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Depot Location Analysis for Capacitated Vehicle Routing Problem: A Case Study of Solid Waste Management

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Abstract— **This paper presents an optimized solution to locate a depot on multiobjective instances of Capacitated Vehicle Pouting Problem (CVRP) using firefly algorithm (FA). The main objective of a depot location routing problem (LRP) is to obtain the optimal position to locate a depot in other to serve a set of customers ensuring the minimum possible total travelled distance across a search space. In this paper, the instances of solid waste management were created to simulate a real-life scenario of CVRP. This was formulated into a multiobjective optimization problem considering various depot positioning. Firefly Algorithm (FA) which is a metaheuristic technique was employed to navigate the travel path towards an optimal depot placement for solving the LRP model. Various depot positions which includes random, optimized, centered and eccentric were evaluated. Results showed that the optimized depot positioning approach obtained the best depot position as against the other possible positions. Results when compared with two metaheuristics approach Unified Hybrid Genetic Search (UHGS) and Iterated Local Search with Set Partitioning (ILS-SP) presented in literature also showed that, optimized depot positioning obtained the best results and FA can compete effectively with other metaheuristics approaches.**

Keywords- Optimized Depot, Firefly Algorithm, Solid Waste Management, Depot Position, CVRP, Logistics Problems

I. INTRODUCTION

There is an eminent problem in general logistics of demand whether people, goods or waste which questions the best position to locate a bus station or a depot [1]. One of the failures in logistics either in arrival times or inadequate distribution across a distribution dimension is bound by the determinant of the depot location. The increase in time for vehicle transition contributes to an increase in CO2 emission into the atmosphere. In Waste Management, environment quality is the extent to which the condition of an environment, relative to the requirements of human need is rapidly deteriorating with concerns to solid waste management, which increases CO_2 emissions in the atmosphere and inevitably gives rise to global warming [2]. Waste management, has over the years been modified and improved using various technologies due to increase in solid waste as a result of the growing population [3]. The problem of waste management is in optimizing the best possible route to pick up waste (waste generation center), take them to a dumpsite (waste collection center) and then to a recycle factory (waste recycling center) as shown below.

Fig. 1 shows the conceptualized framework that describes the stages of waste management. The bins in the waste generation center denotes the container that holds the quantity of the waste (demand). This quantity also doubles as the number of customers and can be further referred to as nodes. It is assumed that there is one bin to a customer. This is the first point of contact by the vehicles to pick up the demand from one node to another. When the pickup is completed, the vehicles proceed (logistics A) to the depot all of these processes is where the model of [1] was applied. At this stage, the demand is collected from various vehicles and put together to deliver (logistics B) to the recycle factory for processing into various products e.g. fertilizers and other by-products to benefit mankind. Several models of CVRP have been applied to real-life problems, such as transportation logistics and waste management. A number of optimization methods which are based on graph theory have been applied to solve the CVRP problems in the past. The major challenges with the methods are their enormous dependent on high computational resources. Recently, researchers have shifted attention towards using metaheuristics algorithms as a better alternative to solve graph problems including the CVRP. Though, the focus of this paper is on investigating various positioning of depot for efficient implementation of CVRPs, we optimized the CVRP model using one of the widely used metaheuristics algorithm called Firefly algorithm. This helps to decide the appropriate position to locate the waste collection center within the search space.

It is important to note that, there is no standard or any empirical techniques available for selecting a suitable metaheuristic algorithm for suitable optimization problem. This is due to the popular theory, called the No-Free Lunch theorem which state that, no single metaheuristic algorithm has the capability to solve all optimization problems better than others. However, in selecting any of these algorithms for solving any optimization problem, the ideal thing is to first study extensively, the success of such algorithm on similar optimization problems reported in literature. Thereafter, a careful study of the biology phenomenon on which the concept of the metaheuristic's algorithm was inspired. This will help to establish a direct relationship between the behavior of such biology phenomenon and practical optimization problem. For this reason, we selected Firefly Algorithm (FA) for our proposed CVRP model. The FA amongst other metaheuristics algorithms is relatively easy to implement and has few parameters to select [4-5]. Again, the attraction of a firefly towards a brighter firefly can be likened to the CVRP based waste management model, where the vehicle is constrained to move towards a bin that has the best cost.

The contributions of this paper are highlighted as follows:

- We first created a CVRP scenario using waste management as a case study. We implemented a benchmark scenario that consisted of 35 sample datasets of waste management.
- We proposed a novel depot location strategy called the optimized placement. In this case, the optimization tool is allowed to determined the best position for locating the depot while simultaneously implanting the vehicle routing.
- We implemented three state of the art depot positioning, namely, Random, Centered and Eccentric. These positioning strategies was benchmarked against the novel Optimized placements as a meaning of validation.
- We have implemented all the positioning strategies using MATLAB and optimize the vehicle routing using firefly optimization algorithm.

The rest of the paper is organized as follows: Section II provide insight on the state-of-the-art research in CVRP. Methods and theoretical information are provided in section III. Discussion on the various positioning strategies are presented in section IV. Results personation and discussion are given in section V. Conclusion and recommendation are given in section VI.

