

# Electric Vehicle Routing Problem with Fuzzy Time Windows using Genetic Algorithm and Tabu Search

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## ARTICLE INFO

## ABSTRACT

### Article history

Received 5 November 2022  
Revised 14 November 2022  
Accepted 18 November 2022

### Keywords

Vehicle Routing Problem (VRP)  
Genetic Algorithm (GA)  
Tabu Search (TS)  
Fuzzy Logic  
E-VRPFTW  
E-VRPTW

The distribution of goods becomes a very calculated thing in the economic aspect, especially in the case of wide and complex distribution. The wider the distribution range of goods, the more precise, fast and accurate calculations are needed. Specifically, the calculation of the distribution required starts from mileage, total travel time, customer satisfaction level based on customer time windows, and operational costs. Vehicle Routing Problem (VRP) is a solution to the problem of distributing goods from the warehouse to its customers. This study aims to determine the optimal route. The methods used for VRP optimization are the Genetic Algorithm (GA) and Tabu Search (TS) methods. Fuzzy logic is used to provide leeway on the limitations of the time windows parameters, thus providing a time tolerance in the event of early arrival of the vehicle or delay in delivery. Data processing using the GA-TS combination was carried out as many as two types of trials, namely trials with the same dataset ten times and trials with various types of datasets ten times. The results of the first trial fitness value on Vehicle Routing Problem with time windows with Fuzzy Logic (E-VRPFTW) average increased by 14.39% compared to the results of the Vehicle Routing Problem with time windows without Fuzzy Logic (E-VRPTW) fitness value that did not use fuzzy. The results of the second trial also experienced an average increase of 8.49% compared to the results of the E-VRPTW fitness value that did not use Fuzzy Theory. Therefore, the addition of Fuzzy Logic has an effect in determining the optimum route of E-VRPTW. Based on a comparison of the results of the number of vehicles and the distance in related research it can be concluded that the use of the GA-TS method and the use of fuzzy can be said to be better due to the factor of shorter mileage and the small number of vehicles.

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## 1 Introduction

Mobility is an important aspect, for example as in 28 European Union countries that contribute almost 561 billion euros to the transport sector (Pereirinha et al., 2018). One of the uses of transportation is for the distribution of goods. Distribution is the process of delivering goods from producers to consumers, when, and where the goods or services are needed (Karundeng et al., 2018). In overcoming transportation and wide distribution problems, the Vehicle Routing Problem (VRP) has many applications in real life (Mohammed et al., 2017). VRP is a combinatorial problem used to determine the distribution route of goods from warehouse (distribution centers) to customers spread across various points or places (Pitaloka et al., 2014). In addition VRP can be described as a problem of designing the shortest path route from one location to a group of geographically distributed locations (Mohammed et al., 2017). Developments in transportation technology produce electric-powered vehicles or so-called Electric Vehicles (EV) without combustion, creating a clean and pollution-free environment.

E-VRP (Electric Vehicle Routing Problem), another variation of the Green Vehicle Routing Problem (G-VRP) coupled with customer uptime restrictions (time windows) becomes a solution for vehicles that have a limited cruising range and demand refueling or refueling propulsion to continue their journey (Schneider et al., 2014). In practice, distribution involves vehicle routes based on time windows which are highly relevant to the level of customer satisfaction (Tang & Huang, 2018). This makes the route determination more specific because it considers the time windows penalty. Where if there is a time penalty in the form of delay or delivery arrives early, it will affect the results of VRP because it must prioritize several customers to avoid time windows penalties (Ghobadi et al., 2021).

In the real case, the time windows on VRP do not always have to be strictly adhered to. The schedule sometimes makes the vehicle arrive early or even late from the specified time windows. This deviation in delivery time can affect the level of customer satisfaction which will affect the distributor's income (Febrita & Mahmudy, 2018). Therefore, the application of Fuzzy Logic to time windows can mask time deviations, because fuzzy is vague or uncertainty. It was found that Fuzzy Theory is useful for describing subjective opinions that should be applied in Vehicle Routing Problem with Time Windows (VRPTW) problems (Adelzadeh et al., 2014). In solving VRP problems, there are algorithms that are often used, such as Genetic Algorithms (GA) and Tabu Searches (TS) (Akbar & Aurachman, 2020). GA which is one of the metaheuristic searches, can be a solution in determining the optimum route because it has a good representation in parallel searches and makes in-depth research on schemes that achieve high quality and low cost (Zhenfeng et al., 2017). Recent research shows that TS, a metaheuristic procedure for solving optimization problems, which can help GA to get out of the trap of local optimization (Utamima et al., 2015). At the TS stage several exchanges of nodes called neighbors, are carried out to find the best structure among the results produced through each iteration for further use (Akbar & Aurachman, 2020). Based on these, this study focuses on improving the results of E-VRPTW with the addition of Fuzzy Logic using GA and TS.

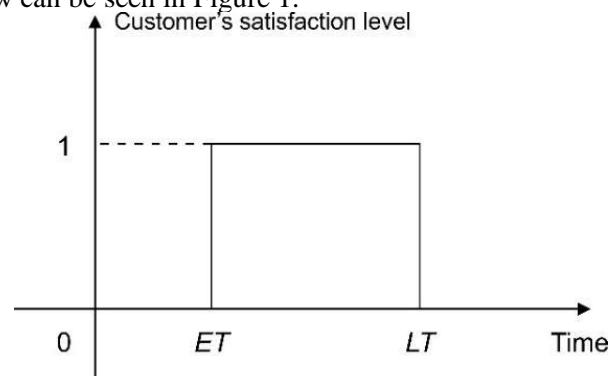
## 2 Theoretical Basis

### 2.1 Electric Vehicle Routing Problem (E-VRP)

VRP is introduced as a delivery truck which is then defined as a combination of optimization problems to determine the optimum route used by the delivery fleet from the depot to the customer (Toth & Vigo, 2002). Another form of VRP is E-VRP which is a variation from G-VRP to Battery Electric Vehicle (BEV), where both have a limited cruising range and demand recharging of drive energy to continue the journey (Zhenfeng et al., 2017).

### 2.2 Time Windows

Time windows in the case of VRP is a time interval in which the delivery must have already arrived at a certain time (Schneider et al., 2014). For service level issues related to time windows violations or penalties in VRP are described using the fuzzy membership function (Ghannadpour et al., 2014). In traditional VRPTW, a viable solution must meet all time windows, called hard time windows. The level of customer satisfaction is determined by the actual arrival time. The satisfaction level function of the hard time window can be seen in Figure 1.

