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Optimized Model Simulation of a Capacitated Vehicle Routing problem based on Firefly Algorithm

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Abstract: This paper presents an optimized solution to a capacitated vehicle routing (CVRP) model using firefly algorithm (FFA). The main objective of a CVRP is to obtain the minimum possible total travelled distance across a search space. The conventional model is a formal description involving mathematical equations formulated to simplify a more complex structure of logistic problems. These logistic problems are generalized as the vehicle routing problem (VRP). When the capacity of the vehicle is considered, the resulting formulation is termed the capacitated vehicle routing problem (CVRP). In a practical scenario, the complexity of CVRP increases when the number of pickup or drop-off points increase making it difficult to solve using exact methods. Thus, this paper employed the intelligent behavior of FFA for solving the CVRP model. Two instances of solid waste management and supply chain problems is used to evaluate the performance of the FFA approach. In comparison with particle swarm optimization and few other ascribed metaheuristic techniques for CVRP, results showed that this approach is very efficient in solving a CVRP model.

Keywords: Optimization, CVRP, Firefly, Solid Waste Management, logistics.

1. Introduction

The rapid advancement in technologies have made logistics systems have become very important for revenue and budgetary considerations for government and its establishments, most importantly for companies in the private sector. The fact that anybody on the planet can be all around connected has prompted complex transport networks that are exceptionally requesting and are winding up progressively critical. Hence, an efficient logistic network will be beneficial to companies and relevant business operations. To highlight the importance of logistics in some sectors, like groceries delivery, online stores delivery of goods, waste management, intra-city public transportation, distribution costs can increase in the production price up to 70%. Thus, the need for vehicle routing become necessary.

Vehicle routing problem (VRP) define a class of optimization problems that involve optimizing itineraries of a fleet of vehicles. Researchers have over the years, developed a serious research interest in VRP due to its practical importance, as well as its complexity. The framework is employed in modelling an extremely broad range of logistic issues in various applications like, supply chain management, delivery services, public transportation, telecommunications and production planning.

However, because of the real-life applications and complexity of these problems, a class of optimization algorithms is used in obtaining optimal solutions. Although various VRP problems can be combined in the form of a multi-objective decision problem which consider providing convenient service distribution for demands between predefined points in the search space. The aim of this study is to maximize route optimization, minimizing the total route distance in a search space using a firefly based capacitated vehicle routing problem model (FFA-CVRP).

There are several variants to name a few are the

i. Capacitated VRP: the capacity of the vehicles is considered for the modelling of the objective function.
ii. VRP performing pickup and delivery simultaneously: models a payload being dropped off and collected at the same node point for all nodes.
iii. VRP with Mixed pickup and delivery: a payload is dropped and picked up but not necessarily from the same node.
iv. Multi depot VRP: more than one depot is considered in simulating this VRP also it can be combined with any other variants
v. VRP with access time windows: time limitations are being implemented in modelling this type of VRP hence, the deliveries are performed in pre-defined periods.

2. Methods

Instances are the arrangement or scenarios formulated by some attributes like number of customers, number of routes in some cases the route duration, the route distance all these will be discussed. Literature demonstrated that the number of point (including the depot) and the number of routes should reflect the naming and formulation of instances. An example of a naming nomenclature $E-n101-k8$ is an instance that has 1 depot, 100 customers and 8 routes. The series are usually named randomly by the authors. In the E series by (Nicos Christofides & Eilon, 1969) where locations are generated at random from a uniform distribution, some of the instances actually come from (Dantzig & Ramser, 1959) and (Gaskell, 1967) while some are modifications on the capacity suggested by (Gillett & Miller, 1974). For the M series, customers are grouped into clusters as an attempt to represent practical cases and some instances are modifications of the E series by considering increment in customers and capacity. For example, instances $M-n200-k17$ and $M-n200-k16$ differs only by the number of routes. These new instances were formulated because $M-n200-k16$ had tightness very close to 1 (0.995625) that finding any feasible solutions maybe difficult. However, the optimal solution of M-n200-k16 instance may costs less than the optimal solution of $M-n200-k17$ (Christofides *et al.*, 1979). The F series presents instances with data set from real-world applications, from grocery deliveries and delivery of goods to a gasoline service station (Fisher, 1994) etc. The A, B and P series by (Augerat *et al.*, 1998) proposed a situation where the customers and depots are randomly positioned in the A series and clustered in the B series while the demands are picked from a uniform distribution in both series. The P series are just modifications in the capacity and the routes of some instances in A, B and E. (N Christofides et al., 1979) defined a CMT benchmark set, which consists of modifications of some E and M series whereby the number of routes are not fixed. This set also has an addition of maximum route duration and service time values while the vehicles are assumed to travel at unitary speed.

