THE NEW METHODOLOGY FOR VEHICULAR NETWORK WITH FUZZY TIME WINDOWS

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ABSTRACT

This work proposes the new methodology for the vehicular network with fuzzy time windows. The Fuzzy technique is applied to produce an initial population and then the evolutionary algorithm is employed to improve the solution. In this work, the inter-route crossover, intra-route mutation, elitism strategy, and onlooker bee probability selection method were enhanced in the original processes of the evolutionary algorithm. The proposed algorithm is tested on 56 datasets of Solomon. The results from the proposed algorithm are shown in comparison with other algorithms in the literature. The findings from the computational results are very inspiring, it shows that the algorithm is very competitive. Comparing with the algorithm in the literature, the proposed algorithm obtains the best solution in terms of the coefficient of variation values for almost 40 instances from the 56 problem instances. In addition, the information regarding the p-value was resolved by the Wilcoxon signed-rank test for the considered testing instances that display statistically superior performance at the 95% significance level (α = 0.05) on comparing algorithms.

Keywords: vehicle routing problem; fuzzy membership function; route construction.

1.0 INTRODUCTION

Transportation is an important section in business and organizations. Efficient transportation systems provide economic and social opportunities and benefits. Transportation costs could be desired as a significant matter in maintaining national expense in many countries such as the United Kingdom, France, and Denmark [1, 2]. Moreover, its cost resulted in an increasing price for goods at 70% [3,4,5]. On the economic level, [6] confirmed that it accounts from 6% to 12% of the GDP in many developed countries. In addition, they pointed out that 10%-15% of the household expenses are related to the transportation cost on average, while it accounts for the cost of each output unit in manufacturing around 4%. In 1989, 76% of the products have been transferred from places to places by vehicle transportation [7] which confirms the significance of the transportation problem.

The vehicle routing problems (VRP) is a combinatorial optimization problem that involves the optimization cost of transportation. It is an NP-hard problem which challenged researchers in the world and has been widely studied. The problem aims to design efficient routes served by the number of vehicles in order to satisfy customer satisfaction. Each customer will at by only one vehicle where each is performed by a vehicle that starts and ends at the depot(s). The summation of customers demand in each route cannot exceed vehicle capacity, a set of operational constraints are satisfied, and the total cost is minimized. After [8] introduced the problem in 1959, the problem has been attracting researchers to study the issue extensively. In the real-world problems, there are many variants of the VRP incorporating constraints and conditions. The Capacitated Vehicle Routing Problem (CVRP) within the vehicles has a limited freight capacity, and with regards to the Vehicle Routing Problem with Time Windows (VRPTW) the time interval of each customer is specified: these are two important examples of the problem. However, Cordeau et al. [9] claim that this class of the problem has been the most intriguing case of VRP. Optimization objective of VRPTW could be travel distance, number of route, and travel time considered for minimization. Some of the significant applications of the VRPTW include distribution products, delivering goods and service to customers, logistics service, and private and public transportation. The vehicle routing problem with time windows was chosen for investigation because it has been the most favorable class of the VRP [9]. In addition, the basic distribution management problem of the VRPTW can be used to model many real-world problems [10] and building up interest in this disciplinary area for further study.

Many techniques have been brought to solve the vehicle routing problems from recent conceptual practice in time. Exact algorithms have been proposed to solve the problem at the earliest time. The methods can solve only the small size problem while the computational time grows exponentially when the problem size has increased [11], which is a drawback of the algorithm. Heuristic methods have been proposed to figure out the drawback of the exact method, they can solve the large scales problems efficiently in an acceptable time. However, these methods often produce poor robustness since they could be sensitive to the datasets given. In some heuristic methods, the accuracy of training data and the coverage of data distribution can significantly affect the performance of the algorithms during the training data [12]. The drawback becomes apparently noticeable when the search space is larger and/or the dataset is more complexing in its scheme. The methods suffer from slow rates of convergence along with its limitation in the search space cover. Metaheuristics have been applied to copes with these drawbacks, they have been proposed as an idea to escape from the trap of local optimality, treat larger instances, and applied in different domains. A metaheuristic is a class of computational approaches, optimizing a given problem by iteratively improving a candidate solution via a given measure of quality. The solution of metaheuristics depends on the set of random variables generated because many of them implement some form of stochastic optimization. The algorithms are approximate and usually non-deterministic [13] and do not guarantee on finding an optimal solution [14]. Evolutionary algorithm (EA) inspired by the natural process selection and swarm intelligent inspired by natural behavior are effective algorithm on solving the VRP. The algorithms and the extension of them have been brought to solve the problem efficiently. The artificial bee colony (ABC) algorithm is one effective algorithm for solving the VRP. The enhanced ABC and hybrid ABC algorithm with other heuristic and metaheuristics e.g. BCiA by [15], ABC-T by [16] and Tabu-ABC by [17] are adopted to solve the problem efficiently. However, the exploration of the algorithm works well but the exploitation is poor. A massive number of hybrid optimization methods have been proposed to solve the combinatorial optimization problem in the last few years [18, 19]. The hybrid genetic algorithm and other heuristics and metaheuristics by [20, 21, 22] have been proposed to solve the VRP effectively. [17] developed a hybrid algorithm by combining an evolutionary local search with the recombination method for the VRP with three-dimensional loading constraints. In 2006, [23] proposed a hybrid multi-objective evolutionary algorithm (HMOEA) which provides outstanding performance on the VRPTW. Although the previous review algorithms have shown great success in solving the problem, the algorithms are sensitive to value and precision.

In this work, an evolutionary algorithm is enhanced by intra-route crossover, intra-route mutation, elitism strategy, and onlooker bee probability selection method in order to minimize transportation costs. The fuzzy technique is applied to deal with uncertainty time windows in the initialization stage to produce the feasible population and then the enhanced evolutionary algorithm is used to improve the population. The remainder of this work is organized as followed: the vehicle routing problem with time windows description is explained in section 2. Relating algorithm approaches to the VRPTW is reviewed in section 3 and then the proposed method is described in section 4. In section 5, the computational results from the proposed algorithm are presented and discussed. Finally, the paper offers a conclusion in section 6.

2.0 VEHICLE ROUTING PROBLEM WITH TIME WINDOWS (VRPTW)

This part describes the problem description and equation in section 2.1 and Solomon's benchmark dataset for the VRPTW is explained in section 2.2.

2.1 Problem Description and Equation

The VRPTW can be reviewed as a combination of vehicle routing and scheduling problem. A set of customers will be satisfied by a fleet of vehicles which start and end the service at the depot. Each customer will be served by a vehicle within their time windows in order to minimize the costs and total of customers demand in the route that does not exceed the maximum of vehicle capacity.

