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Solving Capacitated Vehicle Routing Problem Using Football Game Algorithm

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Abstract. *The Capacitated Vehicle Routing Problem (CVRP) plays an important role in the logistics transportation sector. Determining the proper route will reduce the company's operational costs. In CVRP, a number of vehicles have a capacity limit that can serve all customers. This research completes a real case study on a bottled drinking water company where the company still uses the subjective method of the driver to determine the transportation route. Based on the conditions in the company, the selection of the best route will consider vehicle capacity and demand to determine the shortest route. The execution of this case study uses the Football Game Algorithm (FGA) which was first initiated by Fadakar & Ebrahimi which proved promising and had the strongest performance in all cases. FGA is expected to be able to determine the shortest distribution route from the existing cases to reduce the distribution costs incurred. This study takes data from 4 days of delivery that served 78 customers. The average daily transportation cost savings result is 42%. This amount indicates that the FGA algorithm is effective for completing a real case study in CVRP.*

Keywords: *capacitated vehicle routing problem; football game algorithm; transportation cost*

I. INTRODUCTION

Recently, one of the major concerns to achieve effectiveness and efficiency in transportation system is the vehicle routing problem. Vehicle routing problem (VRP) is a well-known combinatorial problem for determining the best route to reduce operational cost in the transportation field. VRP is an extension of the Traveling Salesman Problem (TSP) by considering vehicle capacity (Garside & Rahmasari, 2017). It is an optimization problem that aims to find the best way to meet the demand of customers in scattered location at the lowest possible cost, while maintaining the constraint that must be met (Mahmud & Haque, 2019). The number of studies about VRP is increasing in response to conditions of real-life problems. Many kinds of literature have classified VRP into several variants based on their objective function and constraint.

One of the most popular kinds of VRP is Capacitated Vehicle Routing Problem (CVRP). In CVRP, each vehicle has a limited capacity to meet customer demand (Mazidi et al., 2016). The purpose of CVRP is to determine a set of routes of the vehicles, starting and ending at one depot, to meet customer demands without disrupting the vehicle capacity constraint (Liu et al., 2020)

CVRP has grown rapidly in terms of solution approach since it was first introduced by Dantzig and Ramserin in 1959. There are three categories of approaches to solve the CVRP problem, namely exact, heuristic, and meta-heuristic algorithms (Liu et al., 2020). Because the CVRP is an NP-hard problem, only small-scale problems can be optimally solved by exact methods because the computation time increases exponentially with the number of customers. Therefore, many scholars apply heuristic and meta-heuristic methods to obtain good solution to large-scale problems within reasonable time. Heuristic and metaheuristic methods are the main choices in solving problems that have high complexity (Đurasević & Jakobović, 2021).

Nowadays, numerous papers have developed various heuristic and metaheuristic

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methods to solve CVRP problems, such as particle swarm optimization (Ahmed & Sun 2018; Alinezhad et al., 2018; Iswari & Asih, 2018; Mauliddina et al., 2020; Ramadhani & Garside, 2021; Son & Tan, 2021). Simulated annealing algorithm also was proposed by Aurachman et al., 2021; Ilhan, 2020; Mari et al, 2018; Rabbouch et al., 2020; Redi et al., 2020. Besides, there are several studies about CVRP using genetic algorithm (Abdelatti et al, 2021; Azad & Hasin, 2019; Lima & Araújo, 2018; Mulloorakam & Nidhiry, 2019; Zhu, 2022). Tabu search was applied by Arockia et al., 2021; Kurniawati et al., 2022; Caballero-Morales et al, 2018; Dam et al, 2017; Obaid, 2018. Furthermore, some scholars use artificial bee colony for solving CVRP (Ding et al., 2018; Karaoglan et al., 2020; Wahyuningsih et al., 2020; Trachanatzi et al. 2020; Katiyar et al.; 2021).