Various algorithms have been applied to CVRP to name a few are: an ant colony algorithm building parallel routes other than sequential routes for its route optimization (Mazzeo *et al.*, 2004). A string model based simulated annealing algorithm is used in optimizing fuel consumption (Xiao *et al.,* 2011). A hybrid genetic algorithm and particle swarm optimization for solving a capacitated vehicle routing problem with fuzzy demand, the study used GA to modify the PSO with the hope of improving its performance and used fuzzy variables to deal with the uncertain parameters in developing the CVRP model. However, the concept of smart bin data was not implemented for the collection, yielding a limited experiment (Kuo *et al.*, 2012). A hybrid algorithm consisting of an iterated local search and a set partitioning formulation which could solve small size instances (Subramanian *et al.,* 2013). An integration of lagrangian spilt and variable neighborhood search (VNS) although its resolution is impractical for relatively large instances (Bauzid *et al.,* 2015). An architecture and intelligent sensing algorithm to detect solid waste at real time in a bin monitoring system which will contribute to solid waste collection, however the sensor sometimes produces inaccurate output data, due to the irregularities of the solid waste pattern (Al Mamun et al., 2016). A new set of Benchmark Instances proposed by (Uchoa et al., 2017) presents a more detailed and balanced experimental scenarios using iterated local search set partitioning (ILS-SP) and unified hybrid genetic search (UHGS) but the UHGS had poor quality solutions for instances of small sizes while the ILS-SP had slow convergence towards the solution for large instances. Furthermore, (Hannan et al., 2018) proposed modified PSO for a CVRP model for waste collection was initiated, the Instances were generated from the A, B and P series, a threshold waste level and scheduling concepts were implemented and however, the optimization technique used could not attain an optimal value for some instances.

2.1 Firefly Algorithm (FFA)

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. (XS Yang 2009). The Firefly algorithm (FFA) like the glow-worm swarm optimization algorithm (GISO) and the bioluminescent swarm optimization algorithm (BiSO) is in the classification of the luminous inspired insect algorithms which all belong to the Biological Inspired Algorithms. (Bo Xing and Wen-Jing Gao 2013). In this study, extracting the rules of the FFA, 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 distinction of light intensity and creation of the attractiveness are two critical issues in the FFA.

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 (Arora & Singh, 2013).

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

The attractiveness β of a given firefly is relative, since its proportional to light intensity of a pre-established firefly (Yang, 2010). 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 kth element of the spatial coordinate xi of ith firefly (Yang & Deb, 2010).

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

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

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

The second segment of equation (4) is due to the attraction while the third segment is randomization with α being the randomization parameter (Sayadi *et al.*, 2010)

2.2 CVRP

Capacitated vehicle routing problem defines the optimal set of routes for a fleet of vehicles to navigate from a depot to a specified set of customers ensuring the vehicle capacity is not exceeded. Figure 1 shows an instance of a capacitated vehicle routing problem. The figure contains 77 nodes (bins), with 1 depot located at the center of the grid across 10 routes (they are segmented in different color codes). Where a vehicle takes off from a depot, moves from one node to another and back to the depot, over a certain distance to form a route.

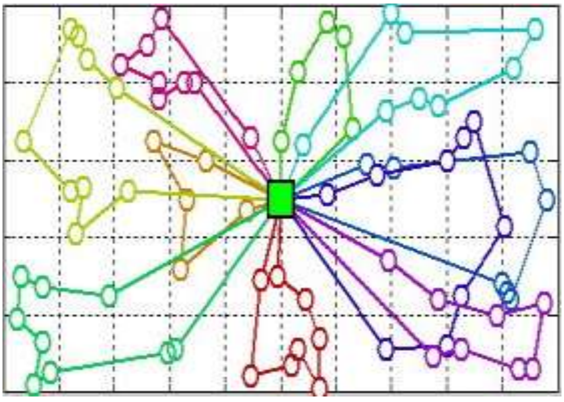


Figure 1. A Scenario of CVRP

The basic concept of VRP is to serve a set of customers to find the least travelled distance but when the capacity of the vehicle is factored, it becomes CVRP. The objective of this model is to develop an optimized routing scheme in other to determine a viable route that minimizes the total distance travelled by the vehicles which invariably reduces the total cost. There are some constraints accredited to the modelling of a CVRP explained in this study. Where 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.