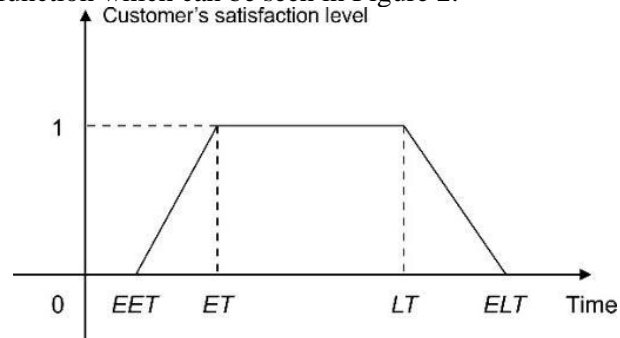


**Figure 1.** Satisfaction level function of the hard time window (Tang & Huang, 2018)

If the distribution service is completed in the time window,  $L=1$  (service satisfaction). Customers have an acceptable time span between  $[EET, ELT]$ . EET for Endurable Earliness Time and ELT for Endurable Lateness Time.

### 2.3 Fuzzy Logic

Fuzzy logic or vague logic is a branch of mathematical science functions in applications involving vagueness, doubt, linguistic uncertainty, inaccuracy of measurement and subjectivity (Nikolić et al., 2020). Fuzzy logic allows the use of linguistic values of variables and relationships imprecise for the behavior of modeling systems. The level of customer satisfaction in VRPTW can be described by the fuzzy membership function which can be seen in Figure 2.



**Figure 2.** Fuzzy time windows satisfaction level function (Teimoori et al., 2014)

In fuzzy logic, there is a membership function which is the value of a curve that shows the mapping of input points into their membership values that have intervals between  $[0, 1]$  (Irfan et al., 2018). This interval value can be a tolerance value in the penalty time window, if a delay in delivery occurs. More specifically, the level of customer satisfaction is directly related to the degree of fuzzy membership of each, when the customer is visited by one of the vehicles from the warehouse (Qamsari et al., 2022). In this diagram the parameters  $e$  and  $l$  are the limits of the crisp time windows (0 or 1) that provide the highest utility for the customer. Thus, the penalty on delivery time is too early or late depending on the service time gets a value between zero and one expressed in the fuzzy time function of windows. The fuzzy time function of windows can be seen in Equation 1.

$$\mu_i = \left\{ \begin{array}{ll} 0, & (t_i - E_i^a)/(a_i^a - E_i^a), \quad t_i < L_i^a \\ E_i^a \leq t_i \leq a_i^a & 1, \quad a_i^a \leq t_i \leq b_i^a \\ (L_i^a - t_i)/(L_i^a - b_i^a), & b_i^a < t_i \leq L_i^a \\ 0, & t_i > L_i^a \end{array} \right\} \quad (1)$$

For consumer ( $i$ ), the time window  $a$  that is expected to be served is denoted by  $[a_i^a, b_i^a]$ , where  $a_i^a$  and  $b_i^a$  is the earliest and last service time. Fuzzy time windows  $a$  denoted as  $[E_i^a, L_i^a]$  where  $E_i^a$  and  $L_i^a$  is the earliest and last tolerable service time (Zheng, 2020).

### 2.4 Genetic Algorithm (GA)

GA is one of the most effective metaheuristic methods used for optimization cases because the search is carried out by exploring a wider solution space (Pitaloka et al., 2014). Fitness value expresses the value of the goal function. The purpose of the GA is to maximize the value of fitness (Adnyana, 2018). Here are the stages in the Genetic Algorithm (Yulastuti et al., 2017).

- Chromosome Representation (Encoding), the term chromosome in GA represents the solution to the problem at hand. In the case of VRP, the chromosomes in question are the sequence of routes of the vehicle to be taken.
- Process Of Initialization is the stages of random parent generation are as many as the specified size (popsize).
- Reproduction Process (Breeding) is aims to produce offspring or alternative solutions that refer to parents. There are 2 ways to produce offspring, namely crossover and mutation. Crossovers require 2 chromosomes as parents to be crossed, while mutations only need 1 chromosome as a parent. These two processes are the stage of changing the genes (nodes) on the chromosome to produce new chromosomes.
- Evaluation Process is the process of assessing the good and bad of a chromosome by calculating the fitness value.
- Process Selective is selection of the best chromosomes as much as popsize.

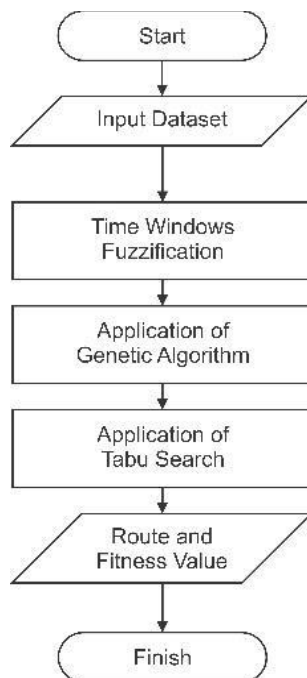
## 2.5 Tabu Search (TS)

TS is a search that explores the solution space for a number of iterations from a random solution to another that was better in the previous environment by including it in the Tabu list to prevent getting stuck in the same set of solutions (Zakouni et al., 2017). The best value obtained can be considered as the real solution when there is no longer a solution that is not a member of the Tabu list (Tiandini & Anggraeni, 2017). The TS algorithm is characterized by a Tabu list containing Tabu solutions and is used to avoid cycles when searching away from the optimum local through a non-improving process (Zidi et al., 2019). Two other important steps in TS are intensification and diversification. Diversification is carried out when no improvement is achieved on the best solution after several iterations, whereas intensification aims to conduct a more thorough search of the environment for an optimal solution (Zakouni et al., 2017).

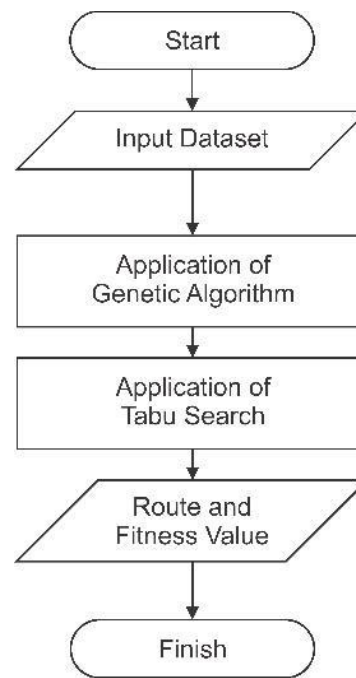
## 3 Methods

### 3.1 Proposed Methods

This study focuses on improving E-VRPTW fitness results or values by adding Fuzzy Logic using GA and TS. The process of improving the results of E-VRPTW consists of several main stages, including the data collection stage, data processing (E-VRPTW and E-VRPFTW), and drawing conclusions. Each of these stages can be seen in Figure 3 and Figure 4.



**Figure 3.** Flowchart E-VRPFTW



**Figure 4.** Flowchart E-VRPTW

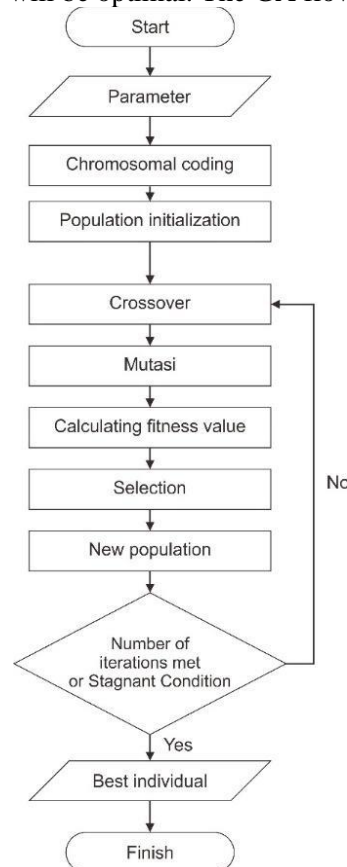
There are two treatments in the dataset to be processed, namely E-VRPTW (non-Fuzzy Logic) and E-VRPFTW (with Fuzzy Logic). E-VRPTW will carry out two processes after dataset input, it called the GA process which is then continued with the taboo search process and then generates the route with the best fitness value that can be found. The second treatment in data processing is that E-VRPFTW is almost the same as the E-VRPTW process. However, in this treatment there is an addition of Fuzzy Logic in the time windows (Fuzzyfication) section, so that it will affect the calculation of GA-TS.

This research begins by entering a pre-prepared dataset. In the E-VRPTW Instances dataset, the StringID and Type variables are not Integer so they will not be used in the GA-TS method. The x coordinate and y coordinates of each instance will be used to find the distance between points (nodes) and the distance will be used to calculate the cost of mileage and travel time. In addition, customer coordinates will also be used to represent fleet travel routes in the form of graphs. Variable demand is used to reduce load when arriving at the customer's location. However, when the number of customer demands have not been visited cannot be met, then the load must be replenished at the

warehouse. However, this will increase the amount of distance and time traveled so that it affects the final fitness value.

Then there are the readytime, duedate, and servicetime variables which are time variables. Each customer has an interval between readytime and duedate (time windows), where the delivery must have arrived at the customer's location when the time is between the two variables. Delays or early arrival will affect the level of customer satisfaction, as it is considered a time penalty. Fuzzy will be used in time windows which plays a role in calculating the fitness value in the customer's time windows section. All variables that have been described above will be processed in the Genetic Algorithm and Taboo Search methods.

The incorporation of the GA-TS method is carried out by applying the GA method first to determine the individuals who have potential based on the highest fitness value. After the solution with the highest fitness value is found, then the output or solution from GA will be the input for use in TS. Therefore, the output from GA-TS will be optimal. The GA flowchart can be seen in Figure 5.

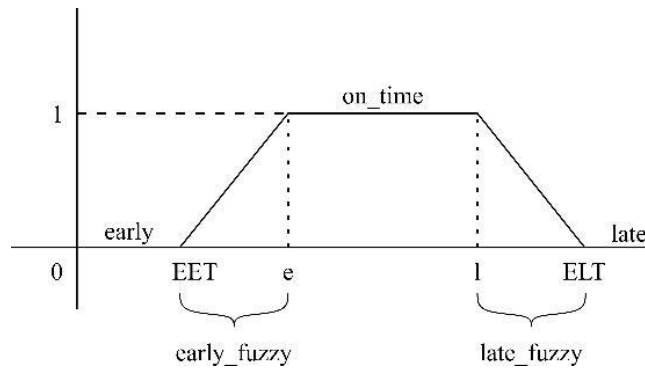


**Figure 5.** Genetic Algorithm Process

This process is carried out to determine the value of fitness that comes from the current population. The population evaluation process is carried out by calculating three main indicators, it is travel\_cost, fuel\_cost, time\_cost, and vehicle\_cost to determine the fitness value of the population. The fitness value can be calculated using a formula such as Equation 2.

$$Fitness = \frac{1}{\sum TravelCost + \sum TimeCost + \sum FuelCost + \sum VehicleCost} \quad (2)$$

Fuzzy time windows will minimize the calculation of the delivery time penalty (TimeCost) value by fuzzifying the windows time limit according to the fuzzy membership function. The calculation of the TimeCost value is calculated when the vehicle will go to the customer, where there are five fuzzy sets of vehicle arrivals, called early, early\_fuzzy, on\_time, late\_fuzzy, late. The fuzzy arrival set representation uses a trapezoidal function that produces a curve as seen in Figure 6.



**Figure 6.** Fuzzy Trapezoidal Function

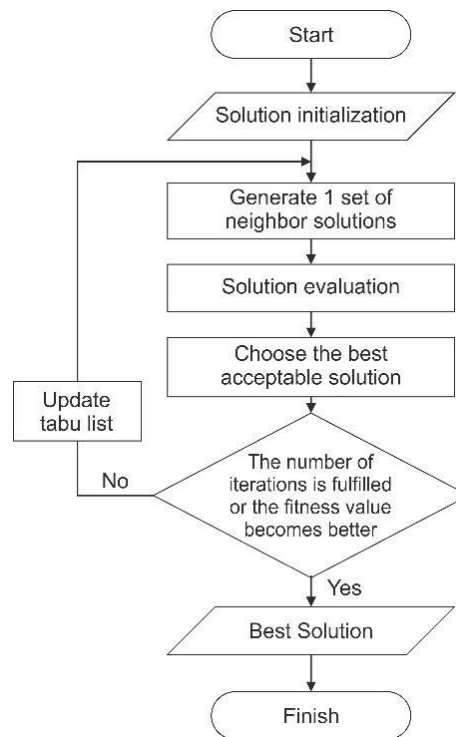
The arrival utility level can be described at various times of service using the  $L(t)$  function which is then accumulated  $\sum$  *TimeCost*. The representation of the equation from the fuzzy set can be seen in Equation 3.

$$L(t) = \left\{ \begin{array}{ll} 0 & t < EET \\ \frac{t-EET}{e-EET} & EET \leq t \leq e \\ 1 & e \leq t \leq l \\ \frac{ELT-t}{ELT-l} & l < t \leq ELT \\ 0 & t > ELT \end{array} \right\} \quad (3)$$

The early category is a condition where the arrival time ( $t$ ) is less than Edge of Early Tolerance (EET), thus getting an *EPU* score where it is added with the *EPU*  $\sum$  *TimeCost* and gets a membership degree of 0 (*early/late*). The *early\_fuzzy* category is used when  $t$  is between *EET* and  $e$  (*customer ready\_time*). A function  $\frac{t-EET}{e-EET}$  is a function up from  $t$  to obtain a degree of membership with a value between [0, 1]. Those membership degrees are then multiplied by the *EPU* value and summed by  $\sum$  *TimeCost*. Category *on\_time* is a condition in which  $t$  is greater than  $e$  and smaller than  $l$ . Category *on\_time* has a membership degree of 1 (on time). This category does not get a penalty score, so  $\sum$  *TimeCost* it does not gain or lose its value.

The *late\_fuzzy* category is used when  $t$  is between *ELT* and  $l$  (*due\_time* customer). A function  $\frac{ELT-t}{ELT-l}$  is a derivative function of  $t$  to obtain a degree of membership with a value between [0, 1]. After getting the degree of membership from *late\_fuzzy*, then the value of the membership degree will be multiplied by the *LPU* value and summed by  $\sum$  *TimeCost*. The late category is a condition where  $t$  is more than the final tolerance time limit *ELT* (Edge of Late Tolerance), thus obtaining a *LPU* score where  $\sum$  *TimeCost* it is summed up with the *LPU* and gets a membership degree of 0 (*early/late*).

This breeding process will continue to repeat until individuals with better fitness values are produced (stagnation) or the number of iterations is sufficient. It is this final individual that is then used as an input on the quest for taboos. The TS Flowchart can be seen in Figure 7.



**Figure 7.** Tabu Search Flowchart

The TS is started by entering a solution that comes from the output of the GA, then continued by forming 1 set of solutions based on the nearest possibility (neighbor). After evaluating existing solutions, the next step is the stage of choosing the best solution. If the solution does not meet the criteria, it will be included in the taboo list and the process will return to the beginning by creating a new set of solutions based on the last solution. The process repeats until results that meet the criteria are obtained. The stopping criterion in this TS method is that the specified iteration has been met., in the case of VRP the number of TS iterations is equal to the number of existing customers. Drawing conclusions are drawn based on preliminary studies, data collection stages, and system development as well as analysis results from research. The conclusions obtained are about how to apply Fuzzy Logic, apply GA and TS and find out the best route results with the highest fitness values optimization results using GA and TS on E-VRP with reference to Fuzzy time windows constraint variables.

### 3.2 Dataset

The dataset used is the "E-VRPTW Instances" dataset based on the research of Schneider et al (2014). The study retrieves datasets available in Mendeley Data public repositories. This dataset has 8 attributes and has a total of data in the range of 5 to 120 instances. A sample of dataset used can be seen in Table 1.

**Table 1.** Sample Dataset

CUST_NO	TYPE	XCOORD	YCOORD	DEMAND	READY_TIME	DUE_TIME	SERVICE_TIME
<i>D0</i>	d	40	50	0	0	1236	0
<i>S0</i>	f	40	50	0	0	1236	0
<i>SI</i>	f	73	52	0	0	1236	0
...	...	...	...	...	...	...	...
<i>C99</i>	c	55	80	10	836	896	90
<i>C100</i>	c	55	85	20	744	798	90

## 4 Results and Discussion

### 4.1 Result

#### 4.1.1 Data Processing

The data processing stage is a stage of computer calculation using the Python Programming Language. Before performing the GA-TS calculation, it is necessary to first determine the parameters that will be used on the GA-TS.

#### 4.1.2 Main Standard Parameters

At this stage, parameter testing is carried out to determine the main parameters that produce the best fitness value. Before conducting the main parameter test, the researcher has created standard parameters for reference, and for testing it is carried out on the "c101\_21" dataset. The main standard parameters can be seen in table 2.

**Table 2.** Main Standard Parameters

Parameters	Value
Max Generation	100
Pop Size	100
Elitism Count	5
Mutation Ratio	0.1
Parent Selection Ratio	0.8
Fuzzy Earliness	250
Fuzzy Lateness	380

In testing the tested parameters, parameters other than those tested use predefined standard parameters. The test results of the main parameters produce the values that can be seen in Table 3.

**Table 3.** Optimum Results of Key Parameters

Parameters	Value
Max Generation	1000
Pop Size	500
Elitism Count	5
Mutation Ratio	0.75
Parent Selection Ratio	0.8
Fuzzy Earliness	120
Fuzzy Lateness	300

#### 4.1.3 Conditional Parameters

Unlike the main parameters, conditional parameters are not too referenced because as the name implies, namely adjusting circumstances or needs. For this study the value of conditional parameters is determined rationally. As for the values of the conditional parameters, they can be seen in Table 4.

**Table 4.** Conditional Parameters

Parameters	Value
Vehicle max distance	160
Vehicle speed average	0.666667
Vehicle capacity	200
Vehicle fuel cost	10
EPU (Earliness Point Unit)	20
LPU (Lateness Point Unit)	30



#### 4.1.4 Application of Genetic Algorithms

The incorporation of the GA-TS method is carried out by applying the GA method first to determine the individual/solution that has potential based on the highest fitness value.

##### 4.1.4.1 Initial Initialization

This initialization is done by specifying the parameters to be used in the GA process.

