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Improving Customer Service in Dealing with the Vehicle Routing Problem with Time Windows Using Optimization Algorithms

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ABSTRACT
Vehicle Routing Problem with Time Window (VRPTW) is one of the combinatorial problems faced in serving customers. The Evolution Strategies (ES) and Genetic Algorithm (GA) are part of the artificial intelligence used to solve this problem. Although these techniques are similar, they possess the following differences GA consists of a crossover process while ES is capable of generating new mutations. Furthermore, ES has advantages over mutations in GA with a rule of 1/5 to obtain better results. Therefore, this study made a comparison between the two algorithms in solving VRPTW cases wherein the distribution of goods need to consider time. Based on the test results on the parameter values, it is seen that GA is better than ES in terms of computation time because the process is faster. However, when viewed from the efficiency of time, ES is better than AG despite its prolonged processing time.
Keywords: *Vehicle Routing Problem with Time Window, Evolution Strategies Algorithm, Genetic Algorithm, optimization*

INTRODUCTION

Artificial intelligence is a methodological tool for solving business related problems [1]. For example, late delivery of goods, to destination makes customers complain. However, the solution to such delays is seeking the best routes by considering the distance traveled, vehicles type, capacity, and different locations with minimum costs using Vehicle Routing Problem (VRP). The proper utilization of travel time and goods tends to reduce distribution costs, delay and number of vehicles utilized [2]. In addition, this is also influenced by the constraints which need to follow the time available to the customer known as the Time Window or Vehicle Routing Problem with Time Window (VRPTW). This technique helps to ensure that the distribution of goods does not exceed the time frame, while the customer demands is not greater than the vehicle's capacity. VRPTW is divided into two types, namely the Routing Problem Vehicle with Hard Time Windows (VRPHTW) and the Routing Problem with Soft Time Windows (VRPSTW). VRPHTW is where customers acquire services for the time specified by the them, while on VRPSTW the reverse is the case and when the time limit is exceeded, it results to penalties [3].
The required solution, therefore, is to determine various methods to fulfill requests from customers with the total travel time of the best trip at minimum cost, thereby, eliminating penalties [4]. Minimum costs are represented by total distance and number of vehicles, while cases need to be resolved by considering the suitability of available customer time [5,6]. Genetic Algorithms (GA) and Evolution Strategies (ES) are algorithms, designed to assist VRPTW settlement. GA consists of a crossover process, while ES has no such method in producing a new generation. Furthermore, GA computing time tends to be stable despite the enormous number of nodes, however, its genetic parameters, especially in population size, are very influential in solving cases [7]. While in ES, computational time tends to be unstable and depends on parameter values, especially on the number of generations [5]. ES mutations has 1/5 advantages over mutations in genetic algorithms, and for this reason, it is deemed necessary to compare the two algorithms in solving errors related to VRPTW.
This study focuses on the differences between GA and ES in determining the correct parameter values and time efficiency in solving errors related to VRPTW, in terms of best algorithms. To solve these problems, several research questions were developed, as follows:
How do the AG and ES algorithm work in solving problems related to VRPTW?
Does the AG and ES which depends on parameter value in solving the errors associated with VRPTW, affect the fitness value and its computation?
What is the time efficiency of an AG which uses a crossover compared to ES that uses none?

Genetic Algorithm
Genetic algorithm is part of the evolution algorithm which acts as a search base for natural selection mechanisms and genetics. It also conducts searches for solutions to various

optimization problems based on existing evolutionary theories [8-10]. The final result of this algorithm is the highest fitness value of all genetic parameters which consists of the following:
Population Size, which consists of the number of individuals involved in each generation,
Crossover Rate (Cr) or Crossover Probability (Pc), which is the possibility of a crossover in a generation,
Mutation Rate (MR) or Probability Mutation (Pm) which is the possibility of mutation or creating a new generation in each individual,
The number of generations formed determines the length of the genetic algorithm process.