A route is established by the summation of multiple links. 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:

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

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

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

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

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

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. Where a represents the depot.

A customer is visited once, by only one vehicle each time,

$$\sum_{k=1}^{K}\sum_{\substack{i=0\\j=0}}^{N} P_{ij}^{k} = 1, \quad j = 1,2,\ldots,N;\ i = 1,2,\ldots,N \qquad (8)$$

There must be route continuity,

$$\sum_{i=0}^{N} P_{it}^{k} - \sum_{i=0}^{N} P_{tj}^{k} = 0, \quad k = 1,2,\ldots,N \qquad (9)$$

A route distance has a limit (not exceeding the total travel distance)

$$\sum_{i=0}^{N}\sum_{j=0}^{N} d_{ij}^{k} P_{ij}^{k} \le D_k \quad k = 1,2,\ldots,K \qquad (10)$$

The number of routes and vehicles must be above 1, else the model becomes a TSP and not a VRP, where the former deals with a vehicle and a single route.

$$\sum_{i=2}^{N}\sum_{j=2}^{N} P_{ij}^{k} > 1 \quad i,j = 2,3,\ldots,N;k = 2,3,\ldots,K \qquad (11)$$

The capacity of the vehicle must not exceed its maximum, there must be no overloading,

$$Q_k \le Q_{k_{\max}} \quad k = 1,2,\ldots,K \qquad (12)$$

The total demand q_T on each route must not exceed the vehicle capacity,

$$\sum_{j=0}^{N} q_j \left(\sum_{i=0}^{N} P_{ij}^{k} \right) \le Q_k, \ k = 1,2,\ldots,k \qquad (13)$$

All the demand must be accomplished,

$$q_T = \begin{cases} \sum_{j=0}^{N} q_j \left(\sum_{i=0}^{N} P_{ij}^{k} \right) & if \ q_{ij} \ne 0 \\ 0 & if \ Otherwise \end{cases} \qquad (14)$$

The total cost and travel distance are minimized,

$$S = \min \sum_{i=1}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K} d_{ij} P_{ijk} \qquad (15)$$

In the implementation of these constraints there are some parameters to consider

Vehicle capacity: this is the ability of the vehicle to accommodate a certain amount of payload without an overload.

Number of vehicles: One major difference between the TSP (travelling salesman problem) and VRP (vehicle routing problem) is that in the latter, more than one vehicle is used to visit the customers in the search space. The number of vehicles to be used for a VRP determines the speed at which customers can be served and also contributes in achieving a shorter service time.

Demand: This is the amount of payload that is required by the customer(s), which inevitably determines the number of vehicles to be used in a specified space to oblige with the constraints where, the total demand for every route, must not exceed the capacity of the vehicle.

Number of customers: the number of customers that are involved in the logistics is a prime factor as it can be used to guide a model in determining the other parameters and variables dependent on the design. It is assumed that the number of customers equals the number of nodes.

Customer positioning: the positions and locations of customers are paramount in the result of an optimum solution because factors like distance and distribution plays part in the architecture and modelling of the solution method. Customers can be positioned randomly, in clusters or both cases. In this study, customers will be randomly positioned.

Route size: this is the number of routes that the distribution can be sectioned into.

Route distance: this is the length of the course taken from the depot to the serve a set of customers and back to the depot. It is the dimension of travel which will determine the total time taken and also the optimum solution for that given set of instances. Although some methods are best used for shorter distances while some for long distances, but in this work will create a common ground for such uprising.

3. CVRP Optimization Using Firefly Algrithm

The firefly based technique simply solves the CVRP model by identifying the nodes (customer points) as the stationary fireflies and a vehicle as the moving fireflies. Evaluating all the points and the given parameters. Then, the vehicles are evaluated knowing which one is to be assigned to which route, after which it is attracted to the nearest customer location guided by the set constraints. This process continues until the CVRP is solved. Illustrations in this research shows two scenarios. First is a total of thirty-six cases of waste management problem and ten cases of supply chain problem was used to validate the model. This information was used along with the parameters for the optimization of the CVRP model as described in subsection 2.2. The total cost and travel distance of the CVRP described in equation (15) was then optimized using the firefly optimization algorithm.

The simulation parameters showing the range of values used to achieve the results for both the Solid Waste Management and Retail Supply Chain are quantified in the given Table below.

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 & Supply Chain)	120 & 500	--

In developing the Optimized routing scheme for the CVRP 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 FFA algorithm which are the initial customer points (i), the next customer point (j), number of iterations, and population were also initialized.

The fitness of these initial positions was evaluated, and each firefly are ranked according to their fitness. The vehicle moves from firefly i to firefly j and progresses in that order from the initial customer points (i), the next customer point (j), to the next point ($i+1$), then to ($j+1$) until the maximum number of fireflies is reached.

The FFA solution search process was then performed in an enclosed loop and the fitness of the new positions were evaluated. The entire process was then evaluated over a number of iterations continuously until the maximum number of iteration is reached and the firefly with the overall best position is taken as the optimum solution as structured in Fig. 2.

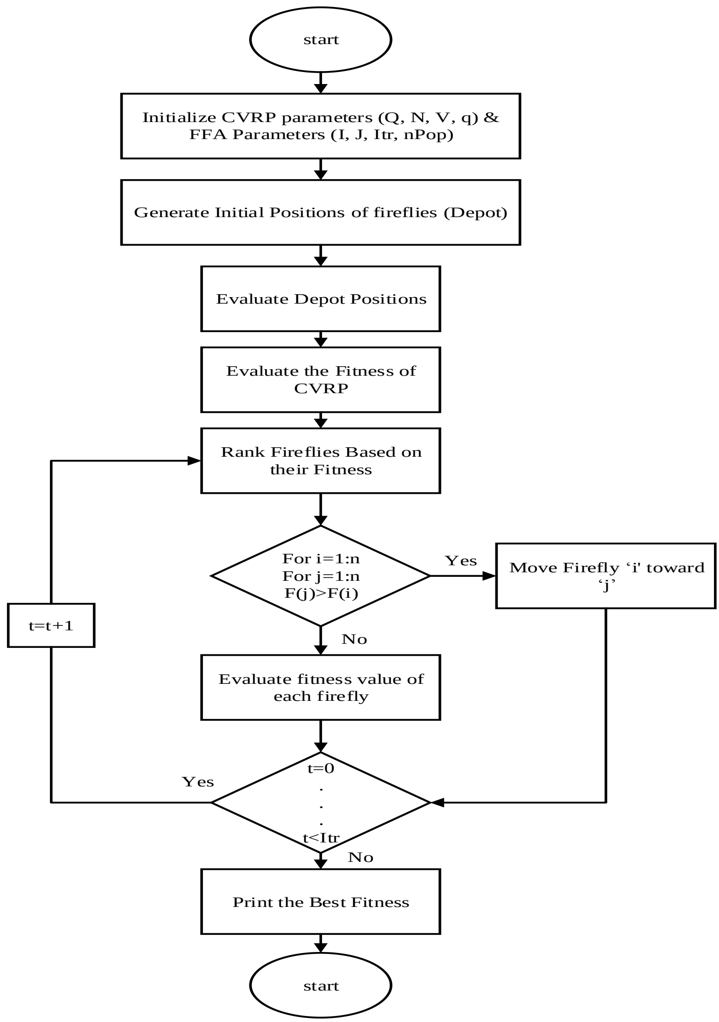


Fig 2. Flowchart of the FFA-CVRP model

Fig.2 shows the flow of the processes involved in the FFA implementation featured in a Flowchart.

4. Results and Discussions

The simulation was conducted in MATLAB R2015b environment, on a computer with Intel Core i3 @ 2.00GHz Processor with 4GB RAM. The main objective of this study is to minimize the total route distance applying all the constraints and using the parameters as earlier explained. It is assumed that a reduction in the total route distance, connotes a reduction in cost and time.