##### 4.1.4.2 Population Initialization

Population initialization is done by randomly generating as many numbers as the amount of data. A sample of the results of population initialization can be seen in Table 5.

**Table 5.** Sampel Population Initialization

Chromosome	Genes [0, ..., 120]
<i>K1</i>	[24, 49, 73, 67, 112, 93, 100, 51, 47, 117, 26, 10, 81, 65, 97, 36, 79, 115, 104, 91, 77, 57, 15, 70, 22, 11, 25, 44, 7, 75, 32, 28, 111, 35, 87, 92, 3, 61, 42, 103, 89, 110, 2, 94, 107, 64, 12, 120, 18, 19, 86, 98, 68, 38, 116, 76, 63, 80, 62, 45, 4, 33, 53, 88, 82, 78, 122, 90, 114, 41, 118, 119, 52, 106, 72, 54, 43, 40, 1, 34, 6, 23, 58, 66, 31, 109, 101, 96, 74, 83, 99, 29, 59, 17, 8, 21, 30, 50, 5, 48, 37, 16, 60, 9, 13, 95, 105, 85, 55, 102, 121, 39, 27, 14, 71, 84, 20, 46, 113, 56, 69, 108]
<i>K2</i>	[83, 96, 103, 89, 12, 31, 18, 100, 98, 2, 62, 50, 90, 20, 36, 71, 117, 55, 59, 107, 58, 110, 93, 105, 81, 82, 32, 4, 27, 88, 94, 8, 104, 116, 38, 26, 106, 11, 108, 49, 102, 91, 23, 40, 44, 48, 52, 61, 39, 120, 85, 9, 57, 41, 28, 51, 46, 43, 15, 67, 78, 45, 75, 74, 19, 72, 24, 1, 13, 118, 113, 95, 21, 69, 68, 65, 7, 114, 86, 109, 92, 80, 16, 77, 66, 35, 115, 79, 14, 42, 97, 84, 33, 64, 34, 37, 122, 56, 99, 54, 29, 60, 101, 70, 87, 17, 76, 112, 53, 73, 22, 47, 25, 6, 30, 63, 10, 3, 119, 111, 121, 5]
...	...
<i>K99</i>	[108, 69, 99, 68, 113, 1, 56, 34, 81, 36, 122, 24, 121, 31, 54, 19, 28, 22, 71, 39, 51, 10, 18, 119, 95, 92, 33, 35, 117, 74, 60, 72, 11, 2, 25, 76, 94, 118, 4, 44, 53, 27, 17, 97, 42, 78, 67, 70, 23, 82, 37, 20, 110, 59, 29, 50, 48, 5, 26, 87, 55, 3, 21, 49, 115, 41, 7, 43, 32, 89, 61, 12, 9, 96, 102, 65, 84, 106, 64, 8, 15, 62, 85, 116, 104, 114, 101, 14, 103, 6, 66, 57, 40, 63, 73, 86, 52, 38, 46, 58, 105, 90, 13, 83, 79, 107, 30, 109, 80, 112, 88, 16, 93, 45, 47, 75, 77, 111, 98, 120, 91, 100]
<i>K100</i>	[35, 47, 93, 79, 111, 120, 23, 32, 56, 72, 9, 105, 98, 45, 85, 52, 2, 19, 90, 81, 75, 76, 106, 107, 1, 80, 71, 46, 20, 59, 33, 7, 62, 40, 60, 16, 68, 30, 29, 53, 37, 89, 13, 10, 49, 104, 41, 77, 117, 8, 96, 97, 100, 50, 54, 67, 25, 102, 74, 119, 86, 42, 99, 91, 108, 51, 113, 101, 94, 88, 24, 11, 73, 116, 114, 61, 39, 58, 31, 12, 48, 15, 82, 92, 6, 115, 66, 14, 122, 4, 57, 5, 110, 70, 18, 95, 27, 43, 78, 34, 112, 17, 22, 55, 26, 38, 109, 28, 63, 65, 36, 121, 3, 118, 87, 84, 103, 44, 21, 64, 69, 83]

##### 4.1.4.3 Population Evaluation

This process is carried out to determine the fitness value derived from the current population. The population evaluation process is carried out by calculating three main indicators, it is travel\_cost, fuel\_cost, and time\_cost to determine the fitness value of the population.

##### 4.1.4.4 Selection

The population selection process is a process to get a good parent of offspring. There are several methods that can be used in conducting population selection. In this study, the method used was the Tournament Selection Method. Tournament Selection is a selection process by bringing together chromosomes until the final result of the selection process is obtained which is then continued with the determination of the parent. In determining the parent for the crossover, the parent range can be determined using a parent selection ratio that can be determined using a formula such as Equation 4.

$$parent_{range} = chromosome_{length} * parent_{selection\_ratio} \tag{4}$$

**4.1.4.5 Elitism**

In this process, several chromosomes will be included in the elite category. The elite category here is that the chromosomes are good chromosomes and do not need to go through the process of crossover and mutation, so that they enter the next generation.

**4.1.4.6 Crossover**

The process of crossing is aimed at forming offspring (child) based on the specified parent. In this crossover stage, the parent selection ratio value is 0.8. As for after getting the parent range, a cross between parents is carried out as can be seen in Table 6.

**Table 6. Parent Crosses**

Chromosome1	Chromosome2
<i>K1</i>	<i>K2</i>
<i>K3</i>	<i>K4</i>
...	...
<i>K97</i>	<i>K98</i>
<i>K99</i>	<i>K100</i>

A crossover is a cross between two parent chromosomes. The method used to carry out crossing in this study is to use the one-point crossover method or one point crossing. The crossing process can be seen in Table 7.

**Table 7. Crossover Process**

Chromosome	<i>G1</i>	<i>G2</i>	...	<i>G95</i>	<i>G96</i>	<i>G97</i>	<i>G98</i>	...	<i>G119</i>	<i>G120</i>
<i>K1</i>	24	49	...	5	<b>48</b>	<b>37</b>	<b>16</b>	...	<b>69</b>	<b>108</b>
<i>K2</i>	83	96	...	56	<b>99</b>	<b>54</b>	<b>29</b>	...	<b>121</b>	<b>5</b>
<i>K1</i> (Child)	24	49	...	5	<b>99</b>	<b>54</b>	<b>29</b>	...	<b>121</b>	<b>5</b>
<i>K2</i> (Child)	83	96	...	56	<b>48</b>	<b>37</b>	<b>16</b>	...	<b>69</b>	<b>108</b>

After the exchange of genes on predetermined chromosomes. The crossover produces a new population which can be seen in Table 8.