In this paper, we present a new metaheuristic method named Football Game Algorithm (FGA) to solve CVRP in a real case study. FGA was initiated by Fadakar & Ebrahimi (2016). Football game algorithm is inspired by the behavior of football players in finding the best position to score. Through the comparison research, FGA is a promising algorithm and has the most robust performance in all the benchmark instances in their research. Djunaidi & Juwono (2018) implemented the football game algorithm to solve CVRP using benchmark instances and compared the results with genetic algorithm (GA) and artificial bee colony algorithm (ABC). The result showed that the performance of FGA is as good as GA and ABC algorithms. Based on the performance of FGA that has been proven by Fadakar & Ebrahimi (2016) and Djunaidi & Juwono (2018), we are interested in using this algorithm to solve CVRP in a real case at a bottled drinking water company. To the best of our knowledge, no previous studies have applied this algorithm in real cases. Therefore, this study will be the newest paper in the application of FGA to solve CVRP in real case.

II. RESEARCH METHOD

Capacitated Vehicle Routing Problem

Capacitated Vehicle Routing Problem considers the loading weight that can be delivered by the vehicle to serve all customers (Hannan et al., 2018). In solving the CVRP, a set of conditions have to be complied. The basic constraints and assumptions are as follows (Toth & Vigo, 2002).

1. Each route is a circuit. The vehicle distributes the products starting from the depot and ending at the same depot.
2. Each customer must be visited only once a day.
3. The sum of customer demands transported on a route does not exceed the capacity of the vehicle used on that route.
4. The capacity of the vehicle used does not differ from one another (homogeneous).

CVRP is a graph $G = (V, E)$ with the vertex set $\{v_0, v_1, v_2, ..., v_n\}$ and the edge set E. The vertex v_0 is a depot that has a number of vehicles with the same capacity, namely Q, so the length of each route is limited by vehicle capacity. Each customer (node i>0) has a non-negative demand of q_i. Each edge (i, j) has a distance of c_{ij}, which is the distance from node i to node j. This trip distance is assumed to be symmetric, i.e., $c_{ij} = c_{ji}$ and $c_{ii} = 0$.

Football Game Algorithm

This research uses an algorithm that is relatively new and has only been used in few researches. Nevertheless, this algorithm is promising and has the strongest performance in all cases in the study of Fadakar and Ebrahimi (2016). The football game algorithm (FGA) is a nature-inspired novel algorithm. It is inspired by the football players' behavior for finding the best position to score. The first step of FGA is to determine the population. The population represents the initial formation of players in the field. The players will transfer the ball to each other. Every player will move around their last position (random position) and tend to move towards the ball. Each player has a fitness value that determines the quality of the player position. The player in the best position has a big chance to get the ball. Then, the coach will note some best positions and use them to lead the other players. Two elements in the game are the general movement of the players and coaching (Fadakar & Ebrahimi, 2016).

General movement of players

Fadakar & Ebrahimi (2016) describes that there are two movements in this stage. First move is a simple random walk and movement toward the ball. Each player moves randomly to find a better position and goes to the player currently holding the ball to make a better chance to score a goal. Then, the new position at time t is given by (1).

$$X_i^t = X_i^{t-1} + \alpha_i \varepsilon + \left(X_{ball}^t - X_i^{t-1} \right) \quad (1)$$

With $\varepsilon \in [-1,1]$ and $\beta \in [0,1]$ being uniformly distributed random numbers and $\alpha > 0$ being the step size. Further improvement on the convergence of the algorithm can be achieved by varying the randomization parameter α so that it decreases gradually as the optima are approaching (Fadakar & Ebrahimi, 2016). For example, we can use:

$$\alpha_i = \alpha_0 \theta^t \quad (2)$$

Where $\theta \in [0,1]$ is the random reduction constant and α_0 is the initial parameter.