The components used to solve a case consist of chromosome formation, initialization, evaluation, calculating fitness functions, and reproduction which comprises of crossover, mutation, and selection. This research uses permutation which is a representation of numbers on genes to illustrate solutions. Initialization will also be used to generate initial populations, which is randomly generated. Furthermore, evaluation is very influential with fitness values because it is used to calculate the functionality of a chromosome.
Based on natural evolution, each individual tends to survive with the possession of a high fitness value, and vice versa [11]. This fitness value is calculated using equation 1 as follows:

$$\text{fitness} = \frac{1}{\text{aTotalPenalty} + \text{aTotalDistance} + \text{aUnserved}} \quad (1)$$

where: Total Penalty = sum of time that exceeds the predetermined time limit
Total Distance = the sum of the travel time
Unserved = number of customers not served in the distribution due to the imposed penalty
Crossover is a cross-displacement or cross-breeding process which involves two randomly selected parents to obtain a new chromosome [12]. A new individual is produced using a crossover probability multiplied by the population size [4]. In this study, the Partially-Mapped Crossover (PMX) method was used to achieve this, with the mutation process conducted by randomly selecting a parent [11].
Mutation aims to create new individuals from changing or updating one or more genes with a new value that is randomly obtained [13, 14]. In this study, the production of new individuals was obtained using the probability of mutations multiplied by the size of the population using the reciprocal exchange mutation method [4]. An elitist selection has a trait in choosing individuals with the highest fitness value, those with the lowest score were not selected to survive in the next generation [11].
Evolution Strategies Algorithm
ES has differences with GA in terms of its reproductive process where crossover and mutation serve as supporting and reproductive operators [4]. It uses some notations to denote its parameters namely μ for population size, λ for number of offspring to be produced, and σ (strategy parameter) to state the level of mutation randomly conducted.
Furthermore, ES relies more on the mutation process, which is its process type (μ, λ) and (μ + λ). The process (μ, λ) does not involve the individuals' offspring and parent, while the process (μ + λ) involves both. Therefore, this study uses the (μ + λ) process with components almost similar to GA which consist of chromosome formation, initialization, evaluation, calculating fitness functions, and reproduction (mutation and selection). Furthermore, the sub-component explains the chromosome formation, initialization, evaluation, and elitist selection using same formula, with slight differences in the fitness function and mutation. Therefore, this study uses the fitness function in equation 2, with additional predetermined constant values to obtain better results [6].

$$\text{fitness} = \frac{1}{(50 \text{ x TotalPenalty}) + (0.5 \text{ x TotalDistance}) + (50 \text{ x Unserved})} \quad (2)$$

The mutation method used in this study is reciprocal exchange, as previously described. The superiority of ES is to have a rule of 1/5, which means the value of σ is raised assuming there is at least 1/5 or 20% of the mutation results from individuals with fitness value higher than the parent, which is increased by multiplying by1, 1 and 0.9 when low[4]. The formulas owned by rule 1/5 is written in equation 3 and the values are recommended around 0.85 ≥ a ≤ 1 assuming the number of generations is greater than 30 [6]. To determine the amount of offspring from the parent (λ) on ES using equation 5 where μ is the population size and C is a constant value in the form of integers [15].

$$\sigma = \begin{cases} \sigma/a, & jika\ P_c < 1/5 \\ \sigma . a, & jika\ P_c \geq 1/5 \\ \sigma, & jika\ P_c = 1/5 \end{cases} \quad (3)$$

$$\lambda = \mu * C \quad (4)$$

Experiments and Result
The data used, were obtained from PT Cahaya Mega Penyimbang which is a gas distribution company in the city of Prabumulih. The data was obtained in March 2017 in the form of customer address, number of individual requests, number of vehicles and its carrying capacity. Meanwhile, the dummy database on informal interviews with distributors, and the distance from one location to another obtained from google maps in kilometers (km), were used to determine the time window and customer service time.
Experiments were carried out with ten tests on each of the genetic and strategic parameter values obtain the highest fitness value. The testing stage begins with generation testing, which is carried out to determine the best number of generations or iterations in solving VRPTW cases based on average firmness values and computation time. This test used the elitist selection, with a population size of 50, combination of crossover and mutation probability values of 0.4: 0.6, vehicle transport capacity of 1680 kg, with a constant speed at 30 km/hr.
Table 1 shows the number of generations with best average fitness value of 0.222, and a computing time of 44.206 seconds from 200 people in the GA test. While table 2 shows the data obtained from the population test results, using a population size of 30, with an average fitness and computational time of 0.177 and 11.301 respectively from 2000 people. The path choices are obtained because GA requires a large population size to achieve its maximum goal. However, the population size used in this study is 100 with a fitness value of 0.357, which means that the route is

duplicated and ineligible in VRPTW cases where the route is visited at least once.
Table 3 shows the data from the test results of the combination of crossover and mutation probability values, with the best average fitness ratio of 0.1: 0.9, at 0.098 with an average computing time of 12.940 seconds. The testing is conducted to determine the right combination value in solving VRPTW cases. To acquire the optimal results in locating and scheduling the destination, this study uses the elitist selection, generation of 2000, population size of 30, carrying capacity of 1680 kg, and vehicle speed constant at 30 km/hr. The computation time is increased by combining the crossover probability and mutation values, which indicates a relatively flat time change. This condition shows that the crossover and mutation probability does not significantly affect computing time, but it dramatically influences the population size and number of generations entered.

Table 1. Number of Generation in Genetic Algorithm

Number of Generations	Average of Fitness Values	Average of Computation Times (second)
500	0,059	11,732
1000	0,063	22,771
1500	0,089	33,095
2000	**0,222**	**44,206**
2500	0,079	54,512
3000	0,074	66,006

Table 2. Total Population in Genetic Algorithms with 2000 Generations

Number of Populations	Average of Fitness Values	Average of Computation Times (second)	Number of Populations	Average of Fitness Values	Average of Computation Times (second)
10	0,059	2,904	60	0,096	73,139
20	0,070	5,609	70	0,070	119,220
30	**0,177**	**11,301**	80	0,115	185,800
40	0,175	22,370	90	0,096	278,760
50	0,122	41,861	100	0,357	403,270

Table 3. Combination of Pc and Pm in Genetic Algorithms with 2000 Generations and 30 Populations

Combination of Crossover Probability Value : Mutation	Average of Fitness Values	Average of Computation Times (second)	Combination of Crossover Probability Value : Mutation	Average of Fitness Values	Average of Computation Times (second)
0,1 : 0,9	**0,098**	**12,904**	0,1 : 0,1	0,052	7,865
0,2 : 0,8	0,057	13,015	0,2 : 0,2	0,066	8,916
0,3 : 0,7	0,060	12,550	0,3 : 0,3	0,071	9,805
0,4 : 0,6	0,066	12,568	0,4 : 0,4	0,067	11,370
0,5 : 0,5	0,083	12,225	0,6 : 0,6	0,076	13,875
0,6 : 0,4	0,097	12,463	0,7 : 0,7	0,071	15,158
0,7 : 0,3	0,096	12,259	0,8 : 0,8	0,074	16,424
0,8 : 0,2	0,085	12,613	0,9 : 0,9	0,077	17,557
0,9 : 0,1	0,091	12,516			

The ES analysis requires input parameters before the algorithm is tested and processed. Each parameter is tested to obtain an effect on the average fitness value and computation time. In table 4, data on the number of generation results, is tested using elitist selection, a population size (μ) of 50, offspring 1μ, a truck size of 1680 kg, and a constant vehicle speed of 30 km/hr. The tests obtained the best number of generations at 2500 with the most significant average fitness value of 181.69 and computing time of 54.14 seconds.

Table 4. Number of Generations in Evolution Strategies

Number of Generations	Average of Fitness Values	Average of Computation Times (second)
500	96,89	11,63
1000	82,26	23,42
1500	87,93	33,96
2000	84,64	44,68
2500	**181,69**	**54,14**
3000	85,19	64,43

Table 5. Total Population in ES With 2500 Generations and Offspring 1μ - 10μ

Number of Populations	Average of Fitness Values	Average of Computation Times (second)	Number of Populations	Average of Fitness Values	Average of Computation Times (second)
$\lambda = 1\mu$			$\lambda = 2\mu$		
10	74,90	0,79	10	88,42	0,86
20	84,24	3,50	20	80,95	2,73
30	82,76	8,21	30	90,79	8,00
40	82,66	13,65	40	82,19	11,38
50	86,59	31,50	50	85,56	19,67
60	91,60	44,22	60	187,64	29,37
70	86,81	44,44	70	91,23	45,57
80	87,17	47,15	80	285,29	67,87
90	88,79	72,23	90	102,69	95,91
100	88,05	102,29	100	287,51	135,85
$\lambda = 3\mu$			$\lambda = 4\mu$		
10	82,25	1,58	10	90,72	2,54
20	84,55	4,56	20	181,55	6,72
30	89,34	9,47	30	93,65	17,59
40	280,34	18,35	40	482,39	26,93
50	88,11	30,35	50	291,49	44,54
60	87,99	46,79	60	88,87	70,95
70	92,42	79,32	70	89,94	110,67
80	88,94	100,04	80	88,89	144,37
90	83,21	136,26	90	90,82	321,51
100	100,31	190,54	100	88,46	634,53
$\lambda = 5\mu$			$\lambda = 6\mu$		
10	91,13	2,58	10	75,59	3,75
20	85,12	10,33	20	90,44	13,44
30	88,38	26,89	30	86,11	29,19
40	98,60	40,64	40	181,68	53,53
50	91,44	85,35	50	88,88	93,81
60	86,96	103,10	60	88,25	145,46
70	91,75	167,68	70	88,53	223,78
80	86,56	209,92	80	138,44	293,70
90	86,83	288,49	90	92,90	395,88
100	90,21	383,37	100	90,95	525,46
$\lambda = 7\mu$			$\lambda = 8\mu$		
10	86,68	4,78	10	87,97	5,08
20	86,71	17,00	20	83,03	20,57
30	88,75	56,41	30	89,95	73,29
40	85,79	71,07	40	89,14	93,73
50	86,60	150,47	50	91,85	191,45
60	87,73	192,58	60	85,05	255,96
70	87,61	301,04	70	87,89	411,52
80	88,30	396,98	80	89,03	535,83
90	86,20	544,72	90	87,70	723,98
100	85,17	706,94	100	88,33	952,67
$\lambda = 9\mu$			$\lambda = 10\mu$		
10	81,04	10,96	10	87,16	17,16
20	78,20	26,129	20	81,69	32,29
30	85,52	91,41	30	87,90	134,80

40	85,86	121,00	40	85,42	152,37
50	90,30	233,89	50	91,97	327,55
60	87,68	324,51	60	85,47	411,59
70	88,36	542,24	70	89,38	697,85
80	87,55	685,14	80	85,47	866,66
90	88,24	965,06	90	88,55	1327,56
100	85,04	1217,46	100	87,60	1547,48

In table 5, the results of the test data obtained significant fitness value using an average computation time of 26.93 seconds, generation number of 2500, population size of 40, and an offspring of 4μ at 482.39. This result shows a new generation of 160 possible solutions with an average computation time which affects the population size and number of offspring, thereby prolonging the ES process.
Furthermore, parameter α was tested to determine values that affect the new generation of mutations in resolving this VRPTW case and reduce computing time. The tests were conducted to obtained optimal results in finding and scheduling the destination, based on the average fitness value and computation time. This test uses elitist selection, with 2500 generations, population size of 40, offspring number of 4μ, vehicle carrying capacity of 1680 kg, and constant speed at 30 km/hour. Because the number of generations is greater than 30, the rule 1/5 states that $0.85 \leq a < 1$ applies, therefore, the α tested is 0.86; 0.90; 0.95; and 0.99.
Table 6 shows that the most significant average fitness value of α obtained at 0.95 is 287.30, and the average computation time parameter (a) is 131.31 seconds. Furthermore, the average computation time does not change significantly, therefore, in conclusion, the parameter α fails to affect the computing time, number of generations, population size, and the number of offspring.

Table 6. Parameter α Value on ES with 2500 Generations, 40 Populations, and Offspring 4μ

Parameter a	Average of Fitness Values	Average of Computation Times (second)
0,86	83,47	144,47
0,90	117,97	133,48
0,95	**287,30**	**131,31**
0,99	287,28	132,28

ANALYSIS

The test results between the two algorithms are analyzed by dividing the "total travel time for all vehicles" by the "maximum total travel time for all vehicles" as shown in equation 5. In addition, their efficiency level was compared which led to a manual simulation as shown in table 7. The manual calculation was based on the VRPTW concept, with distribution carried out in a day using the search and scheduling routes with an estimated time and distance of the manual process as shown in table 7.

$$\text{Eff} = \frac{\sum t_{\text{vehicle}}}{\sum t_{\text{max of vehicle}}} \times 100\% \qquad (5)$$

where: Eff = time efficiency
$\sum t_{\text{vehicle}}$ = total travel time of all vehicles
$\sum t_{\text{max of vehicle}}$ = maximum total travel time of all vehicles

The VRPTW settlement using GA and ES is shown in table 8, in the form of distance and time taken on the journey of each vehicle. Furthermore, the VPRTW was processed using a GA with the best parameter values as follows: 2000 number of generations, population size of 30, and the right combination of crossover probability values and mutations of 0.1: 0.9. VPRTW was also processed using ES with 2500 generations, population size of 40, number of 4μ offspring, and parameter values α of 0.95.

Table 7. Results of Manual Route Scheduling

Vehicle #	Routes Search & Scheduling		Estimation of Travelling Distance & Time
1	0 = Jalan Flores Dwikora 2 16 = Jalan Flores 17 = Jalan Flores 18 = Jalan Flores Leman (Flores 5) 19 = Jalan Sukarela 20 = Jalan Belitung 28 = Jalan Sudirman (Zipur)	21 = Jalan Nias 22 = Jalan Nusa 2 12 = Stasiun Kereta Api 1 = Jln Basuki Rahmat (Padi) 11 = Jalan Sosial (Majasari) 0 = Jalan Flores Dwikora 2	30,71 km 6 hr. 49 minutes

2	0 = Jalan Flores Dwikora 2 2 = Jalan Bakaran 14 = Jalan Sudirman Patih Galung 4 = Jalan Sudirman (Zipur)	30 = Jalan Pipa Bawah Kemang 7 = Anak Petai 0 = Jalan Flores Dwikora 2	63,2 km 4 hr. 58 minutes
3	0 = Jalan Flores Dwikora 2 9 = Yayasan Bakti 10 = Yayasan Bakti 13 = Jalan Urip (Nasional) 5 = Jalan Wonosari 8 = Jalan SPM (Wonosari)	32 = Jln Prof M. Yamin 33 = Wonosari 15 = Jln Ade Irma (Batang Asem) 29 = Jln Sudirman (Prabu Jaya) 0 = Jalan Flores Dwikora 2 1	18,65 km 8 hr. 53 minutes
4	0 = Jalan Flores Dwikora 2 31 = Taman Baka Prabu Jaya 34 = Alai Batu 3 = Tanjung Telang	6 = Padat Karya Gunung Ibul 23 = Jalan Lingkar Timur 24 = Jalan Lingkar Timur 0 = Jalan Flores Dwikora 2	52 km 4 hr. 12 minutes
5	0 = Jalan Flores Dwikora 2 25 = Cambai 26 = Cambai	27 = Cambai 0 = Jalan Flores Dwikora 2	12,2 km 1 hr. 34 minutes

Table 8. Results of the VRPTW Process Optimization by GA and ES

Using Genetic Algorithm				Using Evolution Strategies Algorithm		
Vehicle #	Routes Search & Scheduling	Travelling Distance & Time		Vehicle #	Routes Search & Scheduling	Travelling Distance & Time
1	0 = Jl. Flores Dwikora 2 15 = Jl. Ade Irma (Btg. Asem) 7 = Anak Petai 8 = Jl. SPM (Wonosari) 28 = Jl. Sudirman (Zipur) 30 = Jl. Pipa Bawah Kemang 14 = Jl. Sudirman Pth Gulung 34 = Alai Batu 3 = Tanjung Telang 19 = Jl. Sukarela 0 = Jl. Flores Dwikora 2	69,4 km 15 hr 52 minutes		1	0 = Jl. Flores Dwikora 2 11 = Jl. Sosial (Majasari) 21 = Jl. Nias 12 = Stasiun Kereta Api (Statsiun Prabumulih Baru) 24 = Jl. Lingkar Timur 26 = Cambai Prabumulih 19 = Jl. Sukarela 14 = Jl. Sudirman Pth Galung 30 = Jl. Pipa Bawah Kemang 34 = Alai Batu 33 = Wonosari Prabumulih 3 = Tanjung Telang 8 = Jl. SPM (Wonosari) 7 = Anak Petai 0 = Jl. Flores Dwikora 2	111,9 km 17 hr. 14 minutes
2	0 = Jl. Flores Dwikora 2 5 = Jl. Wonosari Prabumulih 32 = Jl. Prof. Moh. Yamin 22 = Jl. Nusa 2 0 = Jl. Flores Dwikora 2	15,72 km 1 hr 40 minutes		2	0 = Jl. Flores Dwikora 2 5 = Jl. Wonosari Prabumulih 13 = Jl. Urip (Nasional) 18 = Jl. Flores Leman 5 16 = Jl. Flores 17 = Jl. Flores 0 = Jl. Flores Dwikora 2	16,96 km 3 hr. 12 minutes
3	0 = Jl. Flores Dwikora 2 33 = Wonosari Prabumulih 31 = Taman Baka Prabu Jaka 0 = Jl. Flores Dwikora 2	15,2 km 1 hr 14 minutes		3	0 = Jl. Flores Dwikora 2 1 = Jl. Basuki Rahmat (Padi) 10 = Yayasan Bakti 9 = Yayasan Bakti 32 = Jl. Prof, Moh. Yamin 25 = Cambai Prabumulih 0 = Jl. Flores Dwikora 2	26,75 km 4 hr. 50 minutes
4	0 = Jl. Flores Dwikora 2 6 = Padat Karya Gunung Ibul 29 = Jl. Sudirman Prabu Jaya 18 = Jl. Flores Leman 5 0 = Jl. Flores Dwikora 2	13,3 km 2 hr 53 minutes		4	0 = Jl. Flores Dwikora 2 2 = Jl. Bakaran 15 = Jl. Ade Irma (Btg. Asem) 31 = Taman Baka Prabu Jaya 0 = Jl. Flores Dwikora 2	24,5 km 2 hr. 50 minutes
5	0 = Jl. Flores Dwikora 2 1 = Jl. Basuki Rahmat (Padi) 23 = Jl. Lingkar Timur	35,2 km 7 hr		5	0 = Jl. Flores Dwikora 2 6 = Padat Karya Gunung Ibul 4 = Gunung Kemala	62,6 km 8 hr.

	11 = Jl. Sosial (Majasari) 16 = Jl. Flores 17 = Jl. Flores 21 = Jl. Nias 26 = Cambai Prabumulih 25 = Cambai Prabumulih 27 = Cambai Prabumulih 0 = Jl. Flores Dwikora 2	19 minutes			29 = Jl. Sudirman Prabu Jaya 23 = Jl. Lingkar Timur 20 = Jl. Belitung 27 = Cambai Prabumulih 0 = Jl. Flores Dwikora 2	25 minutes
6	0 = Jl. Flores Dwikora 2 2 = Jl. Bakaran 12 = Stasiun Kereta Api (Stasiun Prabumulih Baru) 10 = Yayasan Bakti 20 = Jl. Belitung 24 = Jl. Lingkar Timur 4 = Gunung Kemala 0 = Jl. Flores Dwikora 2	60,3 km 9 hr		6	0 = Jl. Flores Dwikora 2 2 = Jl. Bakaran 12 = Stasiun Kereta Api (Stasiun Prabumulih Baru) 10 = Yayasan Bakti 20 = Jl. Belitung 24 = Jl. Lingkar Timur 4 = Gunung Kemala 0 = Jl. Flores Dwikora 2	6,3 km 45 minutes
7	0 = Jl. Flores Dwikora 2 9 = Yayasan Bakti 23 = Jl. Urip (Nasional) 0 = Jl. Flores Dwikora 2	13,85 km 45 minutes				

Table 9 shows a comparison between the results from the manual calculations and distributors of the VRPTW used to process GA and ES, based on time efficiency. There were differences in the fitness values with additional constant values on the ES which produced better results. A total of five (5) vehicles were produced by manual calculation. However, 13 customers were not served, because the scheduled location does not consider their availability, with gas cylinders delivered according to the location closest to the distribution point (depot). The manual calculation has a time efficiency of 48%, while the VRPTW solution using genetic algorithms is completed with 7 vehicles and 4 unserved customers. Furthermore, VRPTW settlement using ES was completed with 6 vehicles and 4 unserved customers. This result shows that there was a reduction in unserved customers because the distribution takes into account the time available to customers in order to prevent a late delivery time. The number of vehicles used depends on distribution scheduling and requests, which is based on time efficiency, with an increase in the results of VRPTW settlement using ES. Therefore, ES is better with time efficiency of 62.17% than the GA of 55.29% and manual calculation of 48%.

Table 9. Comparison of Manual Results with Genetic Algorithms and Evolution Strategies Results

No.	**Observations**	**Manual Calculation**	**Genetics Algorithm**	**Evolution Strategies Algorithm**
1.	Total of overall visited location	34	34	34
2.	Number of visited vocations those were successfully passed	21	30	30
3.	Unserved customers	13	4	4
4.	Number of vehicles those used	5	7	6
5.	Population size	-	30	40
6.	Number of generations	-	2000	2500
7.	Crossover Probability (Pc)	-	0,1	-
8.	Mutation Probability (Pm) / Offspring (λ)	-	0,9	4μ
9.	Vehicles Speed Rate	30 km/hr	30 km/hr	30 km/hr
10.	Vehicles Capacity	1680 kg	1680 kg	1680 kg
11.	Fitness Value	-	0,05816	73,6643
12.	Computation Time	-	10,814 second	135,162 second
13.	Total Distance	176,76 km	222,95 km	249,01 km
14.	Time Efficiency	48%	55,29%	62,17%

CONCLUSIONS

In conclusion, from the test results in solving the VRPTW case using GA or ES, it is proven that the solution depends on the input of the parameter value. GA and ES have the ability to solve the problems of VRPTW with varying strengths and weaknesses. When viewed from computational time, GA is said to be better than ES owing to its fast processing time. While from time efficiency, ES is better due to increase in distribution from the results of the original manual calculation and the VRPTW process using GA. Therefore, ES is better used than GA, despite its prolonged processing time.

In further research, it is recommended to examine a combination of VRPTW with variations of VRP using GA, ES, hybrid genetic algorithms, or ES with other algorithms to influence time efficiency. It is also recommended to combine these algorithms with random values to improve the mechanism of work processes.

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