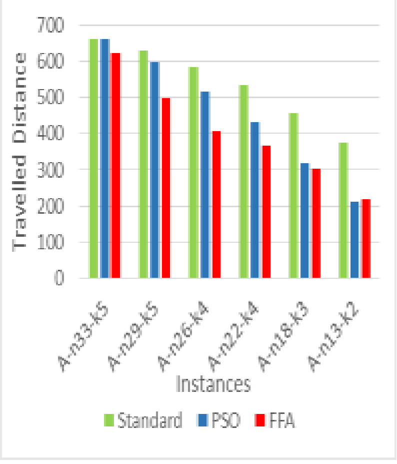
Table 2 below shows the actual values used in formulating the thirty-six instances featured in (Hannan et al., 2018).

Table 2. Result of FFA on CVRP Model for Instances of Solid Waste Management

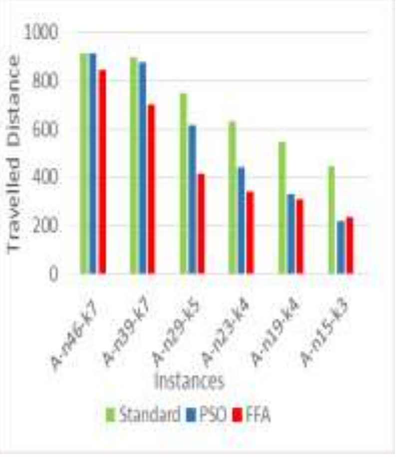
5	Datasets	Q (unit)	q (unit)	TWL (%)	N	V	Distance				
							FFA	Standard	Improvement (%)	PSO	Improvement (%)
1	A-n33-k5	100	10	0	32	5	622	661	5.87	661	5.87
2				60	28	5	499	629	20.6	599	16.63
3				70	25	4	407	585	30.51	518	21.52
4				75	21	4	367	533	31.12	430	14.62
5				80	17	3	304	457	33.48	316	3.8
6				90	12	2	219	374	41.57	212	-3.07
7	A-n46-k7	100	10	0	45	7	842	914	7.82	914	7.82
8				60	38	7	699	895	21.91	876	20.22
9				70	28	5	413	750	44.94	615	32.86
10				75	22	4	339	634	46.53	440	22.96
11				80	18	4	310	548	43.51	329	5.91
12				90	14	3	235	449	47.59	221	-6.47
13	A-n60-k9	100	10	0	59	9	1121	1371	18.21	1371	18.21
14				60	41	8	909	1258	27.75	1154	21.24
15				70	38	8	834	1223	31.81	1091	23.56
16				75	31	6	663	1048	36.77	801	17.27
17				80	29	6	528	979	46.04	699	24.43
18				90	19	4	317	693	54.19	350	9.29
19	P-n40-k5	140	10	0	39	5	359	458	21.62	458	21.62
20				60	34	4	345	417	17.27	380	9.21
21				70	32	4	334	388	13.92	329	-1.52
22				75	25	4	333	352	5.4	271	-22.88
23				80	18	3	266	294	9.52	189	-40.74
24				90	12	2	192	232	17.24	118	-62.71
25	B-n78-k10	100	10	0	77	10	1091	1263	13.6	1263	13.6
26				60	54	9	828	1124	26.33	1000	17.19
27				70	43	8	732	1069	31.49	912	19.69
28				75	27	6	409	732	44.16	424	3.6
29				80	21	4	304	613	50.41	298	-2.01
30				90	11	2	111	346	68.01	95	-16.52

31	P-n101-k4	400	10	0	100	4	489	705	30.64	705	30.64
32				60	81	4	442	616	28.25	538	17.84
33				70	70	4	436	564	22.7	451	3.33
34				75	62	3	424	545	22.2	421	-0.71
35				80	55	3	411	494	16.8	346	-18.79
36				90	33	2	193	351	45.01	175	-10.29