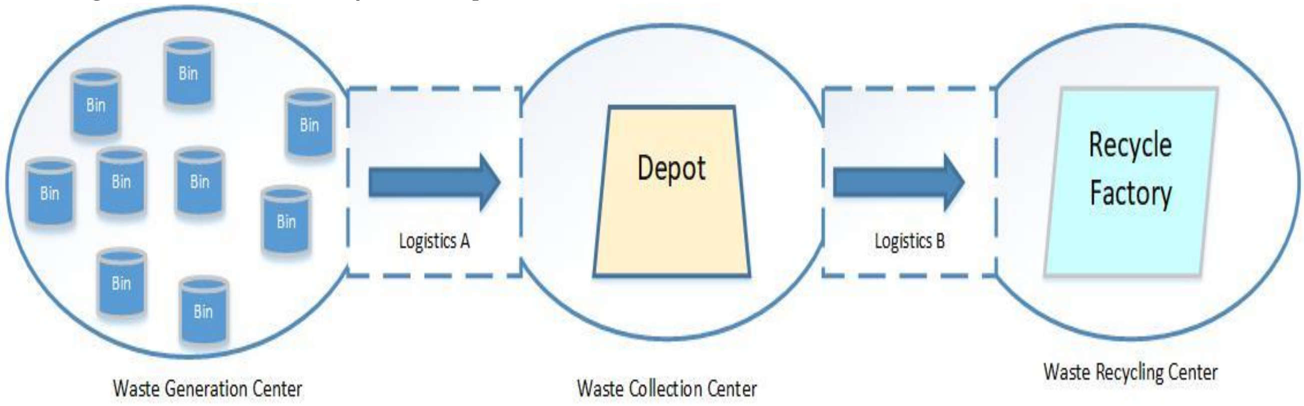


Fig. 1 Stages of Waste Management

II. STATE OF THE ART

This section discuses the literature relevant to VRP and the methods of solutions. For example, [8] presented an attendant home delivery embedded with time slot management. The customers were mapped with their respective geographical region. The expected travel time between customers who visited different zones at the same time were computed using different approaches. Two different problem-solving approaches were described and considered demand clustering to reduce travel cost. In the first approach, the expected cost of a particular assignment of time slot was estimated using a continuous approximation. The initial assignment was then optimized using an iterative greedy heuristics algorithm. In the second approach, an Integer Programming (IP) model was implemented with an approximate cost delivery. Ref [25] optimized a CVRP based fuel consumption model using a string based simulated annealing. The proposed algorithm was developed based on hybrid exchange rule that mitigated the problem of fuel consumption in the CVRP. The simulation results showed that, a better fuel consumption was obtained when computational experiments on 27 well-known CVRP benchmark instances was carried out, and the fuel consumption CVRP (FCVRP) achieved a 5% reduction on the fuel consumption compared to the normal CVRP model. In [22], a Mixed-Integer Linear Programming (MILP) was used to proposed a green vehicle routing problem (G-VRP). Two, algorithms were proposed for solving large problem instances: the modified Clarke and Wright Savings (MCWS) heuristic algorithm and density-based clustering algorithm (DBCA). The DBCA was employed to discover clusters of arbitrary shapes in spatial distance database, like, satellite images, x-rays images etc. Also, two tour improvement techniques which includes across tour vertex exchange and within-tour edge were design for the GVRP. This can be applied to in series once a tour is constructed. The techniques consider a set of vehicle tours that optimize total distance travelled to serve a fleet of customers considering stops at AFSs in route plans. This is to eliminate the risk of running out of fuel. Numerical results showed that, their proposed techniques performed better compared to exact solution methods. Ref [34] proposed a hybrid algorithm involving Particle Swarm Optimization

(PSO) and Genetic Algorithm (GA) for solving CVPR problem with fuzzy demands. This is developed by using a change-constraint model which uses the idea of a particle's best solution and the global best solution in the PSO in combination with the crossover and mutation in the GA. Hence, the study used GA to improve the performance of PSO and used fuzzy variables to deal with the uncertain parameters in developing the CVRP model. Ref [28] proposed a hybrid algorithm for some group of VRPs with homogeneous fleet. This hybrid algorithm consists of an iterated local search heuristic with a set partitioning ILS-SP. The paper model an interaction between a solver and a metaheuristic algorithm, to sole a MILP problem. An efficient scheme of dynamically controlling the size of the SP models when solving large size instances was also developed. Thus, the proposed technique was used to solve the problem associated with vehicle routing problems, since it can handle large size instances. Simulation results showed that the proposed techniques can compete effectively with other heuristics approach. In [10], an architecture with an intelligent sensing algorithm for practical solid waste bin monitoring system. The monitoring application uses wireless sensor network in sensing solid waste data. The architecture is built on three levels smart bin, gateway and control station. The elementary concept is that the smart bin collects the status of the waste at any change occurrence then transmits the data to the server in real time via a gateway, hence the field test shows that the system has been able to monitor the real time bin status, that made it feasible to decide the payload of which bin to be collected and which not. This information can be used for waste collection planning, route optimization and collection cost. Ref [26] proposed a simultaneous facility location and VRP arising in health care logistics in the Netherlands. The major concern in the health care logistics, was to determine which lockers to open, from a group of possible locker locations and to create routes that visit the opened lockers and routes that visit the patients which are not covered by the opened lockers. This is will be done such that, the routes cost and the opening costs of the lockers are minimized. The simultaneous facility location and vehicle routing problem was used to mitigate the stated problem associated with the health care logistics. The heuristic approach was used to iteratively improve the solution by changing the set of opened lockers, updates the routes accordingly and applies a variable neighborhood search (VSN) algorithm to improve the routes. And the exact method based on branch and bound algorithm was used to mitigate the problem, which was compared with the proposed technique. The simulation results showed that, the proposed technique outperform the exact method which have proven to be extremely robust. Ref [35], presented a discrete firefly algorithm to solve a rich vehicle routing problem modelling a newspaper distribution system with recycling policy. To meet complex restrictions and constrained in such a problem, it has been modelled as a rich vehicle routing problem, which can be more specifically considered as an asymmetric and clustered vehicle routing problem with simultaneous pickup and deliveries, variable costs and forbidden paths. A benchmark of 15 instances was proposed and using a discrete firefly algorithm which outperformed two classic meta-heuristics in comparison. The principles, first is to treat each town or cities as separate units then vehicles do not only have to meet the delivery of customers but to collect at each point and finally a period where the service is performed taking into considerations prohibited routes in a direction. Ref [18], presented a heuristic for tactical time slot management in a periodic vehicle routing problem. The tactical problem occurred when a time slot schedule for delivery service over a given planning horizon was selected in each zone of a geographical area. This, then makes the heuristic search which was able to evaluate each of the scheduling selection by constructing a corresponding tactical routing plan of minimum cost based on the demand and service time. The tactical problem was solved using the three-phase approach of the heuristic, where the issue of periodic vehicle routing problem was mitigated and then a repair phase and a final improvement phase where the vehicle routing problem with time windows was also mitigated for each period of planning horizon. The proposed technique provided a solution to the tactical problem that decomposes the problem into a PVRP and a number of VRPTWs. Uchoa et al., in [27], proposed a new set of benchmark instances ranging from 100 to 1000 customers, designed in order to provide a more comprehensive and balanced experimental setting using exact and heuristic methods. The methodology was to consider an efficient neighborhood-based method, the iterated local search-based metaheuristic algorithm and a population-based method, the unified hybrid genetic search. The ILS is coupled with a integer programming solver over a set partitioning (SP) formulation, which seeks to create new solutions based on known routes from the past local optimums, while the UHGS implements a continuous diversification by modifying the objective during parents and survivors selection to promote not only good but also diverse solutions. Both methods achieved quality results although the UHGS outperformed the ILS but for instances containing few customers per route the ILS produced solutions of generally higher quality. For instances with large number of customers per route, the ILS exhibits slower convergence and generally leads to solutions of lower quality. Ref [17] proposed a modified PSO algorithm in a capacitated vehicle routing problem model in determining an accurate waste collection and route optimization solution. A threshold waste level and scheduling concepts are applied to the model using various datasets. The acquired results from the datasets provides a competitive solution on efficiency on the travel distance, waste collection efficiency and tightness as compared with previous heuristics used.

From the literature reviewed, it is evident that researchers have paid little attention determining the best position to locate a depot and that there are various methods developed to solve the VRP scenario for large- and small-scale instances. Thus, this paper will develop a model to optimally locate the best depot position and also use a single technique to solve large and small case scenarios putting into consideration the capacity of the vehicle and the demand of the customer.

III. METHODS

In this section, we discourse the methods employed to analyze the effectiveness of the different depot positioning.

A. Firefly Algorithms (FA)

This algorithm is used to improve the route within the search space. It is modelled after the behavior of the flashing characteristics and movement of the Firefly [4]. The Firefly algorithm (FA) is in the classification of the luminous inspired insect algorithms which all belong to the Biological Inspired Algorithms.