**Table 8. Crossover Results**

Chromosome	<i>G1</i>	...	<i>G96</i>	<i>G97</i>	...	<i>G120</i>
<i>K1</i>	24	...	99	54	...	5
<i>K2</i>	83	...	48	37	...	108
<i>K3</i>	83	...	34	102	...	86
...	...	...	...	...	...	...
<i>K99</i>	108	...	43	78	...	83
<i>K100</i>	35	...	46	58	...	100

**4.1.4.7 Mutation**

The mutation process is execute by replacing the genes on the chromosomes with new genes, and aims to get the best fitness value. Using the parameter that was previously tested, named the mutation probability used is 0.75, then look for the total genes that when formulated can be seen as in Equation 5.

$$Mutation_{range} = Chromosome_{length} * Mutation_{probability} \tag{5}$$

After getting the mutation range, the next step is to calculate the total genes and the maximum mutation. In calculating the total genes and the maximum mutations can be seen in Equation 6 and Equation 7.

$$Gen_{total} = Gen_{size} * Pop_{size} \tag{6}$$

$$Max_{mutation} = Mutation_{probability} * Gen_{total} \tag{7}$$

After getting the max mutation, then the generation of random numbers is carried out as many as the Total Gen. This random number will be used as an index number that will experience as many mutations as max mutations. The mutation process can be seen in Table 9.

**Table 9.** Mutation Process

Chromosome	<i>G1</i>	<i>G2</i>	<i>G3</i>	...	<i>G119</i>	<i>G120</i>
<i>K1</i>	24	<b>49</b>	73	...	69	<b>108</b>
<i>K2</i>	83	96	<b>103</b>	...	<b>121</b>	5
<i>K3</i>	<b>46</b>	37	15	...	<b>95</b>	53
...	...	...	...	...	...	...
<i>K99</i>	108	69	<b>99</b>	...	69	83
<i>K100</i>	35	47	93	...	91	100

After selecting a gene to be mutated randomly, the gene value will be replaced with another gene value at random as well. If the gene value has been altered, the gene that has the same gene value as the mutated gene. The gene value will change to the gene value before mutating in other words, there will be an exchange of gene values between the mutated gene and the gene that has the same gene value as the mutation result. A sample of the results of gene values that have undergone mutation can be seen in Table 10.

**Table 10.** Mutation Results

Chromosome	<i>G1</i>	<i>G2</i>	<i>G3</i>	...	<i>G119</i>	<i>G120</i>
<i>K1</i>	24	<b>99</b>	73	...	69	<b>34</b>
<i>K2</i>	83	96	<b>22</b>	...	<b>55</b>	5
<i>K3</i>	<b>62</b>	37	15	...	<b>87</b>	103
...	...	...	...	...	...	...
<i>K99</i>	108	69	<b>26</b>	...	69	83
<i>K100</i>	35	47	93	...	91	100

#### 4.1.4.8 Evaluation of New Populations

This evaluation process is the last process in 1 iteration which produces a new population called the 1st Generation. A sample of population evaluation results based on fitness values can be seen in Table 11.

**Table 11.** Chromosome Evaluation Results

Chromosome	<i>Travel_cost</i>	<i>Fuel_cost</i>	<i>Time_cost</i>	<i>Fitness</i>
<i>K1</i>	4721.795	54569.415	1616.795	1.641820303290677e-05
<i>K2</i>	4226.273	14607.415	1544.2406	4.907269865858811e-05
<i>K3</i>	4866.775	25631.601	1493.697	3.125774241289036e-05
...	...	...	...	...
<i>K99</i>	4528.2001	31449.851	1579.079	2.6626101966699667e-05

<i>K100</i>	4670.765	36851.1307	1491.609	2.3248511684498962e-05
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At the beginning of the initialization, researchers have determined that the maximum generation or the maximum number of generations is as many as 1000. Then the GA process will undergo a re-iteration starting from the population evaluation stage and will stop when it reaches the 1000th generation. Chromosomes with the highest fitness value are considered the best solution in that generation and we can use them for the next process. GA best population results can be seen in Table 12.

**Table 12.** GA Best Population Results

Variable	Value (Fuzzy)	Value (Non-Fuzzy)
<i>Fitness</i>	0.000203	0.00005076786656953438
<i>Travel_Cost</i>	3441.396	4742.34
<i>Fuel_Cost</i>	0	13255.158
<i>Time_Cost</i>	1481.475	1700
<i>Vehicle_Route</i>	[[0, 83, 96, 103, 12, 70, 17, 76, 0], [0, 118, 113, 109, 79, 30, 21, 69, 68, 65, 7, 114, 0], [0, 86, 48, 52, 61, 39, 120, 0], [0, 85, 1, 13, 74, 72, 33, 24, 19, 0], [0, 97, 42, 14, 40, 91, 102, 11, 106, 26, 104, 8, 94, 2, 88, 27, 0], [0, 105, 82, 32, 4, 110, 93, 100, 18, 59, 0], [0, 62, 50, 90, 20, 71, 36, 31, 9, 57, 28, 0], [0, 51, 46, 45, 78, 67, 15, 111, 25, 6, 119, 115, 35, 0], [0, 66, 77, 3, 92, 80, 16, 10, 0], [0, 64, 54, 29, 60, 73, 22, 99, 101, 122, 37, 0, 0], [0, 43, 121, 5, 0]]	[[[0, 83, 96, 103, 0], [0, 89, 12, 70, 0], [0, 87, 17, 76, 118, 113, 0], [0, 109, 79, 0], [0, 63, 30, 21, 69, 68, 65, 7, 114, 0], [0, 86, 48, 52, 61, 39, 120, 0], [0, 85, 1, 13, 0], [0, 112, 74, 72, 33, 24, 19, 0], [0, 84, 97, 0], [0, 42, 14, 44, 40, 0], [0, 23, 91, 102, 49, 0], [0, 108, 11, 106, 26, 38, 116, 104, 8, 94, 98, 2, 88, 27, 0], [0, 107, 105, 0], [0, 81, 82, 32, 4, 0], [0, 58, 110, 93, 100, 18, 55, 59, 0], [0, 62, 50, 90, 20, 71, 36, 0], [0, 117, 31, 9, 57, 41, 28, 0], [0, 51, 46, 45, 78, 67, 15, 111, 0], [0, 34, 47, 25, 6, 95, 119, 115, 35, 0], [0, 66, 77, 3, 92, 80, 16, 0], [0, 56, 10, 64, 54, 29, 60, 73, 22, 99, 0], [0, 101, 122, 37, 53, 75, 0], [0, 43, 121, 5, 0]]]
<i>Vehicle Count</i>	11	23
<i>Deport Visit</i>	12	23
<i>Working Hours</i>	14.605	13.291

#### 4.1.5 Application of Tabu Search

After the solution with the highest fitness value is found, then the output/solution from GA will be the input for use on TS. Therefore, the output from GA-TS will be optimal. TS has the same goal as GA, TS is also looking for solutions with the best fitness value. This combination of GA-TS enables GA solutions, out of the optimum local result to the optimum global. The TS steps are as follows:

##### 4.1.5.1 Initialization of the Solution

The first step is to initialize the initial solution and declare the initial solution as the optimum solution at the 0th iteration. The initial solution of TS in this study used the output from GA which had gone through data processing. With this process, the initial solution was obtained, namely routes: [83, 96, 103, 12, 70, 17, 76, 118, 113, 109, 79, 30, 21, 69, 68, 65, 7, 114, 86, 48, 52, 61, 39, 120, 85, 1, 13,

74, 72, 33, 24, 19, 97, 42, 14, 40, 91, 102, 11, 106, 26, 104, 8, 94, 2, 88, 27, 105, 82, 32, 4, 110, 93, 100, 18, 59, 62, 50, 90, 20, 71, 36, 31, 9, 57, 28, 51, 46, 45, 78, 67, 15, 111, 25, 6, 119, 115, 35, 66, 77, 3, 92, 80, 16, 10, 64, 54, 29, 60, 73, 22, 99, 101, 122, 37, 43, 121, 5].

#### 4.1.5.2 Starting Iteration

The next stage is to determine the next iteration and look for alternative solutions that do not violate the Tabu criteria. An alternative solution is obtained by exchanging the position of two points (nodes) or customers based on indices.

In the 0th iteration obtained Tabu list : [83, 96, 103, 12, 70, 17, 76, 118, 113, 109, 79, 30, 21, 69, 68, 65, 7, 114, 86, 48, 52, 61, 39, 120, 85, 1, 13, 74, 72, 33, 24, 19, 97, 42, 14, 40, 91, 102, 11, 106, 26, 104, 8, 94, 2, 88, 27, 105, 82, 32, 4, 110, 93, 100, 18, 59, 62, 50, 90, 20, 71, 36, 31, 9, 57, 28, 51, 46, 45, 78, 67, 15, 111, 25, 6, 119, 115, 35, 66, 77, 3, 92, 80, 16, 10, 64, 54, 29, 60, 73, 22, 99, 101, 122, 37, 43, 121, 5], then alternative solutions can be:

If the index (1) then the position of the 1st point is exchanged for the position of the 2nd point, obtained the 1st alternative path : [96, 83, 103, 12, 70, 17, 76, 118, 113, 109, 79, 30, 21, 69, 68, 65, 7, 114, 86, 48, 52, 61, 39, 120, 85, 1, 13, 74, 72, 33, 24, 19, 97, 42, 14, 40, 91, 102, 11, 106, 26, 104, 8, 94, 2, 88, 27, 105, 82, 32, 4, 110, 93, 100, 18, 59, 62, 50, 90, 20, 71, 36, 31, 9, 57, 28, 51, 46, 45, 78, 67, 15, 111, 25, 6, 119, 115, 35, 66, 77, 3, 92, 80, 16, 10, 64, 54, 29, 60, 73, 22, 99, 101, 122, 37, 43, 121, 5].

If the index (2) then the position of the 1st point is exchanged for the position of the 3rd point, obtained the 2nd alternative path : [103, 83, 96, 12, 70, 17, 76, 118, 113, 109, 79, 30, 21, 69, 68, 65, 7, 114, 86, 48, 52, 61, 39, 120, 85, 1, 13, 74, 72, 33, 24, 19, 97, 42, 14, 40, 91, 102, 11, 106, 26, 104, 8, 94, 2, 88, 27, 105, 82, 32, 4, 110, 93, 100, 18, 59, 62, 50, 90, 20, 71, 36, 31, 9, 57, 28, 51, 46, 45, 78, 67, 15, 111, 25, 6, 119, 115, 35, 66, 77, 3, 92, 80, 16, 10, 64, 54, 29, 60, 73, 22, 99, 101, 122, 37, 43, 121, 5].

...

If the index (11) then the position of the 1st point is exchanged for the position of the 12th point, obtained the 11th alternative path : [30, 83, 96, 103, 12, 70, 17, 76, 118, 113, 109, 79, 21, 69, 68, 65, 7, 114, 86, 48, 52, 61, 39, 120, 85, 1, 13, 74, 72, 33, 24, 19, 97, 42, 14, 40, 91, 102, 11, 106, 26, 104, 8, 94, 2, 88, 27, 105, 82, 32, 4, 110, 93, 100, 18, 59, 62, 50, 90, 20, 71, 36, 31, 9, 57, 28, 51, 46, 45, 78, 67, 15, 111, 25, 6, 119, 115, 35, 66, 77, 3, 92, 80, 16, 10, 64, 54, 29, 60, 73, 22, 99, 101, 122, 37, 43, 121, 5]. And so on until the index reaches the stop criteria.

#### 4.1.5.3 Choosing the Best Solution

The next step is to choose the best solution among the alternative solutions that have been obtained in step 4.1.5.2.

#### 4.1.5.4 Evaluation

If the solution obtained is on the Tabu list, the solution will be ignored. Then if the fitness value of the best solution in step 4.1.5.2 is greater than the value of the initial optimum solution, then the best optimum solution obtained is chosen as the optimum solution.

#### 4.1.5.5 Tabu List

Update the Tabu list by adding the optimum solution route obtained in step evaluation.

#### 4.1.5.6 Stop Criteria

If the dismissal criteria are met, the process stops. If not, then the process is restarted starting step 4.1.5.2 with the last optimum solution as initialization and will stop when the dismissal criteria are met. The stop criteria in this study is that the maximum index has been met or TS managed to find one iteration with a fitness value better than the fitness value of the GA result.

## 4.2 Discussion

In this study, a comparison of the results will be carried out between E-VRP which uses fuzzy in increasing time windows and E-VRP which only uses time windows. The greater the fitness value obtained, the better the quality of the solution. There are two types of trials carried out, specifically trials with the same dataset and trials with randomly selected datasets. This study applies GA and TS in optimizing the route determination of the E-VRP with the limitation of time windows parameters combined with Fuzzy Logic. The dataset used is E-VRPTW Instances which contains VRP data with cluster, random, and random cluster types. This dataset presents cartesian coordinates (x-coordinates and y-coordinates), the number of requests, the start time and end time, as well as the total time in serving customers. Each of the available datasets has instances ranging from 5 instances, up to 120 instances.

#### 4.2.1 Testing One Dataset

The parameter determination stage is performed with the aim of determining the appropriate parameters for the GA-TS method in order to increase the effectiveness and work efficiency of the GA method. After testing with several values, the optimum parameters shown in Table 3 were obtained. These optimum parameters are then used for the process of finding the optimum route with GA-TS. After going through the parameterization stage, the next stage is data processing on E-VRPTW with and without using Fuzzy Logic. The results of data processing execution on the "c101\_21" dataset can be reviewed in Table 13.

**Table 13.** Results of Ten "c101\_21" Trials

Trial	Fuzzy	Non-Fuzzy
1	0.00021	0.00019
2	0.000228	0.000197
3	0.000237	0.000198
4	0.000244	0.000217
5	0.000218	0.000197
6	0.00021	0.000184
7	0.000228	0.000196
8	0.000239	0.000206
9	0.000227	0.000193
10	0.00022	0.000195

After ten E-VRPFTW trials, the fitness value with and without fuzzy was taken from the average value. The average fitness results from the E-VRPTW data processing process with and without fuzzy can be seen in Table 14.

**Table 14.** Average Results of "c101\_21" Trials

E-VRPTW	Fitness Value
Fuzzy	0.000226
Non-Fuzzy	0.000197

Based on the fitness value results from Table 14, the average result of ten E-VRPTW executions with fuzzy in the "c101\_21" dataset got a value of 0.000226 with fuzzy and 0.000197 without fuzzy. The difference between fuzzy and non-fuzzy usage is 0.000028.

#### 4.2.2 Testing Random Datasets

In addition to using one dataset ten times for trials, researchers also conducted trials on several different datasets. The datasets used are: c101C10, c102\_21, c106C15, c101\_21, r101\_21, r202\_21, rc205\_21, r211\_21, rc201\_21, rc208\_21. The results of the data processing execution on the dataset used can be seen in Table 15.

**Table 15.** Random Dataset Trial Results

Trial	Fuzzy	Non-Fuzzy
c101C10	0.001247	0.001152
c102_21	0.000242	0.000216
c106C15	0.001385	0.001333
c101_21	0.000229	0.000206
r101_21	0.000211	0.000171
r202_21	0.000271	0.000245
rc205_21	0.000188	0.000171

r211_21	0.000287	0.000254
rc201_21	0.000201	0.000175
rc208_21	0.000222	0.000207

After ten trials of a randomly selected dataset, fitness scores with and without Fuzzy were obtained. Based on the results in Table 15, all fitness value results using Fuzzy are superior to non-Fuzzy. Furthermore, the fitness value is calculated as the average value. The average results of ten random dataset trials can be seen in Table 16.

**Table 16.** Average Random Dataset Trial Results

E-VRPTW	Fitness Value
Fuzzy	0.000448
Non-Fuzzy	0.000413

Based on the second type of experiment, called a random dataset, the fitness values can be seen in Table 16. The average result of ten E-VRPFTW executions on ten different datasets, resulted in greater results than without the use of E-VRPFTW. The second type of trial gets a score of 0.000448 with fuzzy and 0.000413 without fuzzy. The difference between fuzzy and non-fuzzy usage is 0.0000351. To find out that the GA-TS method and the use of Fuzzy used in this study are the right methods, the researchers compared the methods with the research conducted by (Schneider et al., 2014). In a study conducted by (Schneider et al., 2014) which focused on mileage and the number of vehicles used with the Variable Neighborhood Search and Tabu Search (VNS-TS) methods, it had differences with researchers' research, especially on the GA-TS method and the use of Fuzzy. A comparison of the accuracy results obtained with previously conducted research can be seen in Table 17.

**Table 17.** Comparison of Results with Related Research

Instances	Fuzzy		Non-Fuzzy	
	Vehicle Count	Distance	Vehicle Count	Distance
C101_5	2	257,75	1	179,23
C208_5	1	158,48	1	158,48
R105_5	2	156,08	2	164,44
RC105_5	2	241,30	2	241,52
C104_10	2	273,93	1	239
R102_10	3	249,19	2	228,82
RC205_10	2	325,98	1	297,14
C106_15	3	275,13	1	210,94
R105_15	4	336,15	3	308,12
RC202_15	2	394,39	2	335,77

In Table 17 comparisons between studies related to research conducted by researchers can be seen that the distance (mileage) in the proposed method has a distance that is mostly shorter than the distance from the previous study, and the number of vehicles used is relatively less. The dataset used in this study and the previous study is the same, named "E-VRPFTW Instances". An average comparison of the results of related studies can be seen in Table 18.

**Table 18.** Comparison of Related Research Averages

Result	Schneider <i>et al</i> (2014)	Proposed Method
Average Vehicle Count	23	16

Average Distance	2668,38	2363,46
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Based on the average results with related studies, the values produced using the proposed method produce better results. This is seen from the smaller number of vehicles and shorter mileage. The first result in the form of a vehicle count experienced an increase in quality of 30.43%, while the second result experienced an increase in quality of 11.35%.

## 5 Conclusion

This paper examines the improvement of E-VRPTW by adding Fuzzy Logic using GA and TS. Fuzzy Logic is used in time windows to provide a tolerance value for arrival time beyond the time windows limit. The results obtained showed that E-VRPFTW has a higher fitness value than E-VRPTW when using GA-TS. The results of the fitness value obtained were that the first type of trial increased by 14.39%, and the second type of trial increased by 8.49%. Also based on a comparison of the results of the number of vehicles and the distance in related research it can be concluded that the use of the GA-TS method and the use of fuzzy can be said to be better due to the factor of shorter mileage and the small number of vehicles.

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