An Enhanced ABC algorithm to Solve the Vehicle Routing Problem with Time Windows

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ABSTRACT

This work proposes an enhanced artificial bee colony algorithm (ABC) to solve the vehicle routing problem with time windows (VRPTW). In this work, the fuzzy technique, scatter search method, and SD-based selection method are combined into the artificial bee colony algorithm. Instead of randomly producing the new solution, the scout randomly chooses the replacement solution from the abandoned solutions from the onlooker bee stage. Effective customer location networks are constructed in order to minimize the overall distance. The proposed algorithm is tested on the Solomon benchmark dataset where customers live in different geographical locations. The results from the proposed algorithm are shown in comparison with other algorithms in the literature. The findings from the computational results are very encouraging. Compared to other algorithms, the proposed algorithm produces the best result for all testing problem sets. More significantly, the proposed algorithm obtains better quality than the other algorithms for 39 of the 56 problem instances in terms of vehicle numbers. The proposed algorithm obtains a better number of vehicles and shorter distances than the other algorithm for 20 of the 39 problem instances.

Keywords: Service Quality, Gap Model, e-Tourism

1. INTRODUCTION

Transportation provides services to businesses and households to deliver goods or people from place to place. The vehicle routing problem challenges researchers throughout the world and has been widely studied for many decades. The report of [1] claims that 76% of products were transferred by transportation in 1989. Many papers claim that it has effects including an increase in goods price [2,3,4], household expenses [5] and adds to the cost of each output unit in manufacturing. It claims that transportation plays an important role, especially for businesses in this era. These causes confirm that businesses should focus on vehicle routing planning.

Recently, the vehicle routing problem (VRP) arises in many real-world applications to minimize costs such as distance, time, or the number of vehicles for use. After [6] introduced the general Traveling Salesman Problem (TSP) in 1959, the problem has been attracting researchers to study the issue extensively. There are many practical applications of vehicle routing problems, especially in transportation and distribution logistics. Some well-known applications of the vehicle routing problem are a collection of waste, gasoline delivery trucks, collection and delivery of goods, snow ploughs, mail delivery, and dial-a-ride problems. In real-world problems, there are many variants of the VRP incorporating constraints and conditions. The Capacitated VRP (CVRP) considers vehicles that have limited freight capacity [7,8] and the Vehicle Routing Problem with Time Windows (VRPTW) occurs when a time interval is specified for each customer [9,10].

In this work, the strategy from [11] is applied to deal with the initialization stage and then the enhanced artificial bee colony (ABC) algorithm is used to improve the population. The paper is structured as follows: Section 2 presents the literature reviews. The vehicle routing problem, the ABC algorithm, and the fuzzy technique in the vehicle routing problem domain are reviewed in this section. The Methodology is explained in detail in section 3. The environmental setting is illustrated, the route representative is clarified, and the processes in the proposed methodology are described. The computational results are displayed in section 4. Finally, the conclusion is stated in section 5.

2. LITERATURE REVIEW

Logistics and transportation are an element of people's lives and the world economy. Their complexity and demands have been emphasized by researchers and organizations. Therefore, a vast number of publications about the vehicle routing problem have been published for many decades. The demand for a third-party logistics business service has been increasing significantly in recent years. Warehousing, inventory management, compiling, distribution and return of products are some examples of businesses that require advanced logistics service [12]. Today, merchandise from an online order, food delivery, and tourism

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are in the attention of people significantly. The requirements exist not only in the city, but also between cities and between countries. Researchers [13-16] worked on case studies in long-haul transportation and published their research works. They announce that their works can reduce the costs of transportation for logistics operators and companies significantly. Many heuristics, metaheuristics, swarm intelligence, and other algorithms have been widely published to solve the VRPTW in the past few decades. The Bee algorithm (BA) and modified artificial bee colony were published to solve the VRPTW, for example, in the publications of [17-19]. The artificial bee colony (ABC) algorithm is a class of nature-inspired algorithm which was proposed by [20]. The algorithm has presented an essential performance increase in solving continuous and combinatorial optimization. The algorithm simulates the behavior of the three groups of the agent which are employed bees, onlooker bees, and scout bees, as the three main processes of the algorithm. In search space, the employed bees and onlooker bees respond for the exploration process while the scout bees respond to the exploitation process. Short pseudocode for the ABC algorithm is shown in Figure 1.

```
START
  Initial population (Randomly)
  REPEAT
        Employ bee (Evaluate fitness function)
        Onlooker bee (Select the individuals from the fitness value)
        Scout bee (Return from the abandon individual(s)
  UNTIL the stopping condition is met
  Return the best solution found
STOP
```