In this study, extracting the rules of the FA, the ideology of the algorithm in relationship to CVRP are as follows: The nodes have high mobility due to the versatility in attractiveness variations, hence, the search space is explored more efficiently i.e. The best route will be more efficiently identified and exploited for vehicles to deliver to customers. The brightness is proportional to the attractiveness. i.e. a less bright firefly will move towards a brighter one. Thus, considering the fitness at each stage of motion, for each iteration, the nodes move to get a better result dropping the previous result to be replaced and continues until the maximum iteration is reach where there are no brighter fireflies, it searches randomly. The nodes represent each firefly. Finally, all fireflies are considered as unisex, one firefly will be attracted to other fireflies regardless of their gender which means the nodes can be heterogeneous relating to vehicles and the customers and still function on the model.

The attractiveness of a firefly is determined by its brightness which is a function of the objective function. Usually, the brightness *I* at a location *x* can be chosen as $I(x) \alpha f(x)$. In a scenario where the light absorption coefficient γ is fixed, the light intensity *I* vary with the distance *r*, where I_0 is the original light intensity. To eliminate the singularity problem at $r=0$ in the expression I_s / r^2 where, I_s is source light intensity, the combined effect of both the absorption and inverse square law can be approximated using the Gaussian form [5].

$$I(r) = I_0 e^{-\gamma r^2} \tag{1}$$

The attractiveness β of a given firefly is relative, since its proportional to light intensity of a pre-established firefly [4, 6]. Thus, leads to a variation with the distance r_{ij} between firefly *i* and firefly *j*. Hence, with an increase in the distance from its source, there is a measurable decrease in the light intensity, and light, is absorbed in the transmission so the attractiveness will vary with the degree of absorption, where, β_0 connotes the attractiveness at $r=0$.

$$\beta(r) = \beta_0 e^{-\gamma r^m} \tag{2}$$

The distance between two fireflies *i* and *j* at x_i and x_j, is represented as the cartesian distance where x_{ik} is the *k*th element of the spatial coordinate *xi* of *i*th firefly [6].

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{3}$$

The movement of a firefly *i* which is attracted to a firefly *j* with higher attractiveness (brightness) is determined by equation (4).

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}(x_j - x_i) + \alpha(rand - \frac{1}{2}) \tag{4}$$

The second segment of equation (4) is due to the attraction while the third segment is randomization with α being the randomization parameter [7]. The pseudocode for implementing the standard FA is giving in Algorithm 1.

B. Location Routing Problem

The CVRP defines the optimum sequence of routes for a fleet of vehicles to serve a set of customers from a depot or multiple depots ensuring the vehicle capacity is not exceeded [8]. This description does not consider where the depot is actually located it only clarifies that there is a depot somewhere in the search dimension. Hence, the depot LRP.

The LRP is the optimal point to serve a given set of customers over a predefined number of routes by a sequenced number of vehicles where the total travel distance is minimized [9 - 12]. This optimal point involves location analysis with the underlying attention to a defined VRP which in this paper is the FA-CVRP model discussed in the work of [1] all constraints explained where taking into cognizance.

The basic concept of the LRP is to identify the best position to locate a depot. The decision on the routes and service to the customers is analyzed in [1]. To guide this decision on the location of the depot, certain constraints are taken into perspective to model the problem for a solution.

Assuming *N* is the number of customers, a nonnegative distance cost d_{ij} represents distance from bins i to j, where $i \neq j$. A set of homogenous vehicles $k = \{1, 2, ..., K\}$ is available at the depot to either collect or deliver demand as the case maybe Z is the number of depot, q is the quantity of demand at a customer point.

Algorithm 1: Pseudocode of FA algorithm

```
Initialize algorithm parameters
Randomly generate the initial positions of Fireflies
Compute the fitness of each initial fireflies
While; Stopping criterion do
    for each firefly i, do
        for every decision variable j, do
            Move fireflies to a brighter firefly
            compute fitness of updated positions
            if (update fitness<previous fitness) then,
                move update fireflies to previous fireflies
            end
            vary attractiveness wit distance r between fireflies
        end
    end
    obtain global best firefly after sorting
    obtain the fitness of the global best firefly.
end
```

A route is established by the summation of multiple links [1, 13-16]. A link is formed with the notation P_{ij}^k which moves from customer i through to customer j, by a vehicle *k*, where the decision variables are dependent of the vehicle capacity and the customer demand which are modelled as follows [1]:

$$P_{ij}^{k} = \begin{cases} 1, \textit{ if vehicle travels from customer i to j} \\ 0, \textit{ if otherwise} \end{cases} \quad (5)$$

The variables take only the integer (s) 0, 1 because the number of customers, vehicles and route cannot be a fraction,

$$P_{ij}^{k} \in \{0,1\},\ j = 0,1,2,...,N; k = 1,2,...,K \quad (6)$$

All vehicles begin and end at the depot i.e. each vehicle isn't used more than once,

$$\sum_{\substack{i=1 \\ j=1}}^{N} P_{\substack{ai \\ ja}}^{k} \le 1,\ k = 1,2,...,K \quad (7)$$

The vehicle must not be re-used, the inequality considers when a vehicle is also not being used at all, out of the pool of vehicles at the depot. When all vehicles are used, the expression will be an equal sign and a represents a potential depot location.

$$Y_a = \begin{cases} 1, \textit{if the depot is located at site a} \\ 0, \textit{if otherwise} \end{cases} \quad (8)$$

The number of depot locations is equal to a predetermined value [1, 14, 17-19]:

$$\sum_{a \in A} a Y_a = Z \quad a = 1,2,...,A \quad (9)$$

Each route is allocated to a single depot [1, 20-23]

$$\sum_{i \in I}^{N} \sum_{j \in J}^{N} d_{ij} P_{ij}^{k} = \sum_{a \in A} a Y_a \quad a = 1,2,...,A;\ i = 1,2,...,I; \quad j = 1,2,...,J;\ k = 1,2,...,K \quad (10)$$

Each route is served by only one vehicle [1, 17, 27]:

$$\sum_{i \in I}^{N} \sum_{j \in J}^{N} d_{ij} P_{\substack{ai \\ ja}}^{k} \le K \quad a = 1,2,...,A;\ i = 1,2,...,I; \quad j = 1,2,...,J;\ k = 1,2,...,K \quad (11)$$

Demand is assigned to customers only in a route including both depot and customers [1, 2-3, 24-27].

$$\sum_{i \in I}^{N} \sum_{j \in J}^{N} d_{ij} P_{\substack{ai \\ ja}}^{k} \le \sum_{\substack{i \in I \\ j \in J}} q_{ij} \left(\sum_{\substack{i=0 \\ j=0}}^{N} P_{ij}^{k} \right) Y_a \quad a = 1,2,...,A;\ i = 1,2,...,I; \quad j = 1,2,...,J;\ k = 1,2,...,K \quad (12)$$

A depot can serve a set of customers when it is established [1, 25, 27-30]:

$$-N + \sum_{i \in I}^{N} \sum_{j \in J}^{N} P_{\substack{ai \\ ja}}^{k} \le Y_a \quad a = 1,2,...,A;\ i = 1,2,...,I; \quad j = 1,2,...,J;\ k = 1,2,...,K \quad (13)$$

The total demand must be less than the Depot capacity [1, 27, 31-34]

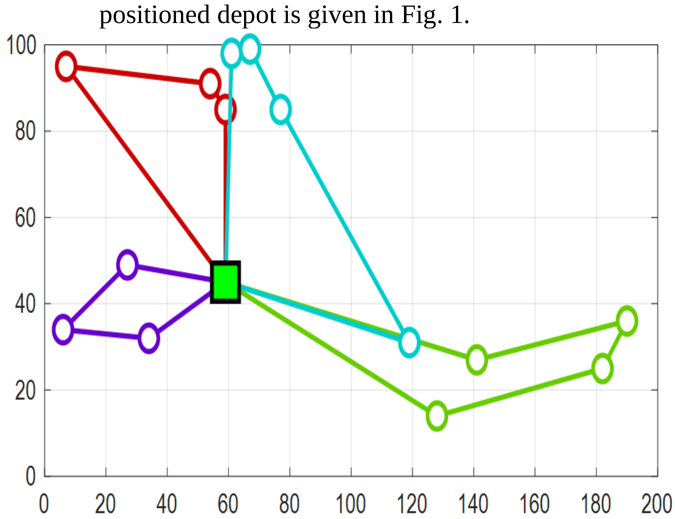
$$\sum_{i \in I}^{N} \sum_{j \in J} q_{ij} \left(\sum_{\substack{i=0 \\ j=0}}^{N} P_{ij}^{k} \right) \le q_T Y_a \quad a = 1,2,...,A;\ i = 1,2,...,I; \quad j = 1,2,...,J;\ k = 1,2,...,K \quad (14)$$

In the implementation of these constraints the parameters considered are the vehicle capacity, number of vehicles, demand, number of customers, customer positioning, route size, route distance, number of depots and the depot location.

IV. Depot Location Modeling

For this LRP one depot is considered. The location of the depot is pivotal in achieving the set objective of the routing scheme. Various depot positions are sampled across all the Instances. An Instance in CVRP are arrangement or scenarios formulated based on the certain parameters, they are standard point of references which can be used for comparison. The different positions considered are:

1. Random (R) – the depot is located at an arbitrary point on the search space (x, y). There is no empirical or systematic approach that guides the decision for this location. However, the depot should be positioned such that the total cost which is the collective distance across all the vehicle pickup points is minimal A typical scenario of a randomly positioned depot is given in Fig. 1.



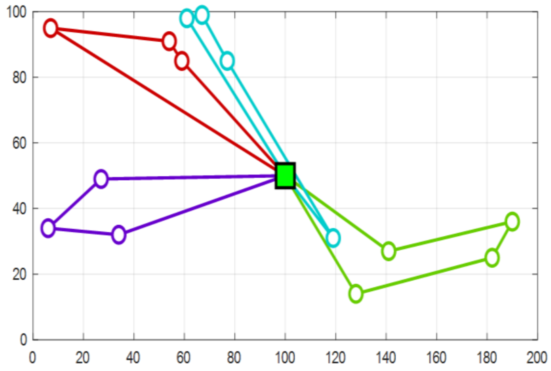
A. Instance A-n26-k4
Fig. 1: A Random Positioned Depot

Fig 1 shows a snippet of randomly positioned depot of a CVRP model. The Instance A-n26-k4 depicts a depot, four (4) route and twenty-five (25) pick-up locations scenarios for the solid waste management system, where the depot is positioned in the search space at random. This number of routes and customer locations are generic for the other samples explaining the various depot positions. Similar randomly positioned depot was implemented for the other scenarios considered in this report.

2. Central (C) – in this case, the depot is positioned at the centre of search dimension. The search space is a 100X200, thus, the depot is positioned at a coordinate given as

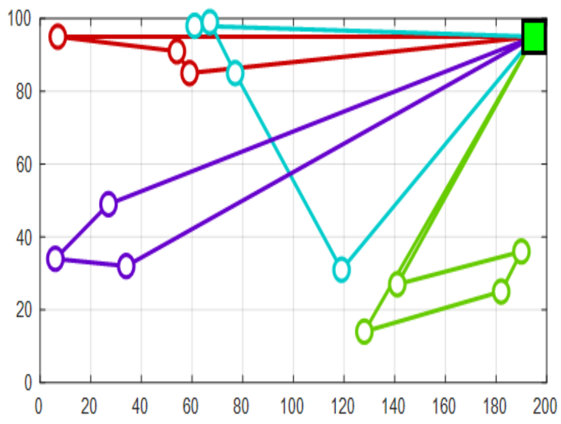
$$D_{\sup} = (x, y) \tag{15}$$

Where x is the coordinate in x-axis and y is the coordinate in y-axis whose values are selected as (100, 50) Fig. 2, shows the snippet of this scenario.



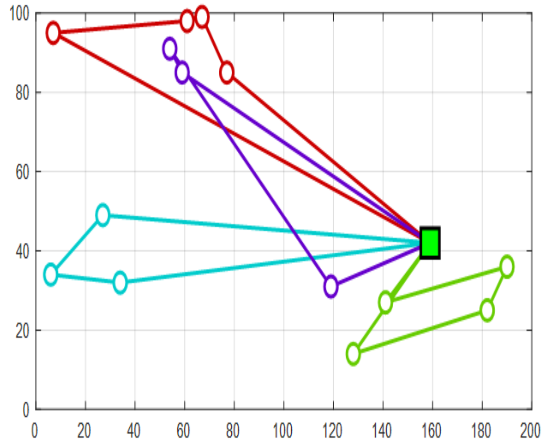
B. Instance A-n26-k4
Fig. 2: A Central Positioned Depot

3. Eccentric (E) – the position of the depot is considered to be located at any of the edges of the search space, x is the coordinate in x-axis and y is the coordinate in y-axis whose values are selected as (195, 95). The snippet of the eccentric positioned depot is shown in Fig. 3.



C. Instance A-n26-k4
Fig. 3 An Eccentric Positioned Depot

4. Optimized (O) – the position (x, y) on the x and y axis on the search space is decided by the algorithm. The search space is explored for the best possible location to fix the depot, relative to the pick-up locations, in order to serve the given set of customers, assuming the customer locations are fixed. The difference between this position and the random (R) position is that in (R) there is no search done and any arbitrary point is just utilized.



D. Instance A-n26-k4
Fig. 4: An Optimized Position of a Depot

Fig. 4, shows the depot position actualized for the instance. The various routes also represent various path taken by different vehicles. From the pictorial scenario above in Fig 4, it can even be visually observed that the locations through which the vehicles move on the route are closer to the depot, which will turn out to have a shorter travelled distance considering all the constraints.
The simulation parameters showing the range of values used to achieve the results for both the Solid Waste Management are quantified in the given Table 1.

Table 1: Simulation Parameters

SN	Parameters	Values	Units
1	Number of customers, *N*	2 - 10	--
2	Number of Vehicles, *V*	11 - 100	--
3	Capacity of vehicle, *Q*	100 - 400	kg
4	Capacity / Quantity of demand, *q*	10	kg
5	Travelled distance, *d*	20 - 1500	km
6	Iteration (SWM)	500	--

In developing the Optimized routing scheme for the depot LRP model, the parameters vehicle capacity (Q), number of customers (N) which correspond to the number of fireflies, number of vehicles (V) which correspond to the search dimensions and the quantity of load (q) were initialized. The parameters of the FA algorithm which are the initial customer points (i), the next customer point (j), number of iterations, and population were also initialized. Prior to the evaluation of the fitness of these initial positions, the various positions of the depot are initialized. The edges of all the nodes (customers) are identified and sampled on different points in the search space. The entire process was then evaluated over a number of iterations continuously until the maximum number of iterations is reached and the firefly with the overall best position is taken as the optimum solution.

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The entire process was then evaluated over a number of iterations continuously until the maximum number of iterations is reached and the firefly with the overall best position is taken as the optimum solution. The pseudocode for implementing the CVRP model is given in Algorithm 2

Algorithm 2: Pseudocode of CVRP Implementation

```
Input: Customers, Route, Demand, Vehicle Capacity etc.
Compute Saving list Using FA
Rank saving list
Calculate the serving cost
while: Stopping Criteria
    Calculate route link
    Calculate the link distance using FA
    if (better solution) then,
        update new serving list obtained by FA
        if (better feasible solution) then,
            Update the best feasible list.
        end
    end
    Rank savings list
end
Output (Best Cost, Best Ffirefly Position, Depot Coordinate)
```

V. RESULTS AND DISCUSSION

The simulation was conducted in MATLAB R2019b environment, on a computer with Intel Core i3 @ 2.00GHz Processor with 4GB RAM. The main objective of this study is to obtain an optimized solution to locate a depot on multiobjective Instances using firefly algorithm (FA) taking into cognizance the constraints and parameters as earlier explained to achieve a minimum travelled distance across a search dimension. It is assumed that a reduction in the total route distance, connotes a reduction in cost and time.

Table 2, shows the actual values used in formulating the thirty-six instances featured in [17] and the total travel distance under the depot positions. The table also expresses the TWL (threshold waste level) that informs the model on the percentage quantity of demand in the bin. From the table, the green colors represent the best result obtained by any of the depot position strategies. The yellow color is used when more than one positioning strategies obtain the same result for a particular data set. In order to differentiate each positioning strategies, the columns holding their respective results are colored differently. From this Table 2, N represents the number of customers and the number of vehicles is represented by V.

A. *Optimized Depot Position*

There are thirty-six instances used for the solid waste management model, out of which the various depot positions where tested to determine which gave a result with the lowest total route distance.

Table 2 shows that, out of the 36 instances, the optimized depot position has 9 times best results, the eccentric depot position has 5 times best results, the central and random depot placement each have 2 times best results each. This description explains the positions with better results in the improved category.

The figure below interprets the number of times each depot position obtained the same results with another depot positions. The summation of the frequency of a position constitute the numbers of the draw column in Table 2.

$$CD \cap ED = 2$$

$$OD \cap ED = 2$$

$$OD \cap CD = 4$$

$$ED \cap RD = 2$$

$$OD \cap RD = 1$$

Fig. 5: Intersection of various depot position

Fig. 5, provides a breakdown on which depot had achieved same travelled distance as another.

This gives a figurative caption on the *Draw* column in Table 2. It is seen that the central and eccentric position obtained same result twice. The optimal and eccentric position also had same result twice. The optimal and central depot positions achieved the same result four times. Twice, the eccentric and randomly placed depot obtained same result, only the optimal and random depot position had same total travelled distance once.

The column *Draw* in Table 2 explains the summary of the above result in Fig 3 which is the total number of times each position had same results with one or more other positions but not all. The optimized depot position had same results 7 times with another depot position, 6 times, both the eccentric and central position shares same result with other depot positions and the randomly placed depot has the same result 3 times.

To further buttress the graphical representation of analysis, the output is shown in Fig. 6.

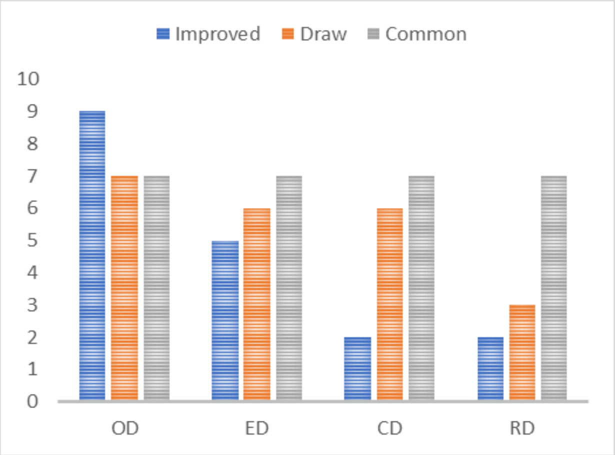


Fig. 6: Plot of Depot Position against Frequency of Result

Fig. 6, shows the plot of the various depot positions against the number of result outcomes of the 36 Instances. This gives a pictorial view of Table 2. It further describes a *Common* result for all the positions (the random, optimized, central and eccentric) acquired the same total travelled distance seven times. The figure also details that the optimized depot placement gives the highest number of best results over the other positions, after which the eccentric, then the centered depot position and randomly placed depot position.

Table 2. Results of Depot Positions

Position	Improved	Draw	Common	Total
OD	9	7	7	36
ED	5	6	7	36
CD	2	6	7	36
RD	2	3	7	36

B. Comparism of Depot Location Trategies

To further evaluate the performance of the developed model under different depot positions, the percentage improvement of the best result obtained by each depot position was determined against the total number of instances. The figure below is based on Table 3.

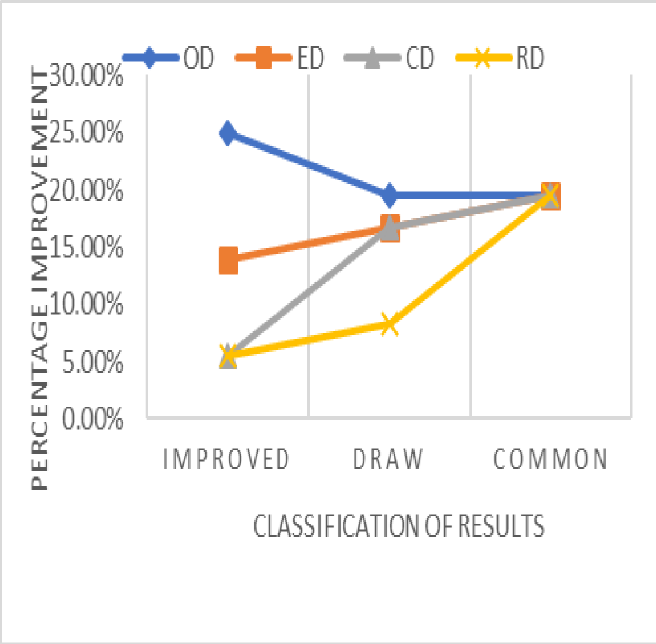


Fig. 7: Line Chart of the Depot location Improvement

The line chat in Fig 7 shows the plot percentage improvement against the classification of the results. It details the depot positions with the percentages of the improved result, the percentage of draw and the common results. Of the 36 instances, this shows that there is a 5.56% improvement positioning the depot at the center or at a random (arbitrary) location. A 13.89% improved result is obtained when the depot is at an eccentric location (refer to Fig 2.3). For an optimal position, there is a 25% improvement when the depot position is being decided by the firefly algorithm within the search space. For the depot positions that obtained the same travelled distance similar to another, a 19.944% same result is obtained by the optimal depot position, both the eccentric and centrally placed depot each had 16.67% and the randomly place depot had an 8.33%. All four positions had same travelled distance obtaining a 19.44% result of the 36 instances.

