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A fuzzy logic-genetic algorithm for full truckload transportation problem

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ABSTRACT

This work addresses a full truckload commodity selection and multiple depot vehicle routing problem with time windows (FTSMDVRPTW). The goal of the problem is to design a set of selective truck routes that maximize overall profit subject to time window constraints. Each truck route is an arrangement of full truckload transportation commodities that begins at a departure point and ends at an arrival point. It is unnecessary to serve all commodities; only those that provide a higher profit are chosen. We introduce a meta-heuristic based on a combination of fuzzy logic controller (FLC) and genetic algorithm (GA) to solve the FTSMDVRPTW, where the crossover and mutation rates are adjusted during the GA's evolutionary process using an FLC. We demonstrate the effectiveness and efficiency of the proposed FLC+GA through experimental results on randomly generated instances for the considered problem.

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1. INTRODUCTION

The vehicle routing problem (VRP) is a combinatorial optimization problem (COP) that has received extensive attention since its introduction in [1]. Its use is critical in various fields, such as logistics, transportation, and resource allocation. In the classic VRP, transportation demands are delivered to their specific customers by a fleet of identical vehicles located at a central depot. The problem's goal is to determine low-cost routes to serve customers while adhering to vehicle capacity constraints. Given the importance of the VRP, several variants of this problem have been proposed by researchers to address more realistic aspects [2], [3]. The full truckload vehicle routing problem (FTVRP) is an essential variant in which full truckload orders (or commodities) must be transported directly from their origins to their destinations. Another variant is the full truckload vehicle routing problem with time windows (FTVRPTW), where each order has a pickup and/or delivery time window during which the truck can perform the service. Moreover, trucking companies can service their clients through numerous depots (full truckload vehicle routing problem with multiple depots (FTMDVRP)). A global survey summarizing the literature on FTVRP variants has been presented in [4].

Like other VRP variants, the problem of the FTVRP is an NP-hard COP [5]. Therefore, various (meta) heuristic approaches are employed to tackle this problem efficiently and find optimal or near-optimal answers for large instances in a reasonable time. These methods include adaptive large neighborhood search (ALNS) [6], reactive tabu search (RTS) [7], [8], genetic algorithm (GA) [9], [10], and ant colony system [11], [12].

GA is an efficient meta-heuristic for various optimization problems. However, it has two significant weaknesses: i) premature convergence and ii) slow search speed. This occurs because parameter settings, which are chosen based on user experience or guidelines provided by studies [13], are fixed during the process of running the GA while the changing environment is omitted. Nevertheless, evolution in biology indicates that the rate of mutation and crossover varies according to the evolution state, and thus, they need to be adjusted to suit different circumstances [14]. Hence, various studies have used fuzzy logic controllers (FLCs) to dynamically control some GA parameter settings during process execution [15], [16].

The main contribution of this study is to introduce a meta-heuristic based on a combination of FLC and GA (FLC+GA) to solve the full truckload commodity selection and vehicle routing problem with time windows and multiple depots for truck starting and finishing points (FTSMDVRPTW), where the crossover and mutation rates of the GA are adjusted using a fuzzy logic technique. The problem entails choosing a subset of commodities to be satisfied, assigning them to trucks, and determining the best commodity servicing sequence for each truck trip while maximizing total net profit and adhering to commodity and truck depot time window constraints. The remainder of this paper is structured as follows. Section 2 describes the problem of the FTSMDVRPTW. Section 3 propose the FLC+GA for solving the problem. The experimental results are reported in section 4. Finally, section 5 concludes the paper and offers directions for future study.

2. PROBLEM DEFINITION

The FTSMDVRPTW can be described on a directed graph $G = (V, E)$, where V is the vertex set and E is the possible arc set. The vertices are the extremity points $\{(L_i, U_i);\ i = 1, \dots, n\}$ of n orders linked to two sets of points: $D = \{D_k;\ k = 1, \dots, m\}$ and $A = \{A_k;\ k = 1, \dots, m\}$, corresponding to the set of starting and finishing depots of m trucks, respectively. L_i (resp. U_i) denotes the origin (resp. the destination) of order O_i $(i = 1, \dots, n)$. Each order O_i is associated with a revenue r_i and two-time windows: the loading time window $[L_i^{min}, L_i^{max}]$ and the unloading time window $[U_i^{min}, U_i^{max}]$. To each arc $(i, j) \in E$ are associated a travel time t_{ij} and a travel cost c_{ij}. If a truck arrives early (or idles) at any pickup or delivery location, a waiting time (or idle time) penalty will be incurred.

The FTSMDVRPTW aims to design a solution composed of m selective routes for trucks of maximum total net profit, equal to total collected revenue minus the total travel cost, including the waiting and dwelling costs before loading or unloading the commodities. Each route is a sequence of selective commodities to be fulfilled while considering time window constraints. A solution representation is illustrated in Figure 1.

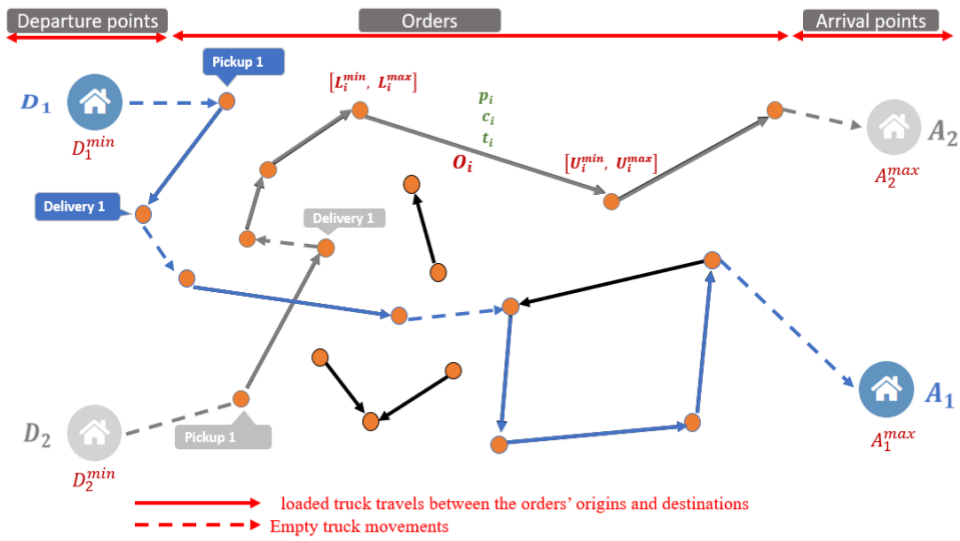

Figure 1. A solution representation of the FTSMDVRPTW

Our assumptions are as follows:

- The locations of the starting and finishing depots of trucks, loading and unloading points of commodities, and durations of loading and unloading activities are assumed to be known in advance.
- Each order consists of a full truckload, which means that when we load merchandise at point L_i, we must unload the merchandise at point U_i to the next step.
- Each truck route must meet the loading and unloading time windows of served orders.
- Trucks have enough capacity to fulfill any order on their tour.

– Each order's revenue is proportional to the distance between the loading and unloading points.
– Each truck k must leave its departure point D_k after the earliest departure time D_k^{min} and return to its arrival point A_k before the latest time A_k^{max}.

3. SOLUTION PROCEDURE (FUZZY LOGIC CONTROLLER+GENETIC ALGORITHM)

To apply a GA to an NP-hard COP, specific components of the GA must be adapted or tailored to the particular structure and characteristics of the considered problem. The key features are the encoding scheme of a solution into a chromosome, parameter settings, initial population creation, fitness function, and genetic operators (selection, crossover, and mutation). In this study, we introduce an optimization technique based on a combination of FLC and GA (FLC+GA) for the problem of FTSMDVRPTW, where the crossover and mutation rates are adjusted using an FLC. Figure 2 depicts a flowchart of the proposed FLC+GA method. The proposed FLC+GA requires the following terminologies:

N_{pop} : Population size
G : The maximal generations
$P_c(g)$: The crossover probability at the present generation g
$P_m(g)$: The mutation probability at the present generation g

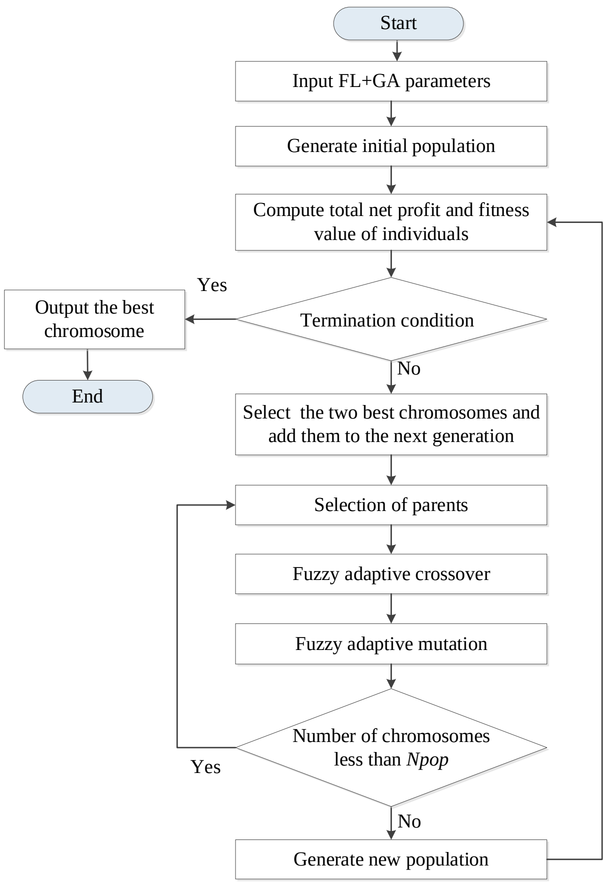

Figure 2. FLC+GA processing

3.1. Genetic algorithm

3.1.1. Chromosome representation

The chromosome representation technique for the FTSMDVRPTW should encode both the assignment of selective commodities to trucks and the arrangement of commodities to be fulfilled within each truck route. One common and effective chromosome encoding technique for this problem is called two-part chromosomal representation, as depicted in Figure 3 [9], [17]. The first part is a permutation of the n orders regardless of any information about the number of orders each truck performs. Each element in the permutation represents an order. The second part is of length $m + 1$, with the first m values indicating the number of orders fulfilled by each truck and the final value providing the number of orders that have not yet been assigned to any truck (allotted to a dummy truck U), where the sum of these $m+1$ values is n.

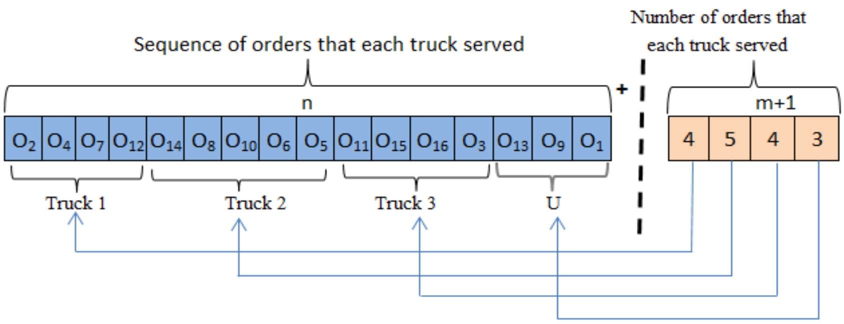

Figure 3. An example representation for an FTSMDVRPTW instance with n=16 and m=3

3.1.2. Initial population

Generating the initial population is a decisive and complicated step in a GA. In this study, we used a constructive heuristic algorithm devised in [9] to build an initial feasible solution set of size N_{pop}. Each solution corresponds to m truck routes that adhere to commodity and truck depot time window constraints.

3.1.3. Fitness function and chromosome selection

The fitness function assigns a numeric value to each chromosome, determining the chance of selecting this chromosome during reproduction. This work uses an elitism and roulette wheel-based selection technique. The best two chromosomes in a generation are passed down to the next generation. Then, the roulette wheel method (RWM) selects a pair of chromosomes as parents to produce two children, and the procedure continues until N_{pop} chromosomes are created for the next generation.

On the one hand, for maximization problems, the objective function is commonly used as the fitness function. This means that the fitness value of an individual should increase as the objective function value increases. On the other hand, the fitness value must be positive in the RWM; a higher value indicates a better chromosome. As a result, the fitness value $F(S)$ of chromosome S is defined as (1)

$$\begin{cases} F(S) = 1 + Profit(S) - \alpha TWV, if\ Profit(S) - \alpha TWV > 0 \\ F(S) = \frac{1}{1 - Profit(S) - \alpha TWV}\ , Otherwise \end{cases} \quad (1)$$

where $Profit(S)$ denotes the total net profit value of chromosome S, α denotes the penalty coefficient for time window constraint violation, and TWV determines the violation amounts of these constraints.

3.1.4. Crossover operator

Here, we consider a crossover method, named $S-TCX$, that addresses the selective aspect of the studied problem as described in [9]. This operator's procedure consists of five primary steps as shown in Figure 4.

- Step 1: To produce a child E_1, two parents P_1 and P_2 are selected, with P_1 serving as the base.
- Step 2: In the first part of the parent P_1, $S-TCX$ handles truck routes individually by arbitrarily selecting a gene segment (subroute) for every route from the first part of parent P_1.
- Step 3: The rest of the genes are arranged in the same ranking as those in parent P_2's first part.
- Step 4: To complete the construction of the first part of child E_1, we generate a series of uniform random positive integer numbers summing to the current value of the remaining genes to set the number of new genes to be added to every truck route.
- Step 5: Last, the S-TCX constructs the child E_1 based on the outcome of the crossover process that occurred in the first part and by updating the traits in the second part.

By changing the roles of P_1 and P_2 and going through the five steps, we can generate another child E_2.

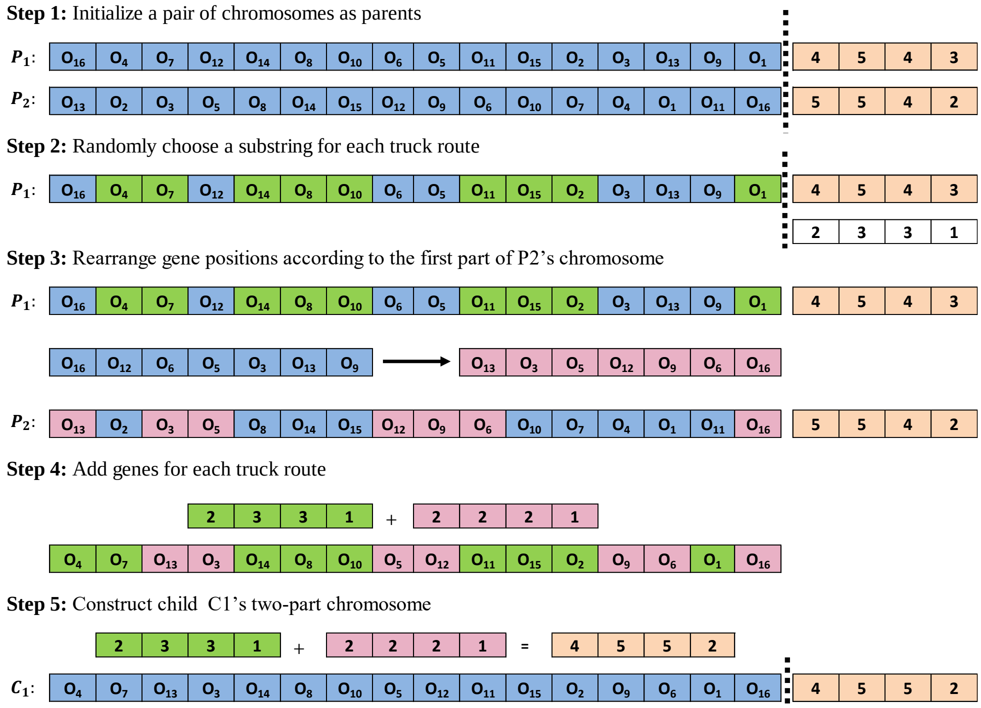

Figure 4. The S-TCX crossover operator

3.1.5. Mutation operator

The mutation operator is a crucial step in the GA process for preventing premature convergence and exploring more regions in the solution space by introducing small chromosome changes. This paper uses an exchange mutation, also known as a two-point mutation. We independently apply this operator in each part of the chromosome, in which two randomly selected genes are swapped as shown in Figure 5.

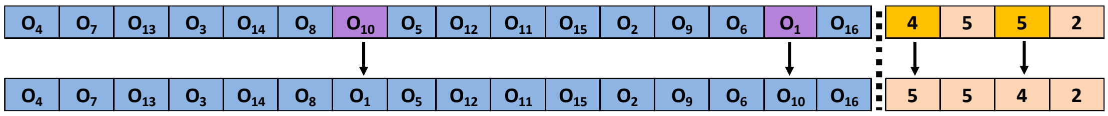

Figure 5. The two-point mutation operator

3.2. Fuzzy logic

Fuzzy logic was first proposed by Zadeh [18], and it has become a powerful and valuable tool for effectively handling uncertainty and vagueness in decision-making problems. It is composed of three major procedures: i) fuzzification, ii) rule-based reasoning, and iii) defuzzification (for more information on fuzzy logic, see [19]). In this paper, FLC is used to dynamically regulate the crossover and mutation probabilities over ten successive generations during the run of GA based on changes in the average fitness and diversity of the population. The fuzzification and rule-based reasoning methods employed in this work are adapted from [20].

3.2.1. Fuzzification

Fuzzification is the process of converting exact input values into fuzzy sets using membership functions (MFs). To represent the uncertainty or vagueness in the data, the MFs assign degrees of membership (between 0 and 1) to each input value based on how well they belong to various linguistic terms [21]. The choice of appropriate MFs in fuzzy logic systems is not governed by general rules or strict criteria. Instead, it depends on the specific problem, the nature of the data, the user's experiences, and judgment [22].

This study employs triangular MFs, which are common and widely used in various fuzzy logic applications. Table 1 lists the definitions of all linguistic terms used in the chosen MFs. There are two fuzzy input parameters, $F_a(g) - F_a(g-9)$ and $d(g)$, where $F_a(g)$ and $d(g)$ denote the population's average fitness value and diversity at generation g, respectively. The input variable strategy can be seen in Figure 6, where each input parameter is grounded in nine MFs. The output variables of the controller are the changes in crossover and mutation rates at generation $(g+1)$ denoted by $\Delta p_c(g+1)$ and $\Delta p_m(g+1)$, respectively. The values of $\Delta p_c(g+1)$ and $\Delta p_m(g+1)$ are normalized in the ranges of $[-0.1, 0.1]$ and $[-0.01, 0.01]$, respectively. These system outputs are grounded in nine MFs, and the output variable design can be seen in Figure 7. These MFs of the two output variables are used in the defuzzification procedure, which will be explained in section 3.3.

Table 1. Meaning of linguistic terms

$F_a(g)-F_a(g-9)$, $\Delta p_c(g+1)$, and $\Delta p_m(g+1)$		$d(g)$	
linguistic term	Meaning	linguistic term	Meaning
NR	Negative largeR	VS	Very Small
NL	Negative Large	SM	SMall
NM	Negative Medium	QS	Quite Small
NS	Negative Small	LM	Low Medium
ZE	ZEro	MD	MeDium
PS	Positive Small	HM	Higher Medium
PM	Positive Medium	QB	Quite Big
PL	Positive Large	BG	BiG
PR	Positive largeR	VB	Very Big

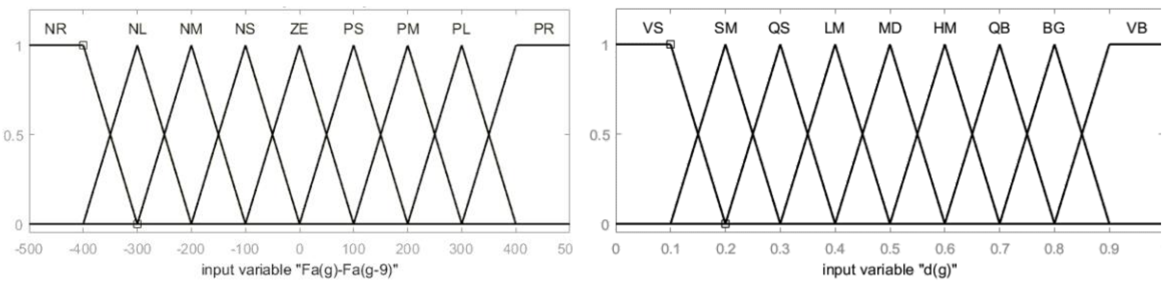

Figure 6. MF for input variables $F_a(g)-F_a(g-9)$ and $d(g)$

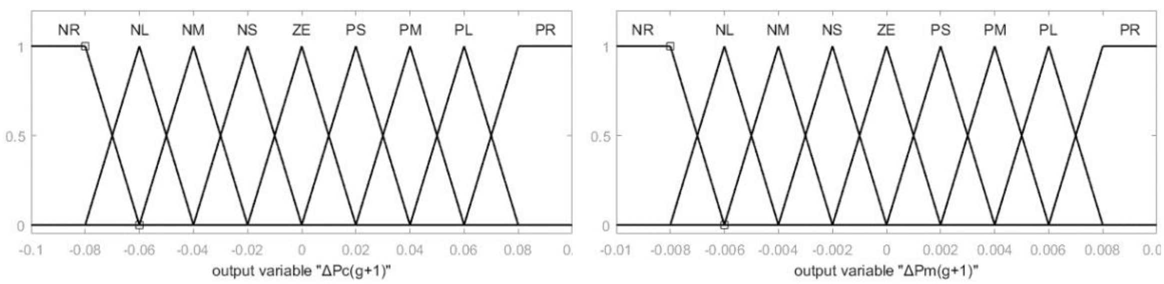

Figure 7. MF for output variables $\Delta p_c(g+1)$ and $\Delta p_m(g+1)$

3.2.2. Rule base reasoning

In the rule base reasoning step, fuzzy rules are used to model the decision-making process. These rules are typically expressed as IF-THEN statements using linguistic variables. The IF part of the rule represents the input conditions, while the THEN part represents the corresponding output. Table 2 presents the rules we designed in this study for the membership values associated with the two output variables $\Delta p_c(g+1)$ and $\Delta p_m(g+1)$ (adapted from [23]). For example, in Table 2(a), IF $F_a(g)-F_a(g-9)$ is PR and $d(g)$ VB, THEN $\Delta p_c(g+1)$ is PR and $\Delta p_m(g+1)$ is NR.

After determining the rule in the upper left corner in Tables 2(a) and 2(b), the other rules can be deduced. "$F_a(g)-F_a(g-9)$ is PR" signifies that after ten successive generations, the population's average fitness value has significantly increased (improved). Simultaneously, the diversity of the population $d(g)$ is VB. Because the crossover role accelerates population convergence by interchanging and/or mixing genes for improved children, the crossover probability needs to be significantly increased to improve search space exploration. However, because mutation's role is to maintain population diversity, the mutation rate needs to be decreased considerably to avoid slowing down the population's convergence speed and causing the search to tend to randomness, inhibiting solution improvement.

Table 2. Rules of fuzzy system, (a) for $\Delta p_c(g+1)$ and (b) for $\Delta p_m(g+1)$

$d(g)$	$F_a(g)-F_a(t-g)$								
	PR	PL	PM	PS	ZE	NS	NM	NL	NR
VB	PR	PR	PL	PL	PM	PM	PS	PS	ZE
BG	PR	PL	PL	PM	PM	PS	PS	ZE	NS
QB	PL	PL	PM	PM	PS	PS	ZE	NS	NS
HM	PL	PM	PM	PS	PS	ZE	NS	NS	NM
MD	PM	PM	PS	PS	ZE	NS	NS	NM	NM
LM	PM	PS	PS	ZE	NS	NS	NM	NM	NL
QS	PS	PS	ZE	NS	NS	NM	NM	NL	NL
SM	PS	ZE	NS	NS	NM	NM	NL	NL	NR
VS	ZE	NS	NS	NM	NM	NL	NL	NR	NR

(a)

$d(t)$	$F_a(g)-F_a(g-9)$								
	PR	PL	PM	PS	ZE	NS	NM	NL	NR
VB	NR	NR	NL	NL	NM	NM	NS	NS	ZE
BG	NR	NL	NL	NM	NM	NS	NS	ZE	PS
QB	NL	NL	NM	NM	NS	NS	ZE	PS	PS
HM	NL	NM	NM	NS	NS	ZE	PS	PS	PM
MD	NM	NM	NS	NS	ZE	PS	PS	PM	PM
LM	NM	NS	NS	ZE	PS	PS	PM	PM	PL
QS	NS	NS	ZE	PS	PS	PM	PM	PL	PL
SM	NS	ZE	PS	PS	PM	PM	PL	PL	PR
VS	ZE	PS	PS	PM	PM	PL	PL	PR	PR

(b)

3.2.3. Defuzzification

The defuzzification process converts the fuzzy output sets produced by the rule base reasoning into crisp values. Various defuzzification methods can be used to find the final crisp output value. The center of area (COA), adopted in this study, is the most commonly used method in the defuzzification process [24]. This defuzzification method is straightforward to implement and computationally efficient, making it a popular choice for defuzzification in many fuzzy logic applications.

3.3. Implementation of fuzzy logic controller+genetic algorithm

The model of FLC+GA is depicted in Figure 8, and its implementation process is as follows. Once generation $(g-1)$ is attained, the $F_a(g-2)$, $F_a(g-1)$, and $d(g-1)$ values are fed into the two fuzzy controllers. d is the average bit difference between all individual pairs in the same generation. It can be computed (2) and (3).

$$d = \frac{2}{N_{pop}\,(N_{pop}-1)} \sum_{i=1}^{N_{pop}} \sum_{j=i+1}^{N_{pop}} \sum_{k=1}^{n+m+1} \frac{\delta(g_{ik}, g_{jk})}{n+m+1} \tag{2}$$

$$\delta(g_{ik}, g_{jk}) = \begin{cases} 1, g_{ik} \neq g_{jk} \\ 0\,, otherwise \end{cases} \tag{3}$$

where g_{ik} denotes the kth gene value on the ith two-part chromosome. The two fuzzy controllers will then calculate the system output values $\Delta p_c(g)$ and $\Delta p_m(g)$. Hence, at generation g, $p_c(g)$ and $p_m(g)$ are adjusted by the (4) and (5).

$$p_c(g) = p_c(g-1) + \Delta p_c(g) \tag{4}$$

$$p_m(g) = p_m(g-1) + \Delta p_m(g) \tag{5}$$

at generation g, the GA will utilize $p_c(g)$ and $p_m(g)$ in place of $p_c(g-1)$and $p_m(g-1)$ t to continue its search process. $F_a(g+8)$, $F_a(g+9)$, and $d(g+9)$ are computed at generation $(g+9)$.

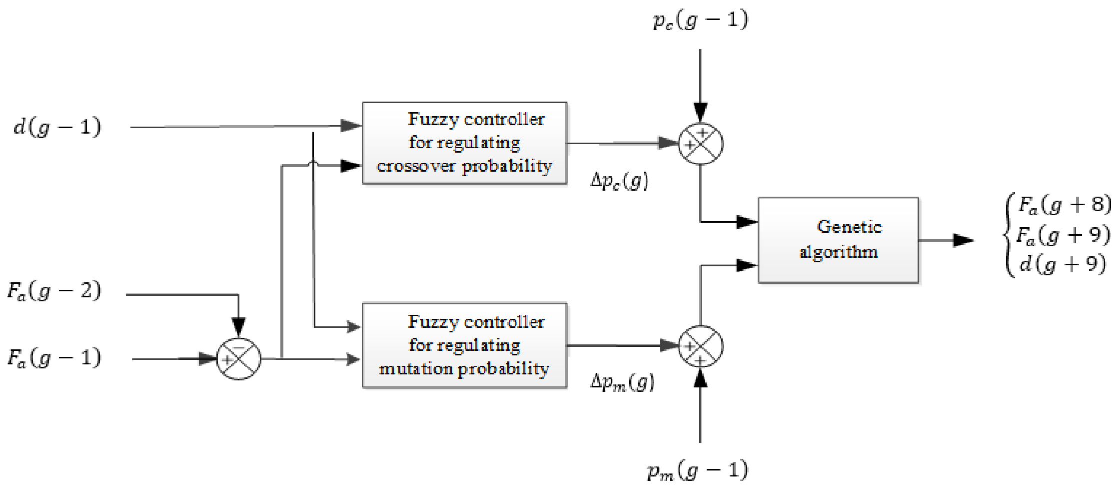

Figure 8. Model of FLC+GA

4. COMPUTATIONAL EXPERIMENTS

The proposed FLC+GA was written and run in MATLAB on a PC with a 2.5 GHz processor and 8 GB of RAM and compared with the CPLEX solver and the standard GA [9]. For the initial value of the FLC+GA parameters, we set $N_{pop} = 100$, p_c=0.8, $p_m = 0.2$, and $G = 2000$. The experiments are conducted across 32 instances proposed by Bouyahyiouy and Bellabdaoui [9], which are randomly generated based on three classes R / C / RC of Solomon's VRPTW benchmark instances [25]. The travel times and costs (loaded/empty) are calculated using the Euclidean distance function; the unitary revenue p of each order is equal to \$6/mile, the processing duration time t_i of an order O_i is taken as the sum of the service time to load at point L_i, the service time to unload at point U_i, and the loaded travel time between L_i and U_i. Table 3 represents a brief instance parameter structure; it specifies the number of orders, number of trucks, service time s for loading/unloading an order, earliest departure and latest arrival times permitted for each truck, and width of the time windows (WTW). Each instance is labeled as Gri_n_m where Gr shows the classical type of instance, $Gr = \{R, C, RC\}$, i is the instance ID, n gives the number of orders, and m gives the number of trucks.

Table 3. The parameter structure for the generated instances

Instance ID	n	m	s (min)	$D_k^{min}(min)$	$A_k^{max}(min)$	WTW (min)
$C1-2\_16\_2$	16	2	30	0	600	180
$C3-4\_16\_2$	16	2	40	0	720	240
$C1-2\_24\_3$	24	3	30	0	600	180
$C3-4\_24\_3$	24	3	40	0	720	180
$R1-2\_20\_2$	20	2	10	0	480	120
$R3-4\_20\_2$	20	2	20	0	720	180
$R1-2\_30\_3$	30	3	10	0	480	120
$R3-4\_30\_3$	30	3	20	0	720	180
$RC1-2\_20\_2$	20	2	10	0	480	120
$RC3-4\_20\_2$	20	2	20	0	720	180
$RC1-2\_30\_3$	30	3	10	0	480	120
$RC3-4\_30\_3$	30	3	20	0	720	180
$R1-2\_50\_5$	50	5	10	0	480	120
$R3-4\_50\_5$	50	5	20	0	720	180
$R1-2\_75\_7$	75	7	10	0	480	120
$R3-4\_75\_7$	75	7	20	0	720	180

Table 4 reports the best (maximum profit P) objective values and corresponding computational times (in seconds) obtained by three search methods for each instance. P^* and Gap1 are the optimal solution (upper bound) and the solution gap reported by CPLEX, respectively. Gap2 is the calculated difference between the FLC+GA and CPLEX solutions, expressed as $100 \times (P^* - P_{\text{FLC+GA}}) / P^*$. Gap3 is the difference between the FLC+GA and standard GA solutions, calculated as $100 \times (P_{GA} - P_{\text{FLC+GA}}) / P_{GA}$. As observed in Table 4, Gap1, Gap2, and Gap3 are equal to zero over instances of up to 20 orders and two trucks. Therefore, the CPLEX solver, FLC+GA, and standard GA can offer optimal solutions. However, the standard GA results are better than the FLC+GA results regarding CPU time.

Table 4. Comparison of results between FLC+GA, GA and CPLEX

Instances	CPLEX					GA			FLC+GA			Gap rate (%)	
	P^*	Type	Gap_1	CPU (s)	# U	P	CPU (s)	# U	P	CPU (s)	# U	Gap_2	Gap_3
C1_16_2	520.00	GOS	0.00	23.88	1	520.00	26.02	1	520.00	20.61	1	0.00	0.00
C2_16_2	810.00	GOS	0.00	2.29	1	810.00	36.07	1	810.00	25.60	1	0.00	0.00
C3_16_2	819.00	GOS	0.00	5.44	2	819.00	30.54	2	819.00	24.25	2	0.00	0.00
C4_16_2	766.00	GOS	0.00	4.34	2	766.00	32.57	2	766.00	26.50	2	0.00	0.00
C1_24_3	894.00	GOS	0.00	4.72	1	894.00	64.84	1	894.00	57.64	1	0.00	0.00
C2_24_3	1100.00	GOS	0.00	717.92	5	1100.00	65.37	5	1100.00	54.25	5	0.00	0.00
C3_24_3	1067.00	GOS	0.00	66.08	3	1067.00	61.61	3	1067.00	56.39	3	0.00	0.00
C4_24_3	1215.00	GOS	0.00	14.07	3	1215.00	61.58	3	1215.00	57.69	3	0.00	0.00
R1_20_2	2130.00	GOS	0.00	53.88	2	2130.00	42.56	2	2130.00	39.85	2	0.00	0.00
R2_20_2	1346.00	GOS	0.00	2.05	0	1346.00	47.43	0	1346.00	36.31	0	0.00	0.00
R3_20_2	2331.00	GOS	0.00	3.88	1	2331.00	44.96	1	2331.00	37.64	1	0.00	0.00
R4_20_2	2176.00	GOS	0.00	2.76	1	2176.00	49.61	1	2176.00	31.32	1	0.00	0.00
R1_30_3	3367.15	FS	7.34	7200	4	3120.00	191.85	4	3120.00	130.08	4	7.3 4	0.00
R2_30_3	2346.00	GOS	0.00	3.25	0	2346.00	175.57	0	2346.00	141.20	0	0.00	0.00
R3_30_3	3494.00	GOS	0.00	855.70	1	3494.00	180.19	1	3494.00	143.12	1	0.00	0.00
R4_30_3	3398.00	GOS	0.00	490.12	1	3398.00	193.64	1	3398.00	144.92	1	0.00	0.00
RC1_20_2	1857.00	GOS	0.00	2.05	1	1857.00	45.91	1	1857.00	30.40	1	0.00	0.00
RC2_20_2	1538.00	GOS	0.00	1.80	0	1538.00	36.37	0	1538.00	36.12	0	0.00	0.00
RC3_20_2	2246.00	GOS	0.00	3.70	1	2246.00	52.13	1	2246.00	37.34	1	0.00	0.00
RC4_20_2	1859.00	GOS	0.00	3.02	0	1859.00	47.65	0	1859.00	38.97	0	0.00	0.00
RC1_30_3	2882.00	GOS	0.00	66.97	2	2882.00	146.05	2	2882.00	130.68	2	0.00	0.00
RC2_30_3	2889.00	GOS	0.00	110.90	4	2889.00	154.79	4	2889.00	138.92	4	0.00	0.00
RC3_30_3	4193.00	GOS	0.00	1237.85	4	4193.00	179.35	4	4193.00	129.52	4	0.00	0.00
RC4_30_3	3852.00	GOS	0.00	10.03	4	3852.00	147.91	4	3852.00	127.22	4	0.00	0.00
R1_50_5	4586.00	GOS	0.00	587.63	1	4586.00	391.04	1	4586.00	327.92	1	0.00	0.00
R2_50_5	4498.18	FS	1.92	7200	1	4428.61	445.89	1	4445.23	335.38	1	1.56	-0.34
R3_50_5	4637	GOS	0.00	88.91	0	4637.00	417.58	0	4637.00	383.15	0	0.00	0.00
R4_50_5	4580.19	FS	1.62	7200	1	4507.08	437.86	1	4527.85	365.08	1	1.6	-0.46
R1_75_7	8959.82[a]	FS	3,39	3451.89	5	8595.39	589.6	5	8734.95	529.78	4	4.07	-1.63
R2_75_7	8960.34[a]	FS	3,50	2753.54	5	8559.02	646.77	5	8694.18	510.39	4	4.48	-1.58
R3_75_7	8983.60[a]	FS	2,87	5375.05	4	8704.39	683.69	4	8725.61	543.02	4	3.11	-0.29
R4_75_7	8964.87[a]	FS	1,84	6319.94	3	8800.11	652.57	3	8835.40	543.85	3	1.84	-0.40

[a] The "out of memory" values, GOS indicates a global optimal solution, and FS indicates a feasible solution.

The CPLEX solver, an exact method, is expected to perform well in all instances with 20 commodities where it can provide optimal solutions in a relatively short time. However, the CPU time required for CPLEX to find the best (optimal) solution becomes prohibitively expensive as the number of commodities grows. As a result, to avoid the need for extensive CPU time, the total computation time for CPLEX is limited to two hours. This is why, when the number of commodities is increased to 50 or more, CPLEX cannot solve some instances optimally within 2 hours and instead returns feasible solutions with varying degrees of solution gaps within the allowed solution time.

The FLC+GA and standard GA significantly outperform CPLEX in terms of solution quality and CPU time, especially on the largest instances where CPLEX either identifies a solution that is worse than that output by our GA or fails to identify a feasible one. This is due to the GA's selection operator, which enables high-quality solutions to be selected for reproduction during every generation. In addition, the crossover operator allows for the sharing of genes among two high -quality solutions, producing enhanced solutions in every new generation. Indeed, the crossover is essential in merging diverse combinations of genes and has an advantage for exploring and exploiting the search space, resulting in improved solution quality and faster convergence. When the number of commodities grows, FLC+GA outperforms CPLEX and the standard GA regarding solution quality and CPU time. In many instances, FLC+GA yields lower CPU times than the standard GA. This demonstrates that FLC can adapt crossover and mutation ratios to improve GA search performance. Furthermore, in FLC+GA, crossover and mutation probabilities can be adjusted in response to environmental changes, altering the anticipated percentage of chromosomes involved in crossover and mutation operators. This adjustment must be founded on the population's most recent status and diversity. If the population's average fitness is higher over ten successive generations, the crossover and mutation probabilities must rise to improve the production of further high-fitness children. Therefore, if the crossover and mutation ratios are dynamically controlled according to the diversity and average fitness of the population, the GA search performance may be enhanced. As expected, the commodity number, time window width, and selective aspect significantly impact CPU time. In all cases, as the unselected commodity number grows, the trucks cannot serve some commodities, resulting in increased CPU time.

5. CONCLUSION

In this paper, we have suggested a meta-heuristic based on a combination of a FLC+GA to solve the FTSMDVRPTW. The crossover and mutation probabilities of the current generation are dynamically adjusted using a fuzzy controller technique according to the population structure in previous generations during GA execution. Experimental results on randomly generated instances demonstrate the effectiveness of the proposed FLC+GA algorithm in terms of solution quality and CPU time consumed compared with the CPLEX solver and standard GA. Because the GA is an evolutionary approach, future research could introduce an innovative, automatic method that combines FLC+GA and an adaptive network-based fuzzy inference system (ANFIS) architecture. Another research direction is considering a dynamic FTSMDVRPTW to address routing under uncertainty.

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