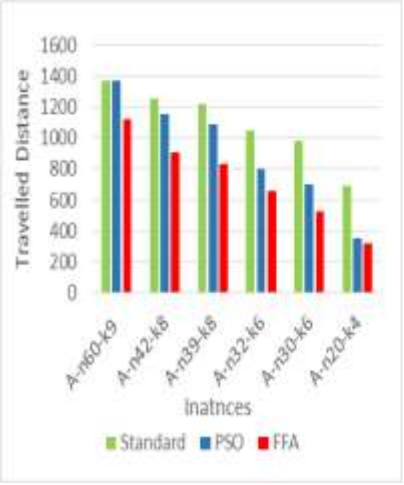
The result obtained using the FFA on the CVRP model shows improvement on the distance across all instances. Each set of instances has same capacity of all vehicles while the number of service points and TWL (quantity of demand) varies. The TWL which is the threshold waste level, provides the information on the actual percentage filled capacity of the bin. As the number of nodes (bins) decreases, the route length logically decreases, it is expected that the distance decreases, thus fewer vehicles are needed. Although, the customer positions are randomly located. Each improvement is realized by the percentage difference between the FFA acquired distance and the standard from literature. When comparing with the standard result from (Hannan et al., 2018), the first set of instances A-n33-k5, gives a collective improvement of 27.19%, A-n46-k7 gives a collective improvement of 35.39%, A-n60-k9 gives a collective improvement of 35.80%, P-n40-k5 gives a collective improvement of 14.16%, B-n78-k10 gives a collective improvement of 39.00% and P-n101-k4 gives a collective improvement of 27.60%.



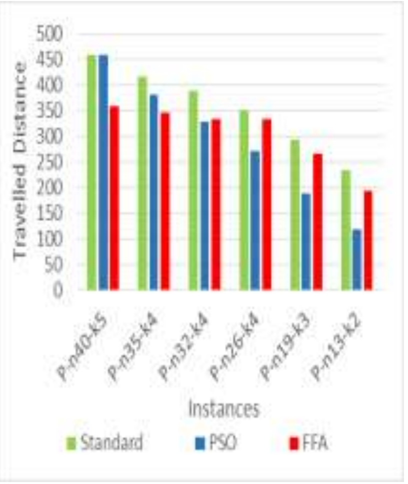
A. Dataset A-n33-k5



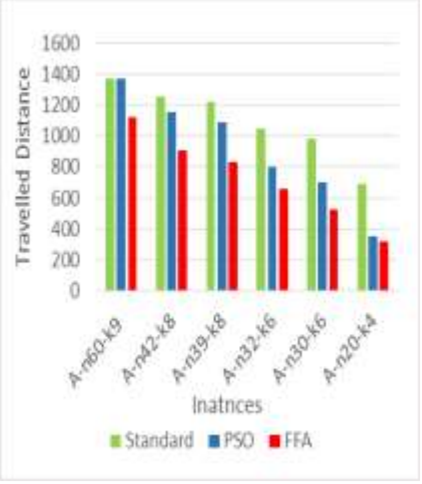
B. Dataset A-n46-k7



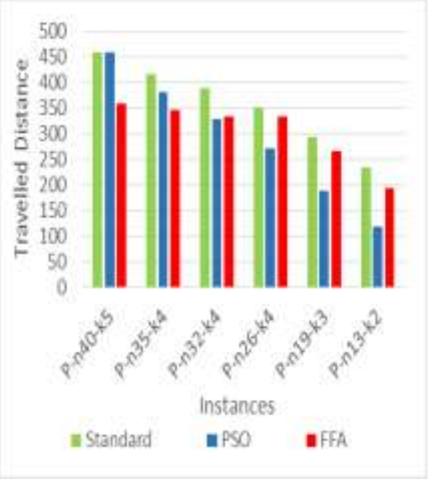
C. Dataset A-n60-k9



D. Dataset P-n40-k5



E. Dataset B-n78-k10



F. Dataset P-n101-k4

Fig. 3 Plot of Travelled distance against the Instances

The collective improvement is the average of the individual improvement in each set of instances. From the table above, using the FFA metaheuristic approach, it is observed that there is total improvement on all instances, this interprets a reduced total route distance. When comparing with the result from the PSO technique from (Hannan et al., 2018), the percentage difference between the FFA acquired distance and the PSO approach is the % improvement of the FFA based model. For the first set of instances A-n33-k5 has an improvement of 9.89%, A-n46-k7 has an improvement of 13.88%, A-n60-k9 has an improvement of 19.00%, P-n40-k5 gives a decline of -16.17%, B-n78-k10 has an improvement of 5.93% and P-n101-k4 has an improvement of 3.67%. From the table above, using the FFA metaheuristic approach, it is observed that five out of the six set of instances have substantial improvements on the total route distance.