From the performance of each depot positioning, the extract from Table 3 and Fig. 8 informs the below figure. The figure below provides a graphical description on the advantaged result of the optimal depot position over the other positions.

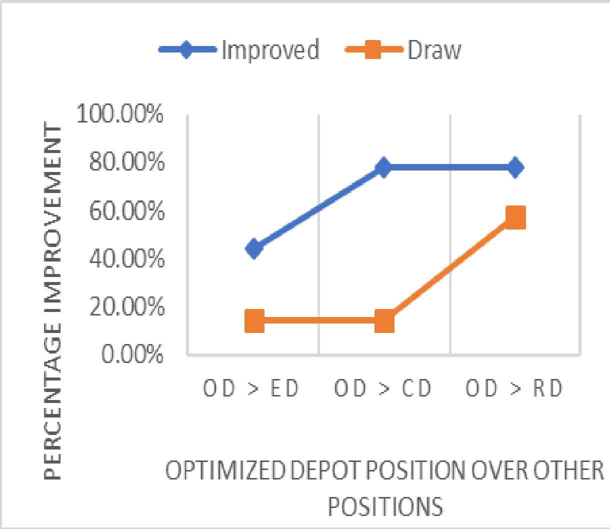


Fig. 8: Improvement of the optimal depot placement

8 shows the plot of the percentage improvement of the optimized depot position over the other three depot positions i.e. the advantage of the optimal depot position (OD) as against the eccentric depot position (ED), the centered depot position (CD) and the random depot position (RD). The detail obtained in the chart shows the OD has a 44.44% improvement over the eccentric position. There is also a 77.78% improvement in results over the centered and random positions.

Also, for the draw, the OD has more same results with either of the other three depot positions, than each of them with other positions. This means the OD achieved more uniform results than either of three depot positions with a 14.29% over the eccentric and centered positions have with either of the two depot positions. The OD also has a 57.14% more draw results than the RD.

Table 3. Result of FA on CVRP Model for Instances of Solid Waste Management

No.	Datasets	Capacity of vehicle (unit)	Capacity of bin (unit)	TWL (%)	N	V	FA			
							OD	**CD**	**ED**	**RD**
1	A-n33-k5	100	10	0	32	5	**323**	**322**	**322**	**324**
2	A-n29-k5			60	28	5	**347**	**352**	**355**	**345**
3	A-n26-k4			70	25	4	**332**	**340**	**338**	**336**
4	A-n22-k4			75	21	4	**305**	**305**	**305**	**305**
5	A-n18-k3			80	17	3	**304**	**309**	**315**	**309**
6	A-n13-k2			90	12	2	**219**	**219**	**219**	**219**
7	A-n46-k7	100	10	0	45	7	**364**	**363**	**353**	**364**
8	A-n39-k7			60	38	7	**364**	**359**	**365**	**370**
9	A-n29-k5			70	28	5	**346**	**347**	**347**	**354**
10	A-n23-k4			75	22	4	**306**	**308**	**306**	**309**
11	A-n19-k4			80	18	4	**303**	**302**	**301**	**302**
12	A-n15-k3			90	14	3	**235**	**235**	**235**	**235**
13	A-n60-k9	100	10	0	59	9	**377**	**377**	**381**	**383**
14	A-n42-k8			60	41	8	**349**	**349**	**348**	**349**
15	A-n39-k8			70	38	8	**356**	**357**	**356**	**361**
16	A-n32-k6			75	31	6	**296**	**296**	**300**	**297**
17	A-n30-k6			80	29	6	**344**	**346**	**343**	**343**
18	A-n20-k4			90	19	4	**286**	**286**	**287**	**287**

19	P-n40-k5	140	10	0	39	5	**340**	**334**	**329**	**335**
20	P-n35-k4			60	34	4	**347**	**345**	**365**	**353**
21	P-n33-k4			70	32	4	**334**	**352**	**342**	**338**
22	P-n26-k4			75	25	4	**333**	**333**	**333**	**333**
23	P-n19-k3			80	18	3	**266**	**266**	**266**	**266**
24	P-n13-k2			90	12	2	**192**	**192**	**192**	**192**
25	B-n78-k10	100	10	0	77	10	**397**	**400**	**405**	**401**
26	B-n55-k9			60	54	9	**362**	**364**	**370**	**363**
27	B-n44-k8			70	43	8	**363**	**364**	**362**	**364**
28	B-n28-k6			75	27	6	**341**	**341**	**340**	**340**
29	B-n22-k4			80	21	4	**302**	**312**	**304**	**304**
30	B-n12-k2			90	11	2	**111**	**111**	**111**	**111**
31	P-n101-k4	400	10	0	100	4	**489**	**493**	**508**	**519**
32	P-n82-k4			60	81	4	**422**	**427**	**423**	**422**
33	P-n71-k4			70	70	4	**436**	**436**	**464**	**446**
34	P-n63-k3			75	62	3	**446**	**453**	**451**	**424**
35	P-n56-k3			80	55	3	**427**	**420**	**411**	**424**
36	P-n34-k2			90	33	2	**192**	**193**	**183**	**190**

C. Comparative Analysis

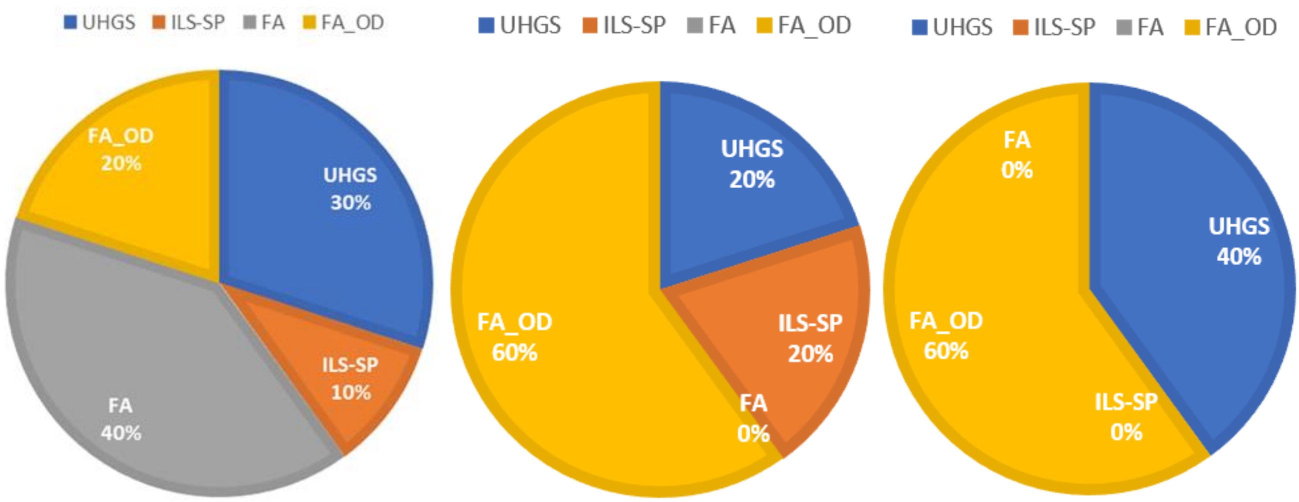
In order to verify the influence of FA on the optimized solution of the CVRP models, we compared the performance of FA with two state of the art algorithms (Unified Hybrid Genetic Search - UHGS and Iterated Local Search with Set Partitioning - ILS-SP), on some randomly selected new benchmark instances presented in [27]. The best values obtained for the selected instance using UHGS and ILS-SP was used for this comparison. For each depot location scenario (ED, CD and RD) implement in [27], 5 instances were randomly selected making a total of 15 instances. For every instance, we implemented FA on the Depot Position (DP) given in [27] and then, change the DP to OD. The results obtained using the FA on the selected instances considering the original DP in [27] and OD are given in the last two columns of Table 4. From this table, the values in bold-italics indicate a scenario where more than one algorithm obtained the same best results while the values in bold indicted a situation where only one algorithm obtained the best result for any of the instance by any of the algorithms. Note in Table 4, that *n* represent the number of customers, Q represents number of vehicles [27], and DP represents the type of depot positioning and FA_OD represent FA based Optimized Depot positioning. the algorithms were ranked based on their respective best results obtained for each instance. The best performing algorithm is ranked as 1 and the worst performing algorithm is ranked 4. If n number of algorithms obtained the same results, then, both algorithms are ranked the same. The result of the next algorithm is then ranked *n+1*.

Table 4: Comparative Analysis of FA based methods with UHGS and ILS-SP [27]

Instance Characteristics					Optimized Cost Using Metaheuristics				
No.	Datasets	n	DP	Q		UHGS [27]	ILS-SP [27]	FA	FA_OD
1.	X-n120-k6	119	ED	21	Best	***13,332***	***13,332***	13,943.05	14,499.78
					Rank	1	1	3	4
2.	X-n195-k51	194	CD	181	Best	***44,225***	***44,225***	44,726.65	44,723.09
					Rank	1	1	4	3
3.	X-n261-k13	260	ED	1081	Best	26,558	26,706	**25,658.28**	25,677.93
					Rank	3	4	1	2
4.	X-n275-k28	274	RD	10	Best	21,245	21,245	18,646.27	**16,468.82**
					Rank	3	3	2	1
5.	X-n294-k50	193	CD	285	Best	***47,190***	***47,190***	48,317.86	48,112.74
					Rank	1	1	4	3

6.	X-n313-k71	312	RD	248	Best	**94,093**	94,192	94,763.46	94,285.88
					Rank	1	2	4	3
7.	X-n401-k29	400	ED	745	Best	**66,243**	66,453	67,879.07	67,951.91
					Rank	1	2	3	4
8.	X-n513-k21	512	CD	142	Best	24,201	24,332	22,640.85	**22,609.63**
					Rank	3	4	2	1
9.	X-n548-k50	547	ED	11	Best	86,822	86,710	**81,525.71**	81.854.12
					Rank	4	3	1	2
10.	X-n586-k159	587	RD	28	Best	190,612	190,612	127,116.51	**122,475.17**
					Rank	3	3	2	1
11.	X-n613-k62	612	CD	523	Best	59,778	60,229	60,592.29	**58,264.91**
					Rank	2	3	4	1
12.	X-n670-k130	669	RD	129	Best	**146,705**	147,045	150,698.41	148,492.75
					Rank	1	2	4	3
13.	X-n733-k159	732	CD	25	Best	136,366	136,832	133,851.93	**132,811.68**
					Rank	3	4	2	1
14.	X-n801-k40	800	ED	20	Best	73,587	73,830	69,951.58	**72,997.65**
					Rank	3	4	1	2
15.	X-n1001-k43	1000	RD	131	Best	72,742	73,776	45,835.70	**44,121.75**
					Rank	3	4	2	1
					Average Rank	**2.20**	**2.73**	**2.60**	**2.13**
					Final Rank	**2**	**4**	**3**	**1**

It can be observed from Table 4 that, both UHGS and OD using FA, obtained the best positioning in 6 and 7 out of the 15 benchmark instances respectively. Also, the ILS-SP obtained the best results in 3 of the instances while the FA obtained the best result in two instances. Though, ILS-SP obtained the best result in 3 instances, these results were jointly obtained with UHGS for X-n120-k6, X-n195-k51 and X-n294-k50 instances. In terms of ranking the performance of the algorithm, the final rank indicates that firefly algorithm implemented on optimized depot positioning performed best on the selected instances. The overall performance of the other algorithms UHGS, FA and ILS-SP are ranked 2, 3 and 4 on the entire instances respectively. This results also demonstrate the superior feasibility of OD when compared with the other positioning strategies. To further justify this claim, we separated the positioning strategies into their respective categories and compared the results independently with OD strategy. Fig. 9, shows the % comparative analysis of OD strategy using FA against the other positioning strategies.



a.) ED positioning with FA_OD b.) CD positioning with FA_OD c.) RD positioning with FA_OD

Fig 9: Comparative Analysis of CVRP Algorithms

The bar charts in Fig. 9, shows that, except in ED positioning where the FA 40% best performance in the instances, it could not obtain best results for any of the instances in the other positioning strategy. Hence, contributing 0% in the bar chart label b and c in Fig 9. The UHGS algorithm obtained the best result in 30%, 20% and 40% of the instances considering ED, CD and RD positioning respectively. The ILS-SP obtained the best result in 10%, 20% and 0% for the ED, CD and RD positioning respectively. However, when the positioning strategies was changed to OD for each positioning strategies and optimized by FA (FA-OD), the % of the best results obtained on each case were 20%, 60% and 60% for ED, CD and RD cluster of instances respectively.

VI. CONCLUSION AND RECOMMENDATIONS

In this paper, we proposed a novel depot location strategy called the Optimized Depot (OD) positioning and analyze its feasibility with three other positioning strategies; RD, CD and ED. Simulation shows that, OD has more improved results and has more same results than the rest of the other depot positions. This will give a better route navigation leading to a more reduced total route distance and reduced cost inevitably with an improvement of 44%, 78% and 78% over the eccentric, center and random positions respectively. This explains that the human eye, is not best to give a random location for a depot to be placed just by mere taking into cognizance of the environmental layout and the customer distribution spread. This further informs us that the algorithm used to determine the best location is substantive. Hence, the optimized position determined by the FA is the optimal depot position to achieve the minimum total travelled distance. Several simulations were performed using MATLAB R2019b simulation environment. Results when compared with Iterated Local Search Set Partitioning (ILS-SP) and Unified Hybrid Genetic Search (UHGS) on a randomly selected instances from [27], showed that this approach is very effective in solving CVRP of different cases. Results also showed that OD is the best positioning strategies even on the randomly selected instances from [27]. For future research, modelling the time windows to the customer availability, considering the effect of variable positions of depot and hybridizing FA with other algorithms such as smell agent optimization (SAO), PSO, SOS etc. for improved performance can be considered.