Coaching

In this stage, the coach memory takes a role to save the best positions and their corresponding fitness values. There are two strategies of coaching. The first one is attacking and the second is substitution (Fadakar & Ebrahimi, 2016). We assume an imaginary Hyper Sphere (HS) with a Hyper Radius (HR), with the poition of the population's best member as its center. A Hyper Radius Limitation Value (HRLV) will be defined, as illustrated in Fig. 3, and will be gradually reduced as the iterations progress. In addtion, every member of the population has a hyper distance (HD) from the best position. As a

Football Game Algorithm

```
Define fitness function
f(X), X = (x_1, x_2, ..., x_dim)^T
Initialize the team formation (players position)
X_i, (i = 1,2,..., N)
Define algorithm parameters θ, γ, λ, CMS
While (t < max number of iterations)
    Compute fitness values
    Rank the players and save best solutions
    Identify the player who possess the ball
    X^t_ball
    If f(x_1) > FLV^1 OR HD_1 > HRLV^t
        Generate a local solution around
        nearest best solution [Equation (5)]
        Update α_i, FLV, HRLV
        α_i, FLV, HRLV [Equations (2), (3), (4)]
    Else
        Generate new positions by general
        movement [Equation (1)]
    End
End while
```

Source: Djunaidi & Juwono (2018)

Figure 1. Pseudo-code of FGA

result, members with a larger distance value than HRLV will be pushed toward the best positions nearest to them. This strategy is called the Hyper Radius Penalty method. (Fadakar & Ebrahimi, 2016).

$$HRLV^t = HRLV_{min} + (HRLV^{t-1} - HRLV_{min}).\gamma \quad (3)$$

With $\gamma \in (0,1)$ is the reduction constant of HRLV.

In the substitution strategy, the coach can substitute some weaker players with better ones. We define a Fitness Limitation Value (FLV) that will be decreased proportionally as the iterations progress. Players with fitness value greater than the FLV will be replaced. The position of the new player is around the nearest best position (Fadakar & Ebrahimi, 2016). The value of FLV is updated using Equation 4.

$$FLV^t = FLV_{min} + \left(FLV^{t-1} - FLV_{min} \right).\lambda \quad (4)$$

where λ has the same role as γ.

The coaching stage is the local search of FGA. After implementing the strategies, players with positions exceeding the FLV will be relocated into a new position. This is done by using a random move from the nearest best solution to their old position, based on Equation 5.

$$X_{new} = X_{nearest\_best} + \alpha \varepsilon_i \quad (5)$$

The steps of FGA can be summarized as the pseudo-code in Figure 1.

Football Game Algorithm for CVRP

FGA is an algorithm designed to solve continuous problems. Because CVRP is a discrete problem, encoding and decoding are needed to adapt FGA to solve CVRP (Djunaidi & Juwono, 2018). The flow diagram of the football game algorithm developed to solve CVRP is presented in Figure 2. We provide the steps for solving CVRP with FGA based on small-instance in Table 1-3. The provided data are the coordinates of the customer location, customer demand, distance matrix and vehicle capacity.