From Table 2, as the number of vehicles and customer points decrease, even with an increasing threshold waste level (TWL) from 0 – 90%, the total travel distance reduces. This is because technically, with a smaller number of vehicles and customers interprets a smaller number of routes which invariably gives a reduced travelled distance. Of the 36 instances where the FFA-CVRP model is tested on, the FFA has a 72% better results over the PSO. The graphical representation of these result can be seen in Fig 3.

The developed model in this research was validated using the iterated local search with set partitioning (ILS-SP), unified hybrid genetic search (UHGS) and branch and cut price (BCP) methods presented in the work of (Uchoa et al., 2017). The data from the result is analyzed in the Table below.

Table 3. Result of FFA on CVRP Model for Instances of Supply Chain

	Instance Characteristics					Travelled distance achieved through Metaheuristic					Improvement	
#	Name	n	Dep	Cust	Q	ILS-SP	UHGS	BCP	BKS	FFA	Distance	(%)
1	X-n101-k25	100	R	RC (7)	206	27591	27591	27591	27591	**22572**	5019	18.19
2	X-n153-k22	152	C	C (3)	144	21340	21220	21140	21140	**20538**	602	2.85
3	X-n200-k36	199	R	C (8)	402	58626	58578	58455	58455	**52052**	6403	10.95
4	X-n303-k21	302	C	C (8)	794	21812	21748	21546	21546	**19784**	1762	8.18
5	X-n401-k29	400	E	C (6)	745	66453	66243	65971	65971	**60194**	5777	8.76
6	X-n502-k39	501	E	C (3)	13	69284	69253	69120	69120	**65785**	3335	4.82
7	X-n613-k62	612	C	R	523	60229	59778	59323	59323	**55361**	3962	6.68
8	X-n701-k44	700	E	RC (7)	87	82888	82293	81694	81694	**78617**	3077	3.77
9	X-n801-k40	800	E	R	20	73830	73587	73124	73124	**70175**	2949	4.03
10	X-n1001-k43	1000	R	R	131	73776	72742	71812	71812	**67927**	3885	5.41

Table 3 shows the outcome the FFA-CVRP model on the supply chain instances. These set of instances is used to validate the FFA approach on the CVRP model. The result obtained from the FFA-CVRP simulation is compared to the best-known solution amongst iterated local search-set partitioning (ILS-SP), the unified hybrid genetic search (UHGS), the branch and cut price (BCP) methods which were used on the Instances (Uchoa et al., 2017). In this scenario, demand is dropped-off at each customer site, unlike the solid waste management where demand is picked. In Table 3, it is observed that in all cases there were improvements in the result. The Table depicts the BKS that was obtained considering the previously used three algorithms (ILS-SP, UHGS and BCP). The BKS was then used to compare the results obtained by the FFA. It is seen that applying the FFA on the CVRP model minimized the total travelled distance for X-n101-k25 by 5019m, for X-n153-k22 by 602m, for X-n200-k36 by 6403m, for X-n303-k21 by 1762m, for X-n401-k29 by 5777m, for X-n502-k39 by 3335m, for X-n613-k62 by 3962m, for X-n701-k44 3077m, for X-n801-k40 2949m and for X-n1001-k43 by 3885m. This result was then implemented to calculate the percentage improvement for each of the Instances considered. Although, a slight percentage is observed in the improvement, this is because the distance covered is large, hence, the percentage difference compared to the largely covered distance will not have a high magnitude.

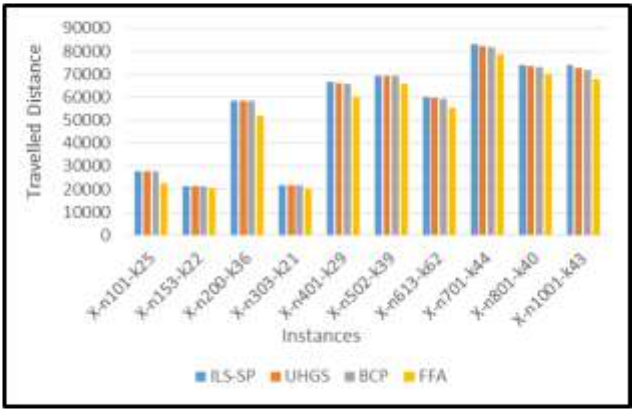


Fig 4 Best Known Solution for supply chain Instances

Fig 4 shows the plot of the travelled distance against the Instances for the supply chain. The result of FFA outperforms the Best Known Solution among the algorithms used in (Uchoa et al., 2017). For all the 10 instances in serving 100 to 1000 customers, it is certified that the FFA now provides the new best known solution (BKS) amongst the four techniques tested on the Instances. In order to further evaluate the performance of the developed method, the performance test given in Fig. 5 was generated.

