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An Improving ABC Algorithm for Time Dependent Transportation Problem

Krittika Kantawong[1] and Roungsan Chaisricharoen[2]

School of Information Technology, Mae Fah Luang University, Chiang Rai, Thailand.
E-mail: [1]krittika.ka@up.ac.th, [2]roungsan.cha@mfu.ac.th

Abstract

An Improving Artificial Bee Colony (ABC) algorithm for dependent transportation problem is proposed in this paper. The triangular fuzzy member and local search method are combined into the ABC algorithm. Instead of random initialization in ABC algorithm, the triangular fuzzy member is applied to select customers to appropriate routes. The convergence of the solution is controlled by the new strategy of neighbourhood operator. The proposed algorithm is tested on Solomon benchmark dataset. The findings from the computational results were very encouraging, it shows that the algorithm is very effective and obtain the best solution for all testing problem instances.

INTRODUCTION

Transportation challenges researchers in the world and widely studied for many decades. In 1992, Halse [1] reports that the vehicles transportation transferred products by 76% in 1989. Many papers claim that it effects to an increasing of goods price [2][3][4], household expenses [5] and accounts to the cost of each output unit in manufacturing. It claims that transportation plays an important role especially in business section in this era. These causes confirm that the vehicle routing planning should be focused.

Recently, the vehicle routing problem (VRP) arises in many real world applications to minimize costs such as distance, time, or on the number of vehicle for use. After Dantzig and Ramser [6] introduced the problem in 1959, the problem has been attracting researchers to study the issue extensively. In reality, to carry products from places to places could be the short or long distance. Short-haul and Long-haul transportation are in the spotlight for researchers equally.

In the literature, a massive number of existing theories and a huge number of algorithms have been published to solve transportation problem by many researchers. Almost of them are very complex and difficult to apply. ABC algorithm and the improved of ABC algorithm also brought to solve the problem in recent time. They are simple and not complex to implement and works efficiently especially for the capacitated vehicle routing problem. However, the performance of the algorithm depends on the neighbourhood operator which leads it to be easily trapped in local optima. Another point of view pays attention to the initial population of the methodologies. Lau et al. [7] pointed that the productive initial population provides an effective starting area so it leads to the improvement of the algorithm to attain good solutions. For many evolutionary algorithms, the proper initial population has an effect on the quality of the final answer. Moreover, it claims that the good initial population can produce the acceptable results in an acceptable time [8]. From these points of view, the fuzzy technique and the new neighbourhood operator technique are enhanced into the important stages of ABC algorithm in this paper. The paper is structured as follows: section 2 reviews relating works including the ABC algorithm and fuzzy membership function in the vehicle routing problem domain. The proposed method is explained in details in section 3 while the computational results and discussions are presented in section 4. Finally, the conclusion is provided in section 5.

RELATING WORKS

Artificial Bees Colony Algorithm (ABC Algorithm)

The ABC algorithm was proposed by Karaboga [9] for numerical optimization problem. The algorithm was modified by Akay and Karaboga [10] for real-parameter optimization problem. It is a new evolutionary meta-heuristic technique inspired by the intelligent behavior of natural honey bees in their search for nectar sources around their hives. The initial food sources (initial population) are produced for employed bees that will evaluate its nectar amount and come back to the dance area. The onlooker bees watch the dance and choose the solutions depending on the dance while the employ bee whose solution is abandoned becomes the scout and explores to find the new solution. The short pseudocode of ABC algorithm as follows:

```
Initialization stage
repeat
        Employed bees phase
        Onlooker bees phase
        Scout bees phase
        Memorize the best solution achieved so far
until (cycle = Maximum Cycle Number or a Maximum CPU time)
```

Figure 1: ABC algorithm [11]

In the literature, transportation is not the main application areas of ABC algorithm [11]. For vehicle routing problem with time windows, a very limited number of ABC algorithms were developed to solve the problem. The Bee Colony-inspired Algorithm (BCiA) [12] contains a Two-Stage Approach for Solving the Vehicle Routing Problem with Time Windows. The algorithm tries to reduce the number of vehicles in the first stage and proceeds to minimize total tour length in the second stage after the first stage cannot produce any of feasible solutions. The algorithm was particularly efficient for the smaller size instances of the Solomon benchmarks [13]. Shi et al. [14] develop ABC-T algorithm to improve the performance of ABC algorithm. The tournament selection strategy is proposed. The main criteria of the algorithm relates to the fitness value. In the paper, few experiments had been done and the result shows that the algorithm works efficiently with the problem R102.

In the basic and improvement of the Artificial Bee Colony algorithm, numbers of food sources (initial solutions) are generated randomly. Each initial solution will be evaluated by their nectar amount (fitness) and then sent to employ the bee, onlooker bee and scout bee processes respectively to be improved. There are several neighbourhood operators applied in the literature such as, local search operator, crossover, mutation and others. Although it claims that the operators and the combination of them can improve the solution, not all of them yield the promising results [15] and are also easy to be trapped in local optima. Therefore, the proposed algorithm aims to improve the algorithm to solve these problems.