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REFERENCES

[1] O. M. Zion, M. B. Mu'azu, A. E. Adedokun, A. T. Salawudeen & A. I. Bello (2018), Optimized Model Simulation of a Capacitated Vehicle Routing problem based on Firefly Algorithm. *Covenant Journal of Informatics and Communication Technology*, Vol. 6 (2), pp 33-50.

[2] Budzianowski, W. M. (2016). A review of potential innovations for production, conditioning and utilization of biogas with multiple-criteria assessment. *Renewable and sustainable energy reviews, 54*, 1148-1171.

[3] Moh, Y. C., & Manaf, L. A. (2014). Overview of household solid waste recycling policy status and challenges in Malaysia. *Resources, Conservation and Recycling, 82*, 50-61.

[4] Yang, X.-S. (2009). *Firefly algorithms for multimodal optimization.* Paper presented at the International symposium on stochastic algorithms.

[5] Arora, S., & Singh, S. (2013). The firefly optimization algorithm: convergence analysis and parameter selection. *International Journal of Computer Applications, 69*(3).

[6] Yang, X.-S. (2010). Firefly algorithm, stochastic test functions and design optimisation. *International Journal of Bio-Inspired Computation, 2*(2), 78-84.

[7] Sayadi, M., Ramezanian, R., & Ghaffari-Nasab, N. (2010). A discrete firefly meta-heuristic with local search for makespan minimization in permutation flow shop scheduling problems. *International Journal of Industrial Engineering Computations, 1*(1), 1-10.

[8] Agatz, N., Campbell, A., Fleischmann, M., & Savelsbergh, M. (2011). Time slot management in attended home delivery. *Transportation Science, 45*(3), 435-449.

[9] Hadian, H., Golmohammadi, A., Hemmati, A., & Mashkani, O. (2019). A multi-depot location routing problem to reduce the differences between the vehicles' traveled distances; a comparative study of heuristics. *Uncertain Supply Chain Management*, *7*(1), 17-32.

[10] Al Mamun, M. A., Hannan, M., Hussain, A., & Basri, H. (2016). Theoretical model and implementation of a real time intelligent bin status monitoring system using rule based decision algorithms. *Expert Systems with Applications, 48*, 76-88.

[11] Archetti, C., Fernández, E., & Huerta-Muñoz, D. L. (2017). The flexible periodic vehicle routing problem. *Computers & Operations Research, 85*, 58-70.

[12] Augerat, P., Belenguer, J. M., Benavent, E., Corberán, A., Naddef, D., & Rinaldi, G. (1998). Computational results with a branch-and-cut code for the capacitated vehicle routing problem.

[13] Bianchessi, N., Drexl, M., & Irnich, S. (2017). The Split Delivery Vehicle Routing Problem with Time Windows and Customer Inconvenience Constraints, *Transportation Science,* Vol. 53 (2), pp 917-1212.

[14] Bocewicz, G., Banaszak, Z., & Nielsen, I. (2017). Delivery-flow routing and scheduling subject to constraints imposed by vehicle flows in fractal-like networks. *Archives of Control Sciences, 27*(2), 135-150.

[15] Bouzid, M. C., Haddadene, H. A., & Salhi, S. (2017). An integration of Lagrangian split and VNS: The case of the capacitated vehicle routing problem. *Computers & Operations Research, 78*, 513-525.

[16] Cattaruzza, D., Absi, N., Feillet, D., & González-Feliu, J. (2017). Vehicle routing problems for city logistics. *EURO Journal on Transportation and Logistics, 6*(1), 51-79.

[17] Hannan, M., Akhtar, M., Begum, R., Basri, H., Hussain, A., & Scavino, E. (2018). Capacitated vehicle-routing problem model for scheduled solid waste collection and route optimization using PSO algorithm. *Waste Management, 71*, 31-41.

[18] Hernandez, F., Gendreau, M., & Potvin, J. Y. (2017). Heuristics for tactical time slot management: a periodic vehicle routing problem view. *International Transactions in Operational Research*.

[19] Grangier, P., Gendreau, M., Lehuédé, F., & Rousseau, L.-M. (2017). A matheuristic based on large neighborhood search for the vehicle routing problem with cross-docking. *Computers & Operations Research, 84*, 116-126.

[20] Chen, A.-l., Yang, G.-k., & Wu, Z.-m. (2006). Hybrid discrete particle swarm optimization algorithm for capacitated vehicle routing problem. *Journal of Zhejiang University-Science A, 7*(4), 607-614.

[21] Christofides, N., & Eilon, S. (1969). An algorithm for the vehicle-dispatching problem. *Journal of the Operational Research Society, 20*(3), 309-318.

[22] Erdoğan, S., & Miller-Hooks, E. (2012). A green vehicle routing problem. *Transportation Research Part E: Logistics and Transportation Review*, *48*(1), 100-114.

[23] Fisher, M. L. (1994). Optimal solution of vehicle routing problems using minimum k-trees. *Operations research, 42*(4), 626-642.

[24] Gillett, B. E., & Miller, L. R. (1974). A heuristic algorithm for the vehicle-dispatch problem. *Operations research*, *22*(2), 340-349.

[25] Xiao, Y., Zhao, Q., Kaku, I., & Xu, Y. (2012). Development of a fuel consumption optimization model for the capacitated vehicle routing problem. *Computers & Operations Research, 39*(7), 1419-1431.

[26] Veenstra, M., Roodbergen, K. J., Coelho, L. C., & Zhu, S. X. (2016). *A simultaneous facility location and vehicle routing problem arising in health care logistics in the Netherlands*: *European Journal of Operational Research,* Vol. 268 (2), p 703-715.

[27] Uchoa, E., Pecin, D., Pessoa, A., Poggi, M., Vidal, T., & Subramanian, A. (2017). New benchmark instances for the capacitated vehicle routing problem. *European Journal of Operational Research, 257*(3), 845-858.

[28] Subramanian, A., Uchoa, E., & Ochi, L. S. (2013). A hybrid algorithm for a class of vehicle routing problems. *Computers & Operations Research, 40*(10), 2519-2531.
[29] Mahmoudi, M., & Zhou, X. (2016). Finding optimal solutions for vehicle routing problem with pickup and delivery services with time windows: A dynamic programming approach based on state–space–time network representations. *Transportation Research Part B: Methodological, 89*, 19-42.
[30] Penna, P. H. V., Afsar, H. M., Prins, C., & Prodhon, C. (2016). A Hybrid Iterative Local Search Algorithm for The Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations. *IFAC-PapersOnLine, 49*(12), 955-960.
[31] Subramanian, A. (2012). Heuristic, exact and hybrid approaches for vehicle routing problems. *Universidad Federal Fluminense. Tesis Doctoral. Niteroi*, 13.
[32] Kumar, S. N., & Panneerselvam, R. (2012). A survey on the vehicle routing problem and its variants. *Intelligent Information Management, 4*(03), 66.
[33] Hasle, G., & Kloster, O. (2007). Industrial vehicle routing *Geometric modelling, numerical simulation, and optimization* (pp. 397-435): Springer.
[34] Kuo, R., Zulvia, F. E., & Suryadi, K. (2012). Hybrid particle swarm optimization with genetic algorithm for solving capacitated vehicle routing problem with fuzzy demand–A case study on garbage collection system. *Applied Mathematics and Computation, 219*(5), 2574-2588.

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