Results for Performance of the FFA-CVRP Model

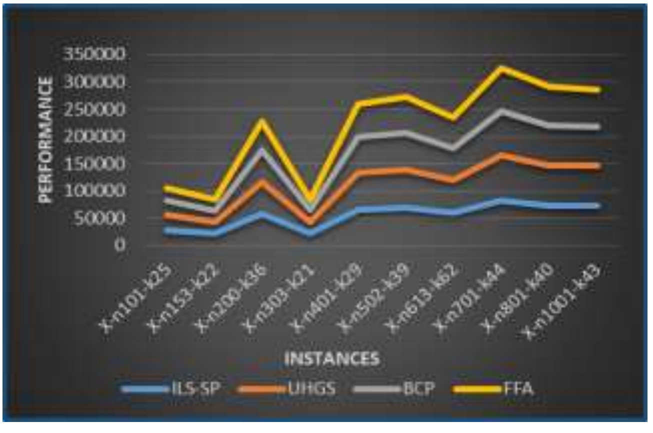


Fig 5 Perfromance of the FFA-CVRP Model

Fig 5 shows a graphical representation of the performance of the FFA-CVRP Model which has shown to provide better results over the other methods used in solving both large and small scale instances for supply chain across all instances.

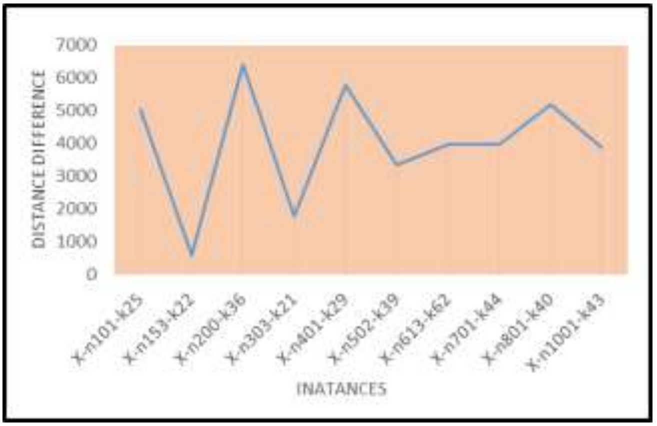


Fig 6 Performance of the Instances

Fig 6 shows the performance if each of the instances, deduced from the difference in the BKS of (Uchoa et al., 2017) and the FFA-CVRP Model. The instance X-n200-k36 has the highest value, which means the FFA-CVRP model is able to navigate channels faster and better with efficient productivity to obtain a more improved solution. This is due to the low ratio of the number of routes and the vehicle capacity to the number of customers and their demand distribution. The dip in the X-n153-k22 instance, shows it possess the lowest difference between the BKS of the earlier techniques used and the FFA based model.

The developed capacitated vehicle routing model using firefly algorithm significantly improved the total route distance on both large and small sized instances. For the solid waste management instances, the FFA-CVRP model contributed an overall improvement of 29.86% to the standard method and a 6.03% over PSO. The model outperformed the best known solution of the ILS, UHGS and BCP approach used on the set of instances for supply chain with an average improvement of 7.36%. All the observations were made assuming same conditions as other techniques used. The developed model achieved a distinct travel path and search in actualizing the best route and position to locate a depot.

5. Conclusion

This paper has presented an optimization of a capacitated vehicle routing model using firefly algorithm. The paper employed two instances comprising of waste management problem and supply chain problem to evaluate the performance of the developed approach. Several simulations were performed using MATLAB R2015b simulation environment. Results when compared with particle swarm optimization, iterated local search set partitioning, unified hybrid genetic search and branch and cut price approaches, showed that this approach is very effective in solving CVRP of different cases. For future research, modelling the time windows to the customer availability, considering the effect of variable positions of depot and hybridizing FFA with other algorithms such as smell agent optimization (SAO) for improved performance can be considered.

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