Fuzzy Membership Function

Fuzzy membership function is a selection technique in the Fuzzy theory which was presented by Zadeh in 1965 [16], whereas many different research areas have found that it is a useful tool to describe subjective opinions [17]. Transportation distance, service satisfaction, waiting time, delay time and space utility are considered by the fuzzy vehicle routing and scheduling problem (FVRSP) by Lin in 2008 [18]. After that Gupta et al.[18] includes the fuzzy service time under time windows and capacity constraints in [19] model. Based on this model, the FVRPTWC is produced by adding a real time application [20]. Fuzzy credibility theory was desired to deal with an uncertainty time windows by Sandhya and Katiyar [21]. Although their works provide effective results, the techniques applied to their specific routing problem. This work intends to apply fuzzy due time technique from [20] and [22] to deal with customer service time windows.

THE PROPOSED METHOD

In this work, An Improving ABC Algorithm is developed to solve the time dependent transportation problem. The important description and procedures of the proposed algorithm are described in details in this section.

Solution Representative

In the solution representation, there are n customers waiting to be visited by m vehicles. K is a set of vehicles, $K = \{k_1, k_2 \ldots, k_m\}$.

v_0	$v_1^{k_1}$	$v_2^{k_1}$	⋯	v_0	$v_{n-x}^{k_{m-1}}$	⋯	v_0	⋯	$v_{n-1}^{k_m}$	$v_n^{k_m}$

Figure 2: Solution representative.

In Figure 2, there are vectors of customer $v_i^{k_j}; i = 1, 2, \ldots, n; \ j = 1, 2, .., m$ and there are m number of v_0, depot, in the vector representing the starting point of each route.

The fuzzy membership function approach to time dependent VRP

To produce the routes, customers will be assigned to the route whilst the following constraints are considered [20]:

1) Each customer has their own demand (d_i) and can be served by only one limited capacity (Q) vehicle (k_i).
2) The service of each vehicle is started and stopped at the depot (v_0), serves each customer only one time in the route with a limited capacity (Q).
3) Each customer v_i must be served by the vehicle k_i within their time windows $[e_i, l_i]$, that means the vehicle cannot service customer before earliest time e_i and after the latest time l_i.
4) The travel times between customers are assumed to be fuzzy variables.
5) There is no sub tour.

The concept of fuzzy due time is applied to improve the satisfaction of the bus service for staff and students of Jain University in Bangalore, India [20]. This experiment applies the same fuzzy due time concept to Solomon's benchmark datasets in the same way as our previous work [22].

In the first step of this experiment, this concept was brought to maximize service time satisfaction and then the results will be improved in the next stage. The membership function of service time, $\theta_1(s)$ can be defined for any service time $(s > 0)$ as the following formula:

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

The triangular membership function is applied to find the preference of customers as a triangular fuzzy number under the following formula:

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

Where s_i represent the time at which the customer is served, u_i represent fuzzy due time, $u_i = e_i + t_i$; t_i is the time spent to service at customer v_i. The satisfaction area is shown in Figure 3.

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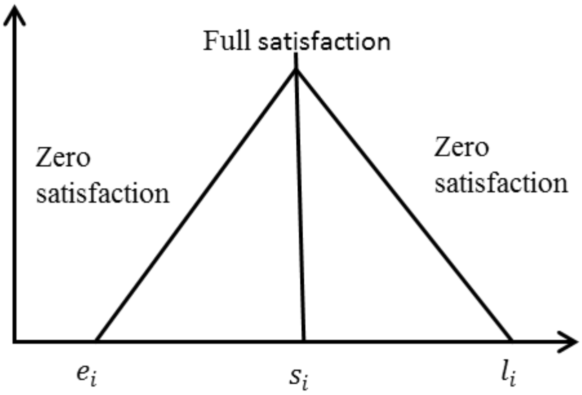

Figure 3: Fuzzy due time.

The Proposed Algorithm

The main target of this work is to minimize the total service distance which is calculated by the following objective function.

$$Min \sum_{i=1, j=1}^{N} c_{ij} x_{ij}$$

Where c_{ij} is the distance between the positions of customers $v_i \ (x_i, y_i)$ and $v_j \ (x_j, y_j)$ calculated by the following Euclidean distance formula.

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

x_{ij} is a decision variable, x_{ij} is equal to 1 if there is a path between customer i and customer j, otherwise x_{ij} is equal to zero. To produce the routes, important constraints are considered as explained in details in the proposed method part.

This work intends to start the processes with feasible initial population. Consequently, the fuzzy membership function is applied to choose the member of the routes instead of random initial population. The experiment aims to minimize the overall distance of the routes while the number of vehicle is considered as the best known solutions in the literature. The routes are constructed by assigning customers to them whilst capacity and time window constraints are not broken. To improve the solutions, the inter-route improving is worked in the employ bee stage and intra-route improving is worked in the onlooker bee stage. Swap/shift movements (1-0, 1-1, 2-2) and 2-opt* are randomly applied between the routes (inter-route) while or-opt and nearest neighborhood operator are randomly applied to improve in the route (intra-route). The important processes are shown in details as the algorithm work flow in Figure 4.