The VRPTW is defined by [24] as follows: it is a complete graph $G=(V,E)$. There is a set of vertices $V=\{v_0,v_1,\ldots,v_n\}$, $v_0 \in V$ represents depot, N is a subset of vertices represents customers, $N=\{v_1,\ldots,v_n\}$. The location of customer v_i represents by (a_i,b_i) and the representation location of the depot, v_0 is (a_0,b_0). For each customer $v_i \in N$, there is a demand d_i, service time or unloading time t_i and a time window $[e_i, l_i]$ where e_i is the earliest time to begin service and l_i is the latest time. Accordingly, s_i denotes the starting time service at customer v_i, the vehicle must wait with the waiting time w_i if the arriving time at customer v_i before time e_i and it is not allowed to arrive after the latest time l_i. Each pair of customers, there is t_{ij} represents a time that takes to go from customer v_i to v_j. Customer v_i is served by a vehicle at the beginning time s_i takes time t_i to unload or pick up goods. At the depot, $v_0 \in V$, there are m homogenous vehicles. Every vehicle starts and ends service to the customer with the specific quantity Q at the depot. The objective of the VRP is to find a set of $K = \{k_1, k_2, \ldots, k_m\}$ routes which serve all customers by m vehicles at the minimum cost. The cost can be the sum of travel distances, times, number of vehicles or other relevant factors of all routes. The overall distance is desired in this paper. The distance between a pair of customers $v_i, v_j \in N$ is denoted by c_{ij} calculated by the Euclidean distance (1).

$$c_{ij} = \sqrt{(a_i - a_j)^2 + (b_i - b_j)^2} \tag{1}$$

The objective of the VRPTW is to minimize cost which is referred to as the distance. The objective function is shown as follows:

$$\text{Min} \sum_{i=1, j=1}^{N} c_{ij} x_{ij} \tag{2}$$

In (2), N customers are waiting to be served by a fleet of vehicles, c_{ij} refer to distance between customer i and customer $j, (i \neq j)$ and 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.

In VRPTW, there are m vehicles at the depot v_0 to serve N customers, $\sum_{k=1}^{m}\sum_{j=1}^{n} x_{ijk} \leq m, for\, i = 0$, each of them can be serviced in a route by their capacity Q. In each route, each customer has their own demand d_i and the demand of all customers in the route must not exceed the vehicle capacity $\sum_{i=1}^{n} q_i \sum_{j=0, j\neq i}^{n} x_{ijk} \leq Q, for\, k \in K$. In the service, all vehicles start and end their routes at the depot, $\sum_{j=1}^{n} x_{ijk} = \sum_{j=1}^{n} x_{jik} = 1 \quad for\, i = 0\, and\, k \in K$ and each customer is served by only one vehicle $\sum_{k=1}^{m} \sum_{j=0, j\neq i}^{n} x_{ijk} = 1, for\, i \in N$, $\sum_{k=1}^{m} \sum_{i=0, j\neq i}^{n} x_{ijk} = 1, for\, j \in N$. In addition, the summation of the arrival time at v_i, the service time of v_i, travel time v_{ij} and the waiting time at v_j of each customer is not less than the earliest time window e_j and not more than the latest time window l_j, $e_j \leq s_i + t_i + t_{ij} + w_j \leq l_j$.

2.2 Solomon Dataset

The experiment is designed for two parts. In the first part, the proposed algorithm is tested on the Solomon benchmark datasets [25] including 56 VRPTW instances and each contains 100 customers. The instances contain a variety of customers who have their own demand and time windows distributions and have proved to be a challenge for both heuristics and exact methods since their introduction. The well-known 56 Solomon benchmark problems for vehicle routing problems with hard time windows are based on six classes of problem instances. The characteristics of each class are summarized as the following table.

Table 1: Solomon benchmark dataset characteristics

Problem set	The geographical location of customers	Vehicle capacity	Time windows
C1xx	a: [0, 100] and b: [0, 90]	200	0 – 1236
R1xx	a: [0, 70] and b: [0, 80]	200	0 – 230
RC1xx	a: [0, 100] and b: [0, 90]	200	0 – 240
C2xx	a: [0, 100] and b: [0, 90]	700	0 – 3390
R2xx	a: [0, 70] and b: [0, 80]	1000	0 – 1000
RC2xx	a: [0, 100] and b: [0, 90]	1000	0 - 960

Table 1 presents the important characteristics of Solomon benchmark dataset. The dataset including six problem classes is named C1xx (C101-C109), C2xx (C201-C208), R1xx (R101-R112), R2xx (R201-R211), RC1xx (RC101-RC108), and RC2xx (RC201-RC208). In the first class, customer locations are clustered (problem sets C1xx and C2xx) in the range [0, 90]. In the second class, customers locations are randomly generated in the range [0, 80] (problem sets R1xx and R2xx) and in the last class customers, locations are mixed with randomly generated and clustered customer locations (problem sets RC1xx and RC2xx) in the range [0, 90]. In addition, the problem classes R1xx, C1xx, and RC1xx have shorter time windows and are serviced by a small size vehicle in each route while problem classes R2xx, C2xx, and RC2xx have long time windows and are served by the large vehicles.

3.0 RELATING ALGORITHMS

This work proposed the hybrid of fuzzy technique and onlooker bee process of ABC algorithm to an evolutionary algorithm. Therefore, the important fuzzy technique, ABC algorithm and evolutionary algorithm approach to the VRPTW are described in this section.

3.1 Evolutionary Algorithm (EA)

The basic idea of the 'Evolutionary Algorithm' (EA) is to allow the individuals that meet certain selection criteria and the least fit members of the population to be eliminated. The survivors are in survival mode until better solutions are determined. The selection, reproduction, and mutation biology concepts of [26] are considered in the evolutionary algorithm. Members of the population set will converge to the solutions based on their quality. Three main subclasses of the evolutionary algorithm are the genetic algorithm (GA), evolution strategies (ES) and evolutionary programming (EP). The evolutionary strategies and genetic algorithm are reviewed in this section.

In the vehicle routing problem with time windows domain, [27] proposal consists of two evolutionary strategies in 1999. The initial population (size = μ) are generated based on savings algorithm of [28]. The stochastic element consists of the random selection of savings elements in the saving list. The parents are randomly selected and one offspring is produced after the recombination process is done. A number of offspring ($\lambda > \mu$) is created in this way. μ number of offspring will be selected to be the next generation based on their fitness values (based on route numbers, total travel distance, and route elimination criteria). The mutation is based on local searches of Or-opt [29], 2-opt* [30] and λ-interchange-move [31] with λ=1. In their proposed model, the number of the vehicle is reduced based on the Or-opt [29] operator. The recombination phased is skipped by an evolutionary strategy ES1 and the ES2 uses the uniform order-based crossover [32] to modify the initially randomly created mutation codes. [27, 33] proposes the method that all customers are served by separate routes at the beginning. Then, the cheapest reinsertions of single customers with varying insertion criteria are applied to create a set of six initial solutions and the best one is used as a starting point for the evolution strategies. The multi-parametric mutation consists of removing a set of customers from a solution randomly based on the distance to the depot or by selecting one customer from each route. Then, the cheapest insertion heuristic is used to reschedule the removed customers. After the mutation, the solution is improved in the same way as [27] and GENIUS heuristic of [34]. [23] proposed a hybrid multi-objective evolutionary algorithm (HMOEA) to solve the VRPTW in 2006. In their work, each chromosome contains a set of routes, where each route includes a list of customers. In the crossover process, the chromosomes would exchange their best route to each other. If the redundant customer(s) exists in the chromosome, the existing customer will be deleted and keep the new added one. In their work, each chromosome contains a set of routes, where each route includes a list of customers. In the crossover process, the chromosomes would exchange their best route to each other. If the newly added route contains the customer that exists in the chromosome, the customer is eliminated and the customer which has been kept will be added in the new position. A multimode mutation operator is proposed in the HMOEA for feasibility handling. If the mutation operator produces an infeasible solution, the original routes will be restored. This does not help to generate feasible solutions, but for avoiding infeasibility.

The Genetic Algorithm (GA) is an adaptive heuristic search method based on population genetics. The basic concepts of the algorithm are developed by [35] in 1975. The creation of a new generation of individuals involves primarily four major steps: initialization, selection, crossover, and mutation. In the VRPTW applications, the extension of the genetic algorithm has been broadly applied. The two-phase hybrid of a genetic algorithm and an evolutionary algorithm was proposed by [36]. The genetic algorithm was applied in the first phase to find feasible solutions and then the best solution was produced by EA in the second phase. The hybridization of the genetic algorithm and constructive heuristic was proposed by [20] in 1998. The nearest neighbor heuristic of [25] was used to create the initial population. Then, the genetic algorithm processes were applied to find the solution. The multi-criteria genetic algorithm was announced by [21] in 2001. The initial population is randomly generated as the 2-opt* from [30], which is then applied in a crossover operation while random reinsertions of customers between routes are applied in the mutation stage. Based on the rank of the individual, the probability selection shall be confirmed as being done. The best-found individual will be chosen to replace the worse one. [22] proposed a GA and developed an elitism strategy, which collected the best individuals from the current population and the offspring to perform a 2-opt improvement.

3.2 Artificial Bee Colony Algorithm (ABC algorithm)

The ABC algorithm is a new evolutionary metaheuristic technique proposed by [37] for a numerical optimization problem. The algorithm was inspired by the intelligent behavior of natural honey bees in their search for nectar sources around their hives. The algorithm was modified by [38] for a real-parameter optimization problem. The main steps of the algorithm are illustrated below:

1: Initialize Population
2: repeat
3: Place the employed bees on their food sources
4: Place the onlooker bees on the food sources depending on their nectar amounts
5: Send the scouts to the search area for discovering new food sources
6: Memorize the best food source found so far
7: until requirements are met

The algorithm starts with the initial population which is randomly generated. Then, during the employed bee stage, onlooker bee stage and scout bee stage are repeated until requirements have been fulfilled or the stopping conditions are met.

For the vehicle routing problem with time windows, a very limited number of ABC algorithms was developed to solve the problem. [15] produced the Bee Colony-inspired Algorithm (BCiA) which 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 the second stage is continued to reduce the total tour length. The algorithm is particularly efficient for the smaller test entities of the Solomon benchmarks. In the vehicle routing problem, [39,40] introduced ABC algorithm for traveling salesman problems. The algorithm has been proposed to solve the capacitated vehicle routing problem in recent years by [41, 42, 43]. The performance of the ABC heuristic has been evaluated for classical benchmark instances by [41]. They proposed an enhanced version of ABC to improve the performance of the basic ABC for solving the CVRP. The computational results of the enhance version obtained better solutions than the original version in all test instances. [44] developed a simulation framework in order to obtain performance comparisons with the other method and proposed the simulation results, which have been achieved by using the ABC algorithm to the traveling salesman problems. The ABC-T algorithm was developed by [16] to improve the performance of ABC algorithm. The tournament selection strategy which has been proposed demonstrated that the main criteria of the algorithm relate to the fitness value. The paper shows that the algorithm works efficiently with VRPTW, especially for problem R102. However, only some few experiments have been done in this work. In comparison with other algorithms, ABC-T ranked 2nd with the shortest distance. [17] proposed a hybrid algorithm based on tabu search and the ABC called TABU-ABC in 2017. After the initial population is randomly generated, the tabu search is applied to improve them and then continued working on other processes of the ABC algorithm.

The TABU-ABC algorithm was tested on the VRPTW and the VRP with time window and pallet loading constraints (VRPTWP) thus leading to an outcome with satisfying results.

3.3 Fuzzy Technique

The Fuzzy theory was presented by [45] in 1965, whereas many different research areas have found that it is a useful tool to describe subjective opinions, [46]. In applications, the basic fuzzy inference algorithm is a generalized implementation of fuzzy logic. A membership function provides a measure of the degree of similarity of an element to a fuzzy set. The design of membership functions for the fuzzy variables and the rules are the design elements of the basic fuzzy inference. For each fuzzy variable, the problem domain has to be determined. Problem domain represents the extent of validity of the fuzzy inference rule on each variable domain, the next stage is to fix the shape of the membership functions then the number of members (or a number of mapping categories) and their locations on the universe of discourse has to be found. There are different shapes of membership functions e.g. triangular, trapezoidal, piecewise-linear, Gaussian and bell-shaped. In this work, the membership function is assumed to be triangular in shape and the assumption is continued in this study.

In the vehicle routing problem, fuzzy membership function has been applied to the problem in several papers. In 1996, [47] developed a model to design vehicle routing when the demand at the nodes is uncertain. The fuzzy theory has been applied to the Chinese postman problem with time windows in 2002 by [48]. They considered two cases in a fuzzy time-constrained of the problem. 1) the arrival time at a node may be fuzzy to describe the degrees of possibility and 2) the upper and lower bounds of time window constraints are uncertain. Their objectives are to minimize the total time to finish the tour and maximize the satisfaction level. [49] proposed a hybrid solution algorithm in 2006, they considered a vehicle routing problem in which the traveling times are assumed to be fuzzy variables. [50] considered travel distance, service satisfaction, waiting time, delay time and space utility to all be integrated into Lin's formulation as the fuzzy vehicle routing and scheduling problem (FVRSP). [51] proposed a genetic approach for fuzzy vehicle routing problems with time windows (FVRPTW). After that, they included the fuzzy service time under time windows and capacity constraints to Lin's formula and then based on this extended model; a real-time application is added by them in 2010 [52] to produce the FVRPTWC. [46] proposed and solved the vehicle routing problem with fuzzy time windows (VRPFTW) in 2009. The proposed VRPFTW works under the concept of fuzzy time windows that targets to minimize the travel distance and to maximize the service level for customers. Fuzzy arithmetic rules and fuzzy logic are included in the two-stage algorithm and applied to attain a Pareto solution. The algorithm was proposed to deal with problem set RC of Solomon's dataset. The model provides effective results but cannot obtain an optimal solution in some cases. The paper suggests that the metaheuristic algorithms should be involved to consider the complexity of obtaining an optimal solution. [53] considered fuzzy VRPTW with uncertainty time windows. Fuzzy credibility theory is applied. The triangular fuzzy number represents fuzzy travel time in their chance, which had been constrained by the proposed model for the problem and found the optimal solution through the ant colony optimization algorithm. [54] proposed a multi-phase method for geographical transportation in 2017. The heuristic method is used to find route numbers in the first phase. In the second phase, the triangular membership function is applied to construct the feasible population and then GA is taken to improve the solution. Based on the previous review, the fuzzy technique can deal with the capacity and time windows constraints of the vehicle routing problem with time windows effectively. However, it was discovered that the technique was usually applied in a small size problem and for a specific organization. Therefore, this paper aims to investigate and apply this technique based on the research studies from [52] and [54] to 56 problem instances of Solomon's benchmark dataset.

4.0 METHODOLOGY

This work proposed the new methodology for the vehicular network with fuzzy time windows. To produce effective searching area, the fuzzy technique based on the work from [52] and [54] are applied to produce a feasible initial population. The proposed algorithm enhances EA exploration ability by adding some random searches around promising individuals under the guidance of onlooker bees.

In the ABC algorithm, the artificial bee colony consists of employ bees, onlooker bees, and scout bees. Each employ bee exploits a food source (candidate solution) and brings the information to the hive and shares the information with onlooker bees in the hive. The nectar amount in a food source represents the quality of the solution (fitness value). An onlooker bee chooses a food source depending on the probability value p_i associated with nectar amount. The probability p_i of the individual $\overline{sl_i}$ is formulated for the minimization objective as equation (3)

$$p_i = \left(\frac{fit(\overrightarrow{sl_i})}{\sum_{i=1}^{SN} fit(\overrightarrow{sl_i})} \right) \Bigg/ \left(1 - \frac{fit(\overrightarrow{sl_i})}{\sum_{i=1}^{SN} fit(\overrightarrow{sl_i})} \right) \tag{3}$$

The steps of the proposed algorithm are described below. The proposed algorithm follows the typical flow of an EA. Chromosome representation is demonstrated in section 4.1 and each step of the proposed algorithm is presented from section 4.2 to 4.4.

*Step*1: Generate the initial population (produce SN individuals; see section 4.2).

Step2: Produce SN offspring. Set $n_o = 0$.

Step2.1: Select two parents randomly.

Step2.2: Inter-Route Crossover (section 4.3).

Step2.3: Intra-Route mutation operator (section 4.4).

Step2.4: $n_o = n_0 + 1$. If $n_o = N$, then go to Step 3; otherwise continue working on Step 2.1-2.4.

Step3: Calculate p_i of each individual by equation (3) (individual number = $SN \times 2$).

Step4: Select SN new generation based on roulette wheel probability selection method (from $SN \times 2$ individuals).

Step5: Evaluate the fitness function of each individual.

Step6: Select individual based on Elitism strategy (from $N \times 2$ individuals) and replace them with the worse individual from *Step4*.

Step7: Continue *Step2*- *Step6* until meet stopping criteria.

The chromosome representative is described in section 4.1 and then the feasible initial population is formed by the fuzzy technique described in section 4.2. After N feasible individuals are constructed to be the initial population, N offspring will be produced in step 2. One problem that the classical one-point crossover encountered is the duplication and omission of customers in the chromosome after reproduction. This paper proposes a simple crossover operator for the proposed algorithm that allows the exchange between the selected routes in the chromosome (individual). Each route in the chromosome acts as a parent that will be chosen randomly (step 2.1). Then, the crossover points of the two parents will be randomly selected and the local search will be applied (step 2.2). The inter-route crossover is described in detail in section 4.3. Previously, the RAR (remove and reinsert) mutation operator was proposed by Gendreau et al. [55]. The route will be feasible by revoking and inserting a node into a random point of the route. In this paper, the nearest neighborhood operator is applied. The processes are explained in section 4.4. Steps 3 – 5 refer to onlooker bee processes. The fitness function of each individual will be evaluated based on an objective function that's given in equation (2). The new generation is chosen depending on the probability value p_i based roulette wheel probability selection method. The elitism strategy selects a small number of good individuals and replaces the worse individuals in the next generation. Because the population size of this work is small, the individual selection based on elitism strategy is 10%. The evolution process will be carried out until the stopping condition is met or no individual has improved over the last 100 generations.

4.1 Chromosome Representative

Chromosome in evolutionary algorithms is almost represented as a fixed-structure bit string which is not suitable for VRPTW. The VRPTW is an order-oriented NP-hard optimization problem where sequences among customers are essential [23]. Each chromosome, including the number of routes (vehicles), serves the number of customers sequentially under the vehicle capacity and time windows constraints.

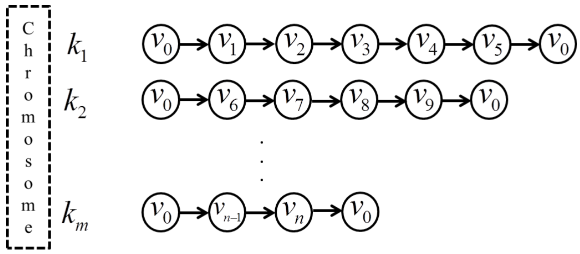

Fig. 1**:** Chromosome representation

In fig. 1, there are n number of customers served by m vehicles. The order of customers (v_i) in each route after v_0 is the sequence of customers served by vehicle k_i. Customer v_1, v_2, v_3, v_4 and customer v_5 are served by vehicle k_1. In vehicle k_2, there are customers v_6, v_7, v_8 and v_9 served by the vehicle sequentially while vehicle k_m services customers v_{n-1} and customer v_n. Customer v_1, v_6 and customer v_{n-1} are the first customer visited by vehicle k_1, k_2 and k_m respectively. Customer v_5 is visited by vehicle k_1, customer v_9 is served by vehicle k_2 and customer v_n is serviced by vehicle k_m before the vehicle returning to the depot v_0.

4.2 Generate Initial Population

In the initialization stage, the fuzzy strategy [52, 54] is considered to be applied in order to produce a feasible population. The feasible routes are construed in the same way as [58]. The triangular membership function is applied to decide the position of the customer in the route. The following constraints are not to be broken during the service routes which are under construction. (1) The service of each vehicle is started and stopped at the depot (v_0) and (2) the travel times between customers are assumed to be fuzzy variables. (3) Each customer will be served by only one vehicle within their time windows $[e_i, l_i]$ in order to minimize the cost c_{ij} and (4) total of customers demand $\sum d_i$ in the route does not exceed the maximum of vehicle capacity q_i.

In order to maximize service time satisfaction, the triangular membership function based on the concept of fuzzy due time from Gupta et al. [52] is brought to grade the satisfaction of service time of customers. The membership function of service time $\theta_1(s)$ can be defined for any service time $(s > 0)$ as the following equation:

$$\theta_i(s) = \begin{cases} 1; e_i \le s \le l_i \\ 0; otherwise \end{cases} \tag{4}$$

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

$$\theta_i(s_i) = \begin{cases} 0; s_i < e_i \; or \; s_i > l_i \\ \dfrac{(s_i - e_i)}{(u_i - e_i)}; e_i \le s_i \le u_i \\ \dfrac{(l_i - s_i)}{(l_i - u_i)}; u_i < s_i \le l_i \end{cases} \tag{5}$$

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 processes to generate the initial population are shown below.

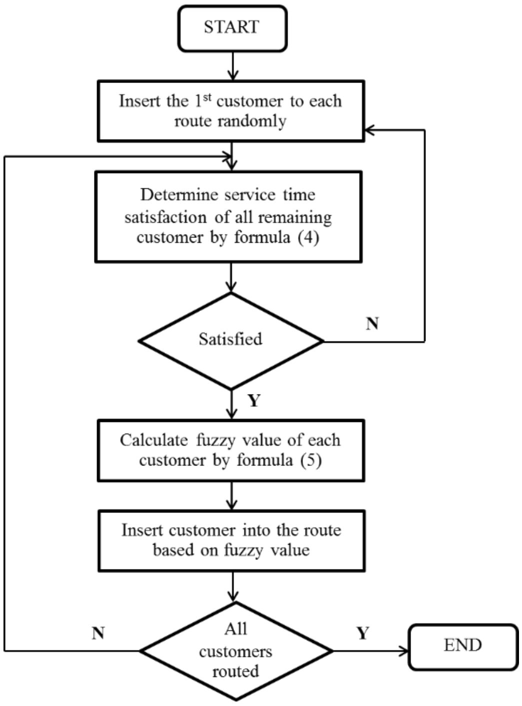

Fig. 2: The procedure for building an initial population

Fig.2 presents the processes to produce the feasible initial population. To produce each feasible individual of the initial population, the first customer will be randomly added to each route. Then, service time satisfaction of all remaining customers will be evaluated by equation (4). After that, the triangular membership function is calculated by the fuzzy value of all satisfied customers in equation (5). Customer(s) will be inserted to an appropriate route based on their fuzzy value. The processes will be continued until all customers are added to the route.

4.3 Inter-Route Crossover.

A local search is an optimization method that explores the given neighborhood solution to generate a local optimal solution. In the inter-route crossover, this work uses four local search operators including swap 1-1, insert swap 1-0, swap 2-2 and 2-Opt* which are described in the following.

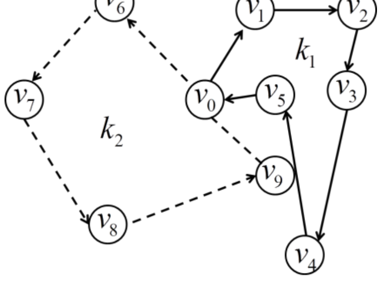

Fig. 3: The example of parent routes

To explain the effect of local search operator, the example of parent routes is shown in Fig.3. The figure represents two example routes served by vehicle k_1 and k_2. The vehicle starts their service from the depot v_0 and returns to the depot at the end of service. Customers v_1, v_2, v_3, v_4 and v_5 are served by vehicle k_1 respectively and customers v_6, v_7, v_8 and v_9 are served by vehicle k_2 sequentially.

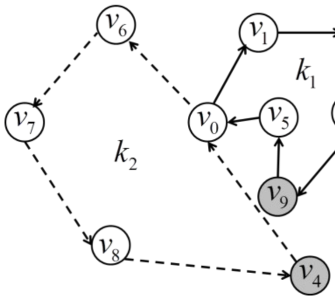

Fig. 4: Swap 1-1 operator

Fig.4 illustrates the route after swap 1-1 operator is applied to the parent routes. In Fig.4, customer v_4 in route k_1 and customer v_9 in route k_2 are randomly selected. After the swap 1.1 is applied, the selected customers from the two routes will exchange their positions. In this example, customer v_4 is moved to route k_2 and v_9 is swapped it's position to route k_1.

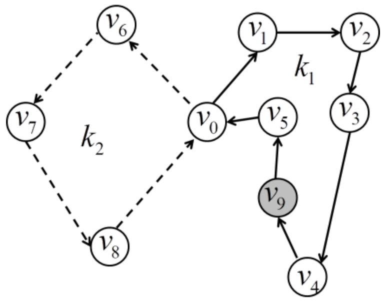

Fig. 5: Swap 1-0 operator

Fig.5 explains swap 1-0 operator. In Fig.5, customer v_9 is eliminated from route k_2 and inserted to route k_1. In the case that the selected route contains only one customer and the customer is chosen to insert to another route, that route will be erased from the solution.

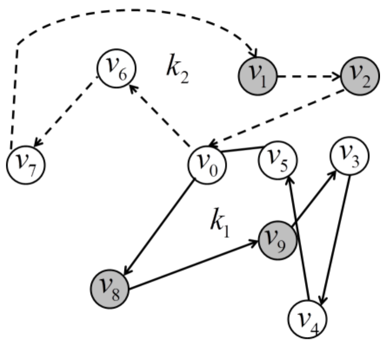

Fig. 6: Swap 2-2 operator

Fig.6 explains the effect to the parent routes after swap 2-2 operator is applied. In Fig.6, the edge between customers (v_1, v_2) in route k_1 and edge between customers (v_8, v_9) in route k_2 are exchanged by their positions.

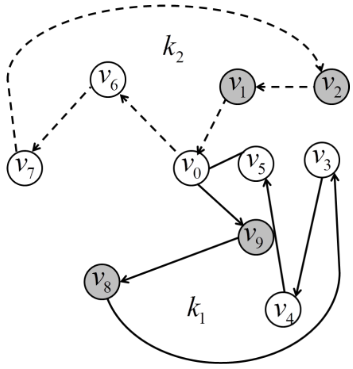

Fig. 7: 2-Opt* operator

Fig.7 explains the effect of swap 2-Opt* operator the parent routes. In Fig.7, customer v_1 and v_8 are randomly selected and they will exchange their position with their next node ($v_1 \leftrightarrow v_2$ and $v_8 \leftrightarrow v_9$). After that, the edge between customers (v_1, v_2) in route k_1 and edge between customers (v_8, v_9) in route k_2 are swapped their position between the routes.

4.4 Intra-Route mutation operator.

1. Start on the first vertex of the route as current vertex
2. Repeat
   - 2.1 find out the shortest edge connecting current vertex and unvisited vertex V.
   - 2.2 Set current vertex to V.
   - 2.3 Mark V as visited.
   - 2.4 If all the vertices in the route are visited, then terminate.

Until stopping Condition is met

Fig. 8: Nearest neighborhood operator workflow

In Fig. 8, the nearest neighborhood operator workflow is shown. In this work, the nearest neighborhood operator is applied to improve each route in the chromosome. In this case, the movement of customers in each route will not affect the vehicle capacity but the time windows of each customer will still be considered and cannot be ignored. The first customer (current customer/ current vertex) is chosen due to its earliest time windows e_i and the next customer is selected due to the shortest edged that is connecting between the current customer and the next customer. This can help to improve the solution by moving the position within the route. However, it should be noted that after the intra-route mutation is done all constraints must be checked and the new solution must be feasible.

5.0 COMPUTATIONAL RESULTS AND DISCUSSION

In this work, the proposed algorithm is tested on 56 problem instances of the Solomon benchmark dataset in evaluating the performance of the algorithm, and the experiment environments are set in the same way for all testing instances. The control parameters in the experiment are set in the same way as the comparing algorithm, HMOEA [23]. However, some control parameters of the HMOEA [23] e.g. elastic rate and squeeze rate are ignored because they are the special parameter used in the method of HMOEA [23]. The control parameters are as follows: (1) number of customers is 100, (2) number of iteration is 1500, (3) crossover rate is 0.7 (4) mutation rate is 0.1 (5) loop will be stopped when the current solutions are not improved for 10 iterations and elitism rate is 10% of the population size. Because the feasible population is produced by a special technique for the initialization stage, the population size used in this work is 20 which caused the elitism rate to be different with HMOEA [23] as well.

In this section, the consistency and reliability of the results obtained by the proposed algorithm are investigated. The algorithm runs 10 times as the comparing algorithms for Solomon's 56 data sets. The results on the VRPTW of the proposed algorithms are indicated in comparison against the other results that have been recently published in other papers shown in Table 2, the best results are bolded.

Table 2**:** Comparing number of vehicle (NV) and the total routing cost (Distance) with other algorithms

Data set	**Cordeau and Maischberger (2012)**				**Zhang et al. (2017)**						**Tan et al. (2006)**						**Propose**					
	Best		**Mean**		**Best**		**Mean**		**SD**	**CV (%)**	**Best**		**Mean**		**SD**	**CV (%)**	**Best**		**Mean**		**SD**	**CV (%)**
	NV	**Dist**	**NV**	**Dist**	**NV**	**Dist**	**NV**	**Dist**			**NV**	**Dist**	**NV**	**Dist**			**NV**	**Dist**	**NV**	**Dist**		
C101	**10**	828.94	**10**	**828.94**	**10**	828.94	**10**	**828.94**	0	0	**10**	**828.93**	10	834.36	10	1.24	**10**	828.94	**10**	**828.94**	0	0
C102	**10**	828.94	**10**	**828.94**	**10**	828.94	**10**	**828.94**	0	0	**10**	**828.19**	10	840.37	17	2.03	**10**	828.94	**10**	**828.94**	0	0
C103	**10**	828.06	**10**	**828.07**	**10**	828.07	**10**	**828.07**	0	0	**10**	**828.06**	10	832.31	9.1	1.1	**10**	828.06	**10**	**828.06**	0	0
C104	**10**	**824.78**	**10**	**824.78**	**10**	**824.78**	**10**	827.93	5.6	0.67	**10**	825.54	10	834.7	6.7	0.8	**10**	**824.78**	**10**	**824.78**	0	0
C105	**10**	828.94	**10**	**828.94**	**10**	828.94	**10**	**828.94**	0	0	**10**	**828.9**	10	844.14	19	2.2	**10**	828.94	**10**	**828.94**	0	0
C106	**10**	828.94	**10**	**828.94**	**10**	828.94	**10**	**828.94**	0	0	**10**	**828.17**	10	832.13	3.9	0.47	**10**	828.94	**10**	**828.94**	0	0
C107	**10**	828.94	**10**	**828.94**	**10**	828.94	**10**	**828.94**	0	0	**10**	**828.34**	10	840.91	13	1.5	**10**	828.94	**10**	**828.94**	0	0
C108	**10**	**828.94**	**10**	**828.94**	**10**	**828.94**	**10**	**828.94**	0	0	**10**	832.28	10	843.77	22	2.64	**10**	**828.94**	**10**	**828.94**	0	0
C109	**10**	**828.94**	**10**	**828.94**	**10**	**828.94**	**10**	**828.94**	0	0	**10**	**829.22**	10	832.21	9.6	1.15	**10**	**828.94**	**10**	**828.94**	0	0
C201	**3**	**591.56**	**3**	**591.56**	**3**	**591.56**	**3**	**591.56**	0	0	**3**	591.58	**3**	633.01	33	5.24	**3**	**591.56**	**3**	591.89	0.7	0.11
C202	**3**	**591.56**	**3**	**591.56**	**3**	**591.56**	**3**	**591.56**	0	0	**3**	**591.56**	**3**	624.7	25	3.98	**3**	**591.56**	**3**	592.02	0.9	0.15
C203	**3**	**591.17**	**3**	599.14	**3**	**591.17**	**3**	591.31	3.7	0.62	**3**	593.25	**3**	648.18	38	5.84	**3**	**591.17**	**3**	591.46	0.5	**0.08**
C204	**3**	**590.6**	**3**	**590.6**	**3**	**594.89**	**3**	603.16	10	1.68	**3**	595.55	**3**	647.01	40	6.17	**3**	**590.6**	**3**	591.23	0.8	**0.13**
C205	**3**	588.88	**3**	**588.88**	**3**	588.88	**3**	**588.88**	0	0	**3**	**588.16**	**3**	626.58	40	6.4	**3**	588.88	**3**	589.35	0.6	0.11
C206	**3**	**588.49**	**3**	**588.49**	**3**	**588.49**	**3**	**588.49**	0	0	**3**	**588.49**	**3**	629.36	61	9.61	**3**	**588.49**	**3**	588.95	0.9	0.16
C207	**3**	**588.29**	**3**	**588.29**	**3**	**588.29**	**3**	**588.29**	0	0	**3**	588.88	**3**	615.57	33	5.34	**3**	**588.29**	**3**	588.47	0.2	0.04
C208	**3**	588.32	**3**	**588.32**	**3**	588.32	**3**	**588.32**	0	0	**3**	**588.03**	**3**	634.96	54	8.51	**3**	588.32	**3**	588.73	0.7	0.12

Table 2**:** Comparing number of vehicle (NV) and the total routing cost (Distance) with other algorithms (Cont.)

Data set	**Cordeau and Maischberger (2012)**				**Zhang et al. (2017)**						**Tan et al. (2006)**						**Propose**					
	Best		**Mean**		**Best**		**Mean**		**SD**	**CV (%)**	**Best**		**Mean**		**SD**	**CV (%)**	**Best**		**Mean**		**SD**	**CV (%)**
	NV	**Dist**	**NV**	**Dist**	**NV**	**Dist**	**NV**	**Dist**			**NV**	**Dist**	**NV**	**Dist**			**NV**	**Dist**	**NV**	**Dist**		
R101	19	**1650.8**	19	1652.13	20	1643.2	20	1645.8	5.5	0.33	**18**	1613.6	**18**	1674.8	53	3.14	19	1650.8	19	1650.9	0.2	**0.01**
R102	**17**	1486.1	**17**	1487.49	18	1460.3	18	**1463.9**	4	0.27	18	**1454.7**	18	1527.1	65	4.25	**17**	1486.1	**17**	1486.3	0.4	**0.03**
R103	**13**	1294.2	13	1282.91	15	1217.4	15	1223.3	2.4	0.2	14	1235.7	14	1240	62	5	14	**1213.6**	14	**1213.8**	0.3	**0.02**
R104	**10**	981.2	**10**	987.58	11	987.61	11	1002.5	6	0.6	**10**	**974.24**	10	1019.4	27	2.65	**10**	982.01	**10**	**982.2**	0.3	**0.03**
R105	**14**	1377.1	**14**	1377.99	15	**1363.9**	16	**1372**	5.5	0.4	15	1375.2	15	1414.4	42	2.98	**14**	1377.1	**14**	1377.4	0.4	**0.03**
R106	**12**	1252.6	**12**	1257.95	13	**1247.9**	13	1256.5	4.8	0.38	13	1260.2	13	1351.6	82	6.03	**12**	1252	**12**	1252.1	0.3	**0.02**
R107	**10**	1104.7	**10**	1111.53	12	1087.5	12	**1097.4**	4.5	0.41	11	**1085.8**	11	1100.6	16	1.47	**10**	1104.7	**10**	1104.8	0.3	**0.02**
R108	**9**	963.99	**9**	971.1	**9**	961.85	11	965.82	5.9	0.61	10	**954.03**	10	1032.1	77	7.49	**9**	960.88	**9**	960.99	0.3	**0.03**
R109	**11**	1194.7	**11**	1201.62	13	**1153**	13	**1163.1**	7.2	0.62	12	1157.7	12	1218.9	49	4.04	**11**	1194.7	**11**	1194.8	0.2	**0.02**
R110	**10**	1118.8	**10**	1128.98	12	1091.5	12	1100.8	8.5	0.77	12	1104.6	12	1146.5	30	2.64	11	**1080.4**	11	**1080.6**	0.6	**0.05**
R111	**10**	1096.7	**10**	1099.83	12	1067.5	12	**1076.6**	7.2	0.67	12	**1057.8**	12	1139	81	7.1	**10**	**1096.7**	**10**	1096.9	0.4	**0.03**
R112	**9**	989.27	**9**	1003.69	10	973.25	11	978.16	6.5	0.66	10	974.73	10	1019.5	34	3.32	10	**953.63**	10	953.88	0.5	**0.05**
R201	**4**	1252.4	**4**	1253.5	6	**1174.7**	6.1	**1178.9**	4.9	0.41	5	1206.4	5	1269	56	4.42	**4**	1252.4	**4**	1255.1	2	**0.16**
R202	**3**	1191.7	**3**	1201	5	**1046.1**	5.1	**1053.4**	7.9	0.75	4	1091.2	4	1293.4	127	9.78	**3**	1191.7	**3**	1193.9	1.5	**0.13**
R203	**3**	941.08	**3**	950.34	5	**884.02**	4.9	**896.05**	7.8	0.87	4	935.04	4	1103	120	10.8	**3**	**939.54**	**3**	940.62	1.2	**0.12**
R204	**2**	825.52	**2**	833.61	4	**750.4**	4	**758.13**	6.5	0.86	3	789.72	3	878.51	78	8.88	**2**	825.52	**2**	826.81	1.4	**0.16**
R205	**3**	994.43	**3**	995.18	5	**960.75**	4.9	**975.83**	7.6	0.78	**3**	1094.7	**3**	1212.9	115	9.48	**3**	994.42	**3**	996.01	1.8	**0.18**
R206	**3**	906.14	**3**	910.93	4	**900.97**	4.3	908.18	6.8	0.74	**3**	940.12	**3**	1013	80	7.85	**3**	906.14	**3**	**907.39**	0.9	**0.1**
R207	**2**	890.61	**2**	901.7	4	**809.72**	4	**826.74**	11	1.37	3	852.62	3	942.9	94	9.96	**2**	890.61	**2**	891.94	1.1	**0.12**

Table 2: Comparing number of vehicle (NV) and the total routing cost (Distance) with other algorithms (Cont.)

Data set	Cordeau and Maischberger (2012)				Zhang et al. (2017)						Tan et al. (2006)						Propose					
	Best		Mean		Best		Mean		SD	CV (%)	Best		Mean		SD	CV (%)	Best		Mean		SD	CV (%)
	NV	Dist	NV	Dist	NV	Dist	NV	Dist			NV	Dist	NV	Dist			NV	Dist	NV	Dist		
R208	**2**	726.82	**2**	733.58	5	**723.14**	3.4	732.31	7	0.95	**2**	790.6	**2**	986.28	100	10.1	**2**	726.82	**2**	**728.09**	1	**0.14**
R209	**3**	909.16	**3**	917.6	5	863.12	4.9	882.22	6.7	0.76	**3**	974.88	**3**	1088.2	91	8.38	**3**	909.16	**3**	910.74	1.3	**0.14**
R210	**3**	939.37	**3**	945.81	5	**927.54**	4.9	**938.63**	9.3	0.99	5	982.31	5	1087.7	86	7.89	**3**	939.37	**3**	940.33	1	**0.1**
R211	**2**	885.71	**2**	912.53	4	**763.22**	4	**781.23**	7.6	0.97	4	811.59	4	879.47	46	5.27	**2**	885.71	**2**	887.67	1.4	**0.16**
RC101	**14**	1697	14	1690.19	16	1646.2	16	1656	6.9	0.42	16	1641.7	16	1667.5	17	1.01	15	**1623.6**	15	**1623.8**	0.3	**0.02**
RC102	**12**	1554.8	**12**	1560.87	14	1481.6	15	79	7.3	9.23	13	**1470.3**	13	1496.7	28	1.88	13	1477.5	13	**1477.7**	0.2	**0.02**
RC103	**11**	1261.7	**11**	1263.06	12	**1208.8**	12	1298.3	19	1.42	**11**	1267.9	**11**	1336.3	31	2.29	**11**	1261.7	**11**	**1261.9**	0.5	**0.04**
RC104	**10**	**1135.5**	**10**	1135.73	11	1162	11	1168.1	5.4	0.46	**10**	1145.5	**10**	1177.4	19	1.65	**10**	**1135.5**	**10**	**1135.7**	0.4	**0.04**
RC105	**13**	1633.7	13	1623.37	16	**1545.3**	16	**1554.8**	8.5	0.55	14	1589.9	14	1590.4	19	1.18	**13**	1629.4	**13**	1629.7	0.5	**0.03**
RC106	**11**	1424.7	**11**	1426.95	14	1401.2	14	1413.4	7.4	0.52	13	**1371.7**	13	1404.9	25	1.75	12	1384.9	12	**1385.1**	0.4	**0.03**
RC107	**11**	1232.2	**11**	1233.11	12	1235.3	13	1257	12	0.95	**11**	**1222.2**	**11**	**1226.8**	22	1.79	**11**	1230.5	**11**	1230.7	0.5	**0.04**
RC108	**10**	1147.7	**10**	1157.82	11	1136.4	11	1149.7	9.8	0.85	11	**1133.9**	11	1150.9	15	1.32	10	1139.8	**10**	**1140**	0.4	**0.04**
RC201	**4**	1406.9	**4**	1410.15	7	1271.8	6.9	**1284.6**	5.7	0.44	6	**1134.9**	6	1337.2	84	6.24	**4**	1406.9	**4**	1407.4	0.6	**0.04**
RC202	**3**	1367.1	**3**	1400.67	6	**1116.2**	5.8	**1123**	5.3	0.47	5	1130.5	5	1169.5	45	3.84	**3**	1365.7	**3**	1366.4	0.7	**0.05**
RC203	**3**	1050.6	**3**	1061.31	5	**941.81**	5.1	**951.3**	6.3	0.67	4	1026.6	4	1085	51	4.66	**3**	1049.6	**3**	1050.9	0.9	**0.08**
RC204	**3**	**798.46**	**3**	800.06	4	801.87	4	809.09	8.1	1	**3**	879.82	**3**	916.53	60	6.56	**3**	**798.46**	**3**	**798.82**	0.8	**0.1**
RC205	**4**	1297.7	**4**	1305.28	7	**1165.8**	7	**1172.8**	16	1.39	5	1295.5	5	1362.1	107	7.88	**4**	1297.7	**4**	1297.9	0.7	**0.05**
RC206	**3**	1153.6	**3**	1160.88	5	**1072.9**	5.5	**1082.9**	8.4	0.78	4	1139.6	4	1237	86	6.91	**3**	1146.3	**3**	1147.4	0.8	**0.07**
RC207	**3**	1061.1	**3**	1067.4	5	**977.11**	5.4	**998.46**	9.8	0.98	4	1040.7	4	1153.3	83	7.19	**3**	1061.1	**3**	1061.9	0.9	**0.09**
RC208	**3**	828.71	**3**	836.45	5	**792.33**	4.7	**809.23**	8.7	1.07	**3**	898.49	**3**	978.44	99	10.1	**3**	828.14	**3**	829.11	1.2	**0.14**

In Table 2, the best distance (Best), mean of the distance from ten runs (Mean), standard deviation (SD) and percent of the coefficient of variation (CV) which is the ratio between the standard deviation and the mean are demonstrated. In the table, SD and CV of [56] are not shown because they are not available in the published paper. As the previous mention, this work finds the best routes number before the distance is considered, then the same number of vehicles are produced for all testing data sets. The table shows that all comparing algorithms provide similar performance for problem class C whereas the coefficient of variation from the proposed algorithm is the best. However, the best distance given by [57] displays the best performance while the results of [23] are the worse. According to [10], a solution which requires fewer vehicles will be considered a better solution with more than one route, regardless of the total traveled distance. The proposed results in Table 2 were selected based upon the number of vehicle (NV). If NV is minimized, then the distance is considered. In problem class C including C101-C109 and C201-C208, all comparing algorithms produce the same number of vehicles. The results (Best) from [23] provide almost better results than others. Problem class R contains R101-R112 and R201-R211. The proposed algorithm provides almost the same results as the results of [56]. From 21 problem instances of this problem class, the proposed algorithm gives the worse results than [56] in problem R103, R110 and R112 while proposes better results in problem R108, R111, R203, and R205 in terms of distance with the same number of vehicles. Comparing to the other two algorithms, the table shows that the proposed algorithm gives a better number of vehicles than [23] for 15 problem instances and better than [57] for 21 problem instances. The last problem class is RC which contains 16 problem instances including RC101-RC108 and RC201-RC208. The table illustrates that [56] produce a better number of vehicles in problem RC101, RC102, and RC106 in comparison to other algorithms. In consideration to the same number of vehicles, the proposed algorithm gives the best distance for 7 instances including RC105, RC107, RC108, RC202, RC203, RC206, and RC208.

Table 3: The average distance over ten runs of pairwise comparison using the Wilcoxon signed-ranks non-parametric test ($\alpha = 0.05$)

Dataset	Propose vs Cordeau, & Maischberger [56]						Propose vs Zhang et al. [57]						Propose vs Tan et al. [23]					
	Negative Ranks	Positive Ranks	Ties	Total	z	Asymp. Sig. (2-tailed)	Negative Ranks	Positive Ranks	Ties	Total	z	Asymp. Sig. (2-tailed)	Negative Ranks	Positive Ranks	Ties	Total	z	Asymp. Sig. (2-tailed)
C1xx	1^a	0^b	8^c	9	-1.000	0.317	2^a	0^b	7^c	9	-1.342	0.18	9^a	0^b	0^c	9	-2.666	0.008
C2xx	1^a	7^b	0^c	8	-1.402	0.161	1^a	7^b	0^c	8	-1.402	0.161	8^a	0^b	0^c	8	-2.521	0.012
R1xx	12^a	0^b	0^c	12	-3.059	0.002	6^a	6^b	0^c	12	-.275	0.784	11^a	1^b	0^c	12	-2.981	0.003
R2xx	9^a	2^b	0^c	11	-2.667	0.008	2^a	9^b	0^c	11	-2.578	0.01	10^a	1^b	0^c	11	-2.845	0.004
RC1xx	7^a	1^b	0^c	8	-1.960	0.05	6^a	2^b	0^c	8	-.420	0.674	6^a	2^b	0^c	8	-1.680	0.093
RC2xx	8^a	0^b	0^c	8	-2.521	0.012	1^a	7^b	0^c	8	-2.380	0.017	6^a	2^b	0^c	8	-0.980	0.327

Note: a, b and c indicating that the average mean of the proposed algorithm is less than, greater than and equal to the comparison algorithm respectively.

Table 3 presents information regarding the p-value (Asymp. Sig. (2-tailed)) resolved by the Wilcoxon signed-rank test for the considered test instances. The propose displays statistically superior performance at the 95% significance level ($\alpha = 0.05$) on [23]. In terms of [56], the proposed algorithm reveals statistically exceeding performance except for C10x and C20x. However, a Wilcoxon signed-rank test showed that they are not significantly different ($z= -1.00$, $p=0.317$ for C10x and $z= -1.402$, $p=0.161$ for C20x). The proposed algorithm provides unsatisfied distance comparing to [57]. Therefore, the average number of vehicles is examined in the next table.

Table 4: The average vehicle numbers over ten runs of pairwise comparison using the Wilcoxon signed-ranks non-parametric test ($\alpha = 0.05$)

Dataset	Propose vs Cordeau, & Maischberger [56]						Propose vs Zhang et al. [57]						Propose vs Tan et al. [23]					
	Negative Ranks	Positive Ranks	Ties	Total	z	Asymp. Sig. (2-tailed)	Negative Ranks	Positive Ranks	Ties	Total	z	Asymp. Sig. (2-tailed)	Negative Ranks	Positive Ranks	Ties	Total	z	Asymp. Sig. (2-tailed)
R1xx	0^a	3^b	9^c	12	-1.633	0.102	12^a	0^b	0^c	12	-3.065	0.002	8^a	1^b	3^c	12	-2.309	0.021
R2xx	0^a	0^b	11^c	11	.000	1	11^a	0^b	0^c	11	-2.956	0.003	7^a	0^b	4^c	11	-2.460	0.014
RC1xx	1^a	3^b	4^c	8	-1.473	0.141	8^a	0^b	0^c	8	-2.521	0.012	4^a	0^b	4^c	8	-2.000	0.046
RC2xx	0^a	0^b	8^c	8	.000	1	8^a	0^b	0^c	8	-2.521	0.012	6^a	0^b	2^c	8	-2.271	0.023

Note: a, b and c indicating that the average mean of the proposed algorithm is less than, greater than and equal to the comparison algorithm respectively.

In Table 4, the average vehicle number over ten runs is investigated. Instances C10x and C20x are disregarded in this table because they are not different in any comparing algorithms. The table shows that average number of the vehicle given by the proposed algorithm and [56] are not different at the 95% significance level ($\alpha = 0.05$) while it claims that the proposed algorithm provides significantly better results than [23] and [57].

6.0 CONCLUSION

This work proposes a new methodology for the vehicular network with fuzzy time windows. In the initialization stage, the fuzzy technique is applied to deal with the uncertainty time windows constraint and produces the feasible population. After that, the intra-route crossover, intra-route mutation, elitism strategy, and onlooker bee probability selection method are enhanced in the original processes of an evolutionary algorithm in order to improve the population. The proposed algorithm is tested on 56 problem instances of Solomon's benchmark dataset and provides some very encouraging results.

In Table 2, the proposed algorithm proposes the same quality results for problem class C (C101-C109 and C201-C208) as other comparing algorithms except for the HMOEA of [23]. Although the HMOEA provides the best results for problem class C, the algorithm presents the worse results in terms of the coefficient of variation (CV). With the same number of vehicles, [56] displays the best distance for 6 problems including R103, R110, R112, RC101, RC102, and RC106 while the proposed algorithm presents the best distance for 11 problems which are R108, R111, R203, R205, RC105, RC107, RC108, RC202, RC203, RC206, and RC208. In addition, the table shows that the proposed algorithm produces 15 and 17 better number of vehicles when comparing to. [23] and [57] respectively. The proposed algorithm provides a better distance than [23] for an equal number of vehicles (problem R2xx and RC2xx). More significantly, the proposed algorithm exhibits the best results for 40 from 56 problem instances in terms of the coefficient of variation values. Table 3 and Table4 illustrate the information regarding the p-value (Asymp. Sig. (2-tailed)) resolved by the Wilcoxon signed-rank test for the considered test instances. The proposed methodology displays a statistically superior performance at the 95% significance level ($\alpha = 0.05$) on comparing algorithms. This claims that the proposed algorithm is effective and competitive for configuring the VRPTW problem.

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