Fig.1: *Short Pseudocode for the ABC Algorithm.*

In the literature, there are some researchers who have improved the ABC algorithm to solve the vehicle routing problem with time windows (VRPTW). Weng and Bin Asmuni 2013 [21] pointed out that the randomly created solutions by scout bees are the main weak point of the algorithm. The process makes the searching area disperse and it is difficult to find a promising area. They improve the algorithm by defining a list of abandoned solutions so that the abandoned solutions will be memorized by the scout bees. Instead of constructing the new solutions randomly, each scout bee chooses a solution from the abandoned list based on a roulette wheel selection. Therefore, the selected solutions are feasible, and each new generation is improved slightly. Kantawong and Chaisricharoen [22] claim that there are two weak points of the ABC algorithm. The first point is the random construction of the initial population. The second point is the local search operator which is easily trapped in local optima. They applied the fuzzy technique of [11] to deal with the feasible initial solutions. In each iteration, the Swap/shift movements (1-0, 1-1, 2-2) and 2-opt* between the routes and or-opt and nearest neighborhood operator are randomly applied to improve in the route. The ABC algorithm and the improvement to the ABC algorithm can solve optimization problems efficiently in the literature. However, there are a limited number of ways the algorithm was developed to solve the transportation problem.

This paper proposes a methodology to solve the vehicle routing problem. The aim of this work is to construct effective routes for customers who live in different geographical locations. The proposed algorithm was tested on Solomon's benchmark dataset [23]. The scatter search [24] was enhanced in the employ bee stage to improve the population and the based selection was applied as the selection tool to choose each new generation and the abandoned solutions. The scout produces the replacement solution at random from the abandoned solutions in the previous stage.

3. METHODOLOGY

The vehicle routing problem with time windows is the most similar application to real-world transportation. In this work, an improved ABC Algorithm is developed to solve the vehicle routing problem with time windows. The main target of this work is to determine the summation of the vehicle (k) service cost (distance) calculated by the following objective function (1).

$$Min \sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} \sum_{k=1}^{m} c_{ij} x_{ijk} \quad (1)$$

Where
c_{ij} is the cost between customer i and j
n = number of customers
m = number of vehicles
$x_{ijk} = 0$ if there is no path between customer i and j otherwise $x_{ijk} = 1$

The position of customer c_i is (x_i, y_i) and the position of customer c_j is (x_j, y_j), the distance between the two customers calculated by the Euclidean distance (2).

$$c_{ij} = \sqrt{((x_i - x_j)^2 + (y_i - y_j)^2)} \quad (2)$$

The proposed algorithm and relating details are described in this section.

3.1 Route Representation

In the route representation, there are customers waiting to be visited by m vehicles from the vehicles set, $K = \{k_1, k_2, \ldots, k_m\}$.

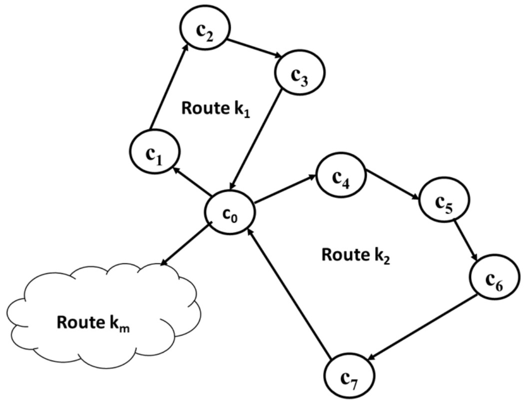

Fig.2: *The Route Representation.*

Fig 2 describes customers served by m vehicle routes, $K = \{k_1, k_2, \ldots, k_m\}$. Each route starts with its service from the depot, c_0. In Fig 2, the vehicle k_1 serves customers c_1, c_2, c_3 respectively. Customers c_4, c_5, c_6, c_7 are sequentially served by the vehicle k_2. After vehicle k_1 and k_2 finished their service, they return to the depot (c_0).

3.2 The Control Parameter

To deal with the problem, the control parameters in the experiment are given in Table 1.

Table 1: *The Control Parameters.*

parameter	number
Population size (FN)	20
Employ bees	20
Onlooker bees	19
Scout bee	1
customer number	100
Iteration number	2000
lm	100

In Table 1, all control parameters are presented. The lm in this table is used to control the improvement loop of the solution. The improvement process will be stopped when the current solutions are not improved and the $lm >= 100$.

3.3 The Proposed Algorithm

In this work, all initial solutions (population) are feasible by using the fuzzy technique from [11]. After that, the employed bees, onlooker bees, and scout bee processes are working to improve the solutions. The scatter search from Glover was included in the employed bees stage and the standard deviation (SD) was used to measure the quality of the produced solutions that help the onlooker bees determine which solutions to choose. The main process of the proposed algorithm is demonstrated in Fig 3.

In Fig 3, FN numbers of feasible solutions (population) are produced based on service time satisfaction by using the fuzzy strategy from [11] and [25].

$$\theta_i(s) = \begin{cases} 1; \ e_i < s < l_i \\ 0; \ otherwise \end{cases} \tag{3}$$

In Equation 3, the service satisfaction of service time, $\theta_i(s)$, can be defined for any service time ($s > 0$). All customers must be served by one vehicle within the range of time e_i and l_i.

$$\theta_i(s_i) = \begin{cases} 0; \ s_i < e_i \ or \ s_i > l_i \\ \dfrac{(s_i - e_i)}{(u_i - e_i)}; \ e_i \le s_i \le u_i \\ \dfrac{(l_i - s_i)}{(l_i - u_i)}; \ u_i < s_i \le l_i \end{cases} \tag{4}$$

Equation 4 is applied to find the preference of customers as a triangular fuzzy number. In this equation, s_i u_i and t_i represent the start service time, fuzzy due time and time spent at customer v_i respectively, where $u_i = e_i + t_i$. Approaches of the fuzzy membership function to the vehicle routing time windows are described in detail by [11].

To produce the initial feasible population, the fuzzy membership function is applied. After the number of vehicles is determined, the membership value is calculated based on equation (3) and fuzzy membership function (4). The membership value calculation is clearly demonstrated in [11]. Each solution is produced as follows:

1) Assign the first customer to each route randomly.
2) Apply the membership function of service time (formula 1) to all remaining customers.
3) Select customers whose satisfaction value $\theta_i(s) = 1$.
4) Apply the triangular membership function (formula 2) to each customer from 3).
5) IF all constraints are not broken
   - TRUE
     - Assign the customer who has got the best membership value to the route.
     - GOTO 6
   - FALSE
     - GOTO 1
6) Continue looping through processes 2) to 5) until all remaining customers are assigned to appropriate routes.

After that, each solution is evaluated and continues to take part in the employed bees stage where each solution is improved by the scatter search of [26]. The template of the algorithm is given in Figure 3.

Each solution will run the scatter search in the employed bees stage, and the better feasible solution produced in each iteration will be memorized as a reference set from the update method. The process will continue until there are no more updates to the solution. After that, the standard deviation (SD),

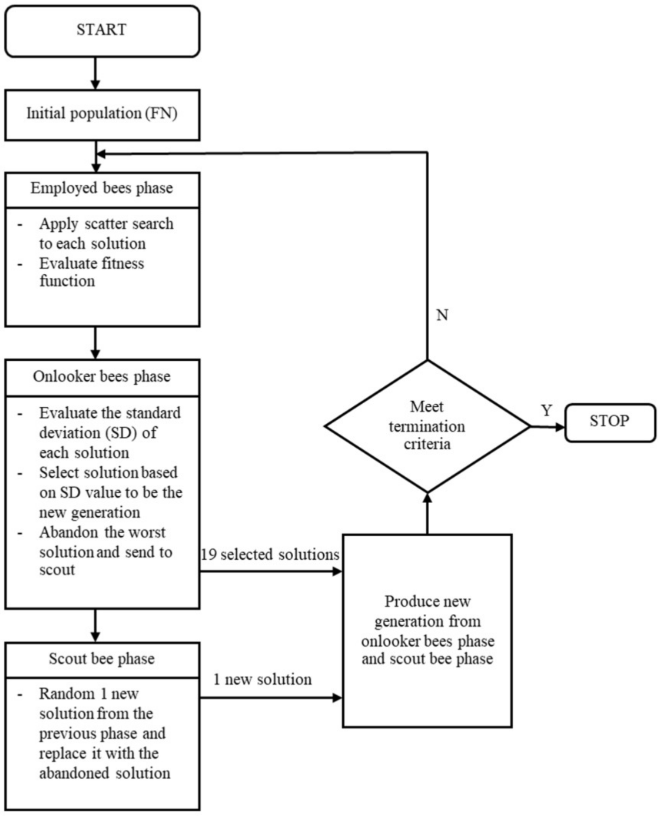

Fig.3: *The Proposed Algorithm.*

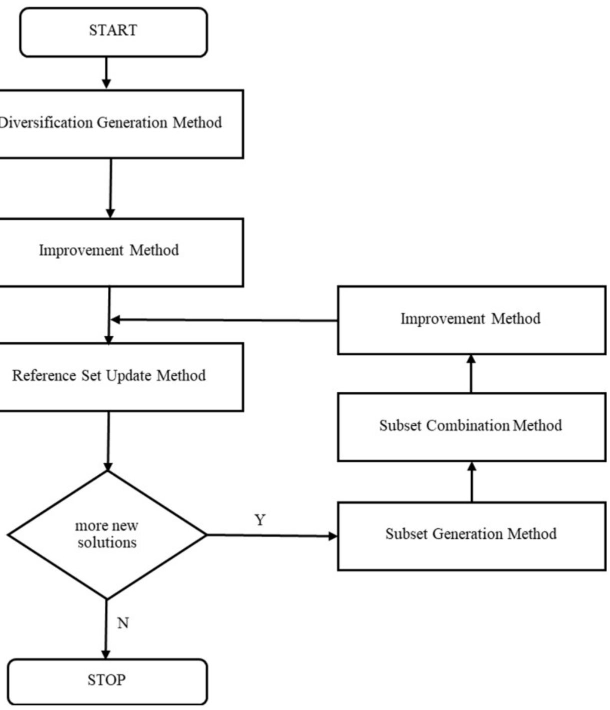

Fig.4: *The Process of Scatter Search Template.*

Table 2: *The Average Computational Results Compared to the Other Algorithms.*

Problem	Vehicle Capacity	Customer's Locations	Propose	[18]	[26]	[27]	[9]	[29]
Cxx	200	x: [0, 100] and y: [0, 90]	**828.38**	835.36	838.47	843.55	828.38	832.13
C2xx	700	x: [0, 100] and y: [0, 90]	**589.86**	593.74	605.41	611.12	589.86	589.86
R1xx	200	x: [0, 70] and y: [0, 80]	**1210.40**	1228.85	1207.76	1241.24	1222.12	1211.55
R2xx	1000	x: [0, 70] and y: [0, 80]	**951.03**	931.56	977.19	961.11	975.12	1001.12
RC1xx	200	x: [0, 100] and y: [0, 90]	**1384.16**	1462.27	1381.96	1419.14	1389.58	1418.77
RC2xx	1000	x: [0, 100] and y: [0, 90]	**1119.24**	1185.23	1099.12	1119.24	1128.38	1170.93

which is a measurement of the difference technique, is calculated from these results. After that, the quality of each solution was put into a descendant ordered by the SD value. In this case, the worst SD value means the best quality as a solution. The onlooker bees choose the solution from the ranking SD value and abandon the worst solution (maximum SD value) that will be sent to the scout. In the scout bee stage, the new solution produced in this stage is randomly selected from all abandoned solutions from the previous stage. This can help to save time and control the dispersion of the searching area. All processes will continue until the termination condition is met, and then the best-found solution is returned.

4. RESULTS

In this work, the performance of the proposed algorithm was tested on three different structures of problem sets from the Solomon benchmark dataset including C1xx (C101-C109), C2xx (C201-C208), R1xx (R101-R112), R2xx (R201-R211), RC1xx (RC101-RC108) and RC2xx (RC201-RC208). In evaluating the performance of the algorithm, the environments are set in the same way for all testing instances. The computational results are presented in Table 2.

The performance of the proposed algorithm was evaluated in comparison with the best-known results of other algorithms which were taken from [18]. Table 2 illustrates the computation results from the proposed algorithm compared to the other five published algorithms. Each problem set of Solomon benchmark dataset is demonstrated in column 1. The vehicle capacity and the position of customers are shown in columns 2 and 3. Columns 4 to 9 present the best mean of each problem set from the proposed algorithm and the algorithms proposed by [18],[27],[28], [9], and [29] respectively. When compared with other five algorithms, it shows that the proposed algorithm produces the best results for all problem instances. The proposed algorithm works efficiently for customers who live in a different geographical position.

Next, the performance of the proposed algorithm was compared in each problem instance of the Solomon benchmark dataset. The compared algorithm was taken from [19] which proposed the modified bee algorithm (BA). The results are presented in this section.

In Table 3, the number of vehicles (NV) and Distance produces from the proposed algorithm and the BA are shown in comparison. The table shows that in no problem instance can the BA produce better results than the proposed algorithm in terms of the vehicle numbers. Moreover, the proposed algorithm uses a smaller number of vehicles than the BA for 39 of the 56 instances (mentioned with the bold number), which means that 69.64% of the time the proposed algorithm is remarkably better than the BA. To compare the distance between the two algorithms, problem set Cxx should be selected because the number of vehicles produced by both algorithms is equal. The results in Table 3 show that the proposed algorithm yields equal quality with the BA in the problem set Cxx for 9 out of 17 instances, while it obtains better results in the 8 other instances. It means that these two algorithms provided equal quality for 52.94% of the cases, but the proposed algorithm obtained better results than the BA for 47.06% of the cases in this problem set. More significantly, the results demonstrate that the propose algorithm even uses a smaller number of vehicles. The proposed algorithm obtains better results in 20 out of 39 instances (R104, R106, R107, R108, R110, R111, R112, R203, R205, R206, R207, R208, R209, R210, RC103, RC104, RC107, RC108, RC204 and RC208), which means that 51.28% of the cases the proposed algorithm is significantly better than the BA.

Table 3: *: The Computational Results Compared to the Bee Algorithm (BA).*

Instances	Proposed		BA	
	NV	Distance	NV	Distance
R101	**19**	1650.80	20	1643.18
R102	**17**	1486.86	18	1480.73
R103	**13**	1292.67	14	1240.87
R104	**9**	1007.31	12	1047.06
R105	**14**	1377.11	16	1369.52
R106	**12**	1252.03	13	1271.13
R107	**10**	1104.66	12	1129.99
R108	**9**	960.88	11	1004.11
R109	**11**	1194.73	13	1170.50
R110	**10**	1118.84	12	1123.36
R111	**10**	1096.73	12	1101.59
R112	**9**	982.14	11	1019.84
R201	**4**	1252.37	8	1185.57
R202	**3**	1191.70	7	1103.15
R203	**3**	939.50	6	958.94

Instances	Proposed		BA	
	NV	Distance	NV	Distance
R204	**2**	825.52	4	818.44
R205	**3**	994.43	6	1020.53
R206	**3**	906.14	5	960.29
R207	**2**	890.61	5	905.70
R208	**2**	726.82	4	764.90
R209	**3**	909.16	6	943.16
R210	**3**	939.37	6	1003.91
R211	**2**	885.71	5	837.66
C101	10	828.94	10	828.94
C102	10	828.94	10	828.94
C103	10	828.06	10	828.94
C104	10	824.78	10	828.90
C105	10	828.94	10	828.94
C106	10	828.94	10	828.94
C107	10	828.94	10	828.94
C108	10	828.94	10	828.94
C109	10	828.94	10	828.94
C201	3	591.56	3	591.56
C 202	3	591.56	3	591.56
C 203	3	591.17	3	600.54
C 204	3	590.60	3	610.01
C 205	3	588.88	3	588.88
C 206	3	588.49	3	588.88
C 207	3	588.29	3	589.58
C 208	3	588.32	3	591.65
RC101	**14**	1696.95	16	1634.52
RC102	**12**	1554.75	15	1492,89
RC103	**11**	1261.67	13	1334.57
RC104	**10**	1135.48	11	1215.62
RC105	**13**	1629.44	15	1546.43
RC106	**11**	1424.73	14	1423.10
RC107	**11**	1230.48	12	1300.00
RC108	**10**	1139.82	12	1193.68
RC201	**4**	1406.94	8	1308.76
RC202	**3**	1365.64	8	1167.00
RC203	**3**	1049.62	6	1041.79
RC204	**3**	798.46	4	881.88
RC205	**4**	1297.65	7	1210.68
RC206	**3**	1146.32	6	1112.38
RC207	**3**	1061.14	7	1059.62
RC208	**3**	828.14	5	882.06

5. CONCLUSIONS

This paper proposes a new methodology to solve the vehicle routing problem with time windows. The traditional ABC algorithm was enhanced by applying the fuzzy technique and the scatter search method of [26]. To construct a feasible population, the fuzzy technique from [11] was applied based on customers' satisfaction. The new generation and an abandoned solution were selected based on the standard deviation of the improvement solution from the employed bees stage. The scout finds the new solution from a set of the abandoned solutions in the previous stage to replace the abandoned solution received from the onlooker bee stage. The proposed algorithm was tested on the six problem sets of the Solomon benchmark dataset which is generated from different geographical. Problem set C1xx and C2xx are classified as geographically generated. Problem set R1xx and R2xx are randomly geographically generated. Problem set RC1xx and RC2xx are mixed between random and classified geographically. The computational results are compared to the best-known results in the literature. It shows that the proposed algorithm obtains the best solutions for all testing instances from the six tested problem sets of the Solomon benchmark dataset. In addition, using the scatter search strategy to improve the solutions and applying the based strategy to choose the new generation are helpful for converging to the best solution efficiently. It can be clearly seen that the proposed algorithm works effectively for the vehicle routing problem with time windows.

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