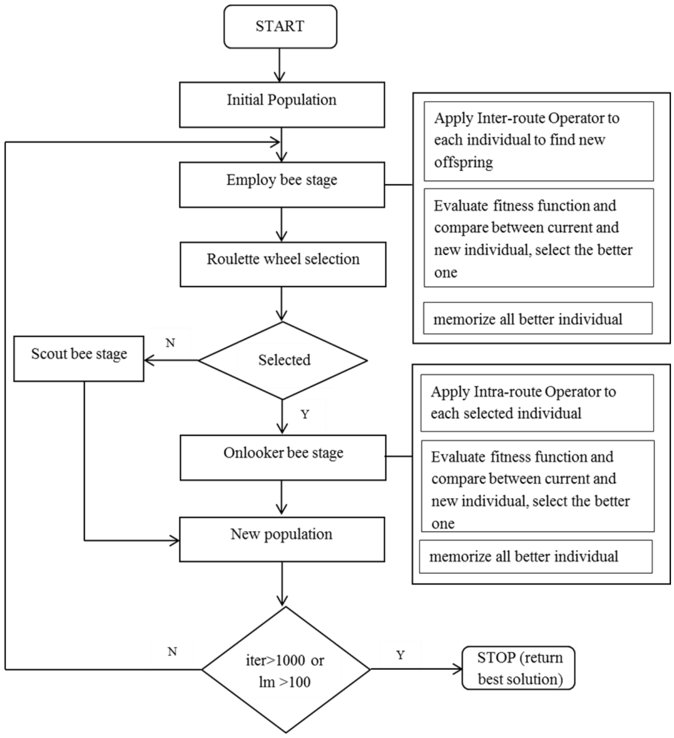

Figure 4: The proposed algorithm work flow.

EXPERIMENTAL RESULTS

The performance of the proposed algorithm is tested on Solomon benchmark dataset. In evaluating the performance of the algorithm, the experiment environments are set in the same way for all testing instances. The control parameters in the experiment are presented in Table 1.

Table 1: Parameters used in the experiment.

Parameters	Values
Population size (N)	20
Number of iteration (iter)	1000
Number of customer	100
Limit (lm)	100
Number of employ bee	20
Number of onlooker bee	20
Number of scout bee	1

In this work, the experiment is designed for the two parts of the proposed algorithm. In the first part, the proposed algorithm is tested on 6 problem sets of Solomon benchmark datasets [13] including the problem sets in which their geographical points are generated randomly as R10x and R20x; problem sets C10x and C20x which the geographical of customers are classified by their geographical position and problem sets RC10x and R20x that the locations of customers are mixed between random and classified position. The computational results from the experiment are illustrates as follows:

Table 2: The average number of vehicles and total distance of 6 problem sets from Solomon benchmark dataset.

Problem Set	Time Windows at the depot	Max Capacity	Authors					
			[23]	[24]	[25]	[26]	[27]	Results
R1	0 – 230	200	12.58 1272.34	12.75 1300.25	12.58 1296.83	12.00 1217.73	12.08 1210.14	11.92 1210.4
R2	0 - 1000	1000	3.09 1053.65	3.18 1124.28	3.00 1117.64	2.73 967.75	2.73 969.57	2.73 951.03
C1	0 - 1236	200	10.00 857.64	10.00 892.11	10.00 838.11	10.00 828.38	10.00 828.38	10.00 828.38
C2	0 - 3309	700	3.00 624.31	3.00 794.13	3.00 590	3.00 589.86	3.00 589.86	3.00 589.86
RC1	0 - 240	200	12.13 1417.05	12.50 1474.13	12.13 1446.25	11.63 1382.42	11.50 1389.78	11.50 1384.16
RC2	0 - 960	1000	3.38 1256.8	3.38 1411.13	3.38 1368.13	3.25 1129.19	3.25 1134.52	3.25 1119.24

In Table 2, the average number of vehicles and total distance from Solomon benchmark datasets produced by the proposed algorithm are demonstrated in comparison with other heuristics algorithms which are taken from [23]. The results in Table 2 demonstrate that the proposed algorithm provides the best average number of vehicles and average total distance for all problem instances comparing to other comparative algorithm as shown in the table.

CONCLUSION

This work intends to develop the algorithm to solve the time dependent transportation problem. The ABC algorithm is improved by fuzzy technique in initialization stage and the neighbourhood operator is randomly select to apply in employ bee and onlooker bee stages. It found that the initialization stage almost provides effective searching area. The new strategy to choose neighbourhood operator is helpful, the exploitation process of employ bee and onlooker bee phase can converge to the best solution efficiently. In addition, the exploration of the limited number of scout is useful to escape from local optima and also searching area is not dispersed. Thus it finally yields satisfied results. To compare with best known solutions in the literature, the proposed algorithm obtains the best solutions for all testing problem sets.

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