problems and focused upon real-world research problems. She has published a number of papers related to her field in reputed journals and conferences. She is an active member of IEEE, ISCA and IAENG.

Dr.T.Amudha is an Associate Professor at Bharathiar University and she has Professional experience of 18+ years. Her research area is focused on Agent-Based Computing, Nature Inspired computing and Biologically Inspired computing. She has completed her MCA from Bharathidasan University in 1999 with distinction, Master of philosophy from Bharathidasan University in 2005 and Ph.D. from Bharathiar University in 2013. She is a member of IEEE, CSI and ACM. She is a reviewer for various highly reputed journals and she has published various publications in national and international journals and presented scientific papers across the world.