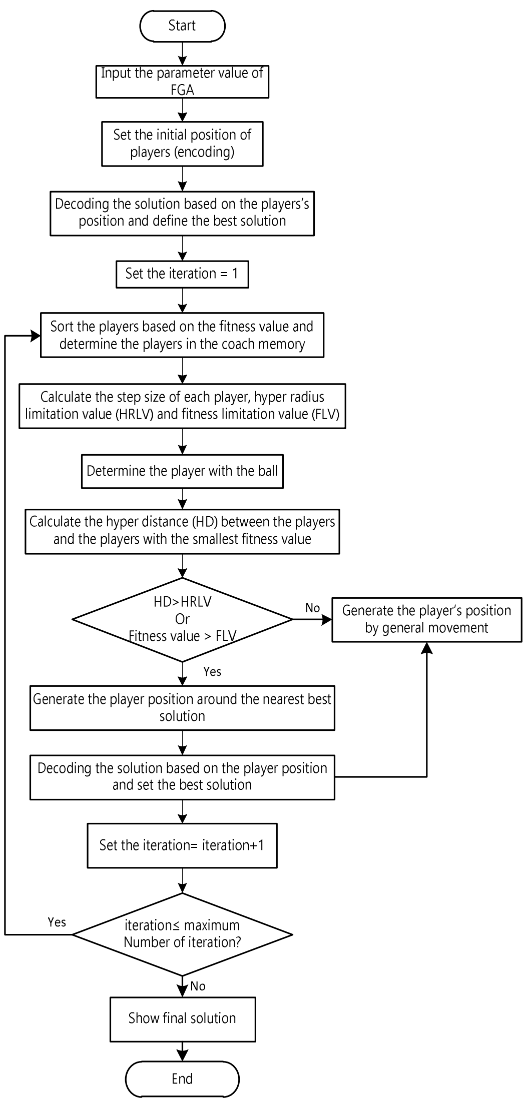

Figure 2. Flow diagram of FGA

Table 1. Customer location coordinates

	X Coordinate	Y Coordinate	Demand
D	0	0	0
C1	37	52	19
C2	87	43	30
C3	52	64	16
C4	68	90	23
C5	52	33	11

Table 2. Distance matrix

	D	C1	C2	C3	C4	C5
D	0	1421	2450	2768	1023	2737
C1	1421	0	147	237	46	244
C2	2450	2509	0	24	337	25
C3	2768	237	1246	0	443	31
C4	1023	999	408	282	0	313
C5	2737	244	1235	31	313	0

Table 3. Vehicle capacity

Number of vehicles	2
Vehicle capacity	60

Input parameter values

The parameter values used in this study refer to the best values proposed by Djunaidi & Juwono (2018), as shown in Table 4.

Table 4. The parameter values

Parameter	Value	Parameter	value
Number of players	3	FLVmin	784
Teta (θ)	1	FLV 0	1000
Gamma (γ)	0.95	HRLVmin	0
Lambda (λ)	0.95	HRLV 0	1000
CMS	2		

Encoding

The player's position is represented by a position vector. In each position, the vector consists of some dimensions. The number of dimensions of the position vector is 3×K, where K is the number of vehicles used to serve customers. The encoding process is performed by generating real numbers with a minimum value of the minimum coordinates of all customers and a maximum value of the maximum coordinates of all customers.

Decoding

There are 4 steps of decoding according to Djunaidi & Juwono (2018). The first step in decoding is to construct the route of each vehicle. The player's position during the decoding process is shown in Figure 3.

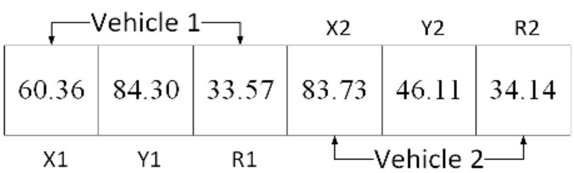

Figure 3. Example of dimension players

Each vehicle has three reference points, i.e., the X coordinate point, Y coordinate point, and the coverage radius of each vehicle. For instance, the position of player 1 consists of X coordinates, Y coordinates, and the radius on vehicle 1, whose values are 60.36; 84.30; and 33.57 respectively. The next step is to assign the customers based on the vehicle coverage radius. Customers whose distance from the vehicle is within the vehicle coverage radius will be served by the vehicle. Therefore, we must calculate the euclidean distance between each vehicle and each customer. The calculation results are as shown in Table 5 and we obtain the customer assignment as follows:

Vehicle 1: C3, C4

Vehicle 2: C2

Table 5. Euclidean distance between vehicle and customer

	C1	C2	C3	C4	C5
Vehicle 1	39.86	49.15	21.95	9.53	51.98
Vehicle 2	47.10	4.51	36.43	46.62	34.33

Furthermore, the route of each vehicle is constructed by sorting customers C2, C3, C4 based on the smallest distance to the vehicle. On the other hand, customers that have not been served (C1 and C5) are sorted based on the furthest distance from the depot. The processes in step 1 results in 2 routes.

Route 1: D-C3-C4-C1-D (Load = 58)

Route 2: D – C2 – C5 – D (Load = 41)

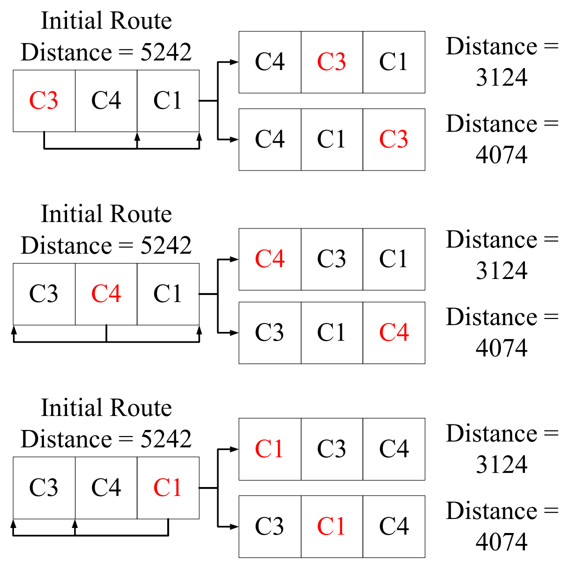

Figure 4. The illustration of local improvement

The second step of decoding is to calculate the total cost of each route. Next, in the third step, local improvement is done for each route by altering the sequence of customers served on each route. If the total distance of the proposed route is less than the initial route, then the proposed route is saved. The local improvement is done repeatedly until the modification process could not generate a new route with a smaller total distance. The illustration of the local improvement process is given in Figure 4. The final set of routes obtained after doing local improvement is given as follows.

Route 1: D – C4 – C3 – C1 – D

Route 2: D – C2 – C5 – D

The fourth step of the decoding is calculating the total distance based on the route obtained by the local improvement. The total distance obtained in this step is the fitness value of the player's position. This is a step for player 1. Then the calculations are carried out for all the players in the population.

Iteration 1

The fitness value of each player is obtained from Table 6. Then, they are sorted and the players with the smallest values will be saved in the Coach Memory (CM).

Fitness value of player 1 = 7732
Fitness value of player 2 = 7732
Fitness value of player 3 = 8336

Table 6. Result of decoding for three players

Player 1 Position	Route	Distance
Route 1	D – C5 – C3 – C2 – D	5242
Route 2	D – C4 – C1 – D	2490
Total		7732
Player 2 Position	Route	Distance
Route 1	D – C4 – C1 – D	2490
Route 2	D – C5 – C3 – C2 – D	5242
Total		7732
Player 2 Position	Route	Distance
Route 1	D – C1 – C3 – C4 – D	3124
Route 2	D – C2 – C5 – D	5212
Total		8336

Next, the distance (steps) between each pair of players is calculated using Equation 6.

$$Distance(a,b) = \sqrt{\begin{array}{l}(X_a^{K1}-X_b^{K1})^2+(Y_a^{K1}-Y_b^{K1})^2+(R_a^{K1}-R_b^{K1})^2+\cdots \\ +(X_a^{Kn}-X_b^{Km})^2+(Y_a^{Kn}-Y_b^{Km})^2+(R_a^{Kn}-R_b^{Km})^2\end{array}} \quad (6)$$

The results are given as follows.

Distance of players 1 - 2 = 40.81
Distance of players 2 - 3 = 45.25
Distance of players 1 - 3 = 39.81

Afterwards, HRLV and FLV are calculated using Equations 3 and 4. The values are 950 and 989.2, respectively.

Table 7. Values of of HD, HRLV and Fitness

	HD	HRLV	Fitness	FLV
Player 1	0		7732	
Player 2	40.81	950	7732	989,2
Player 3	39.81		8336	

Because the fitness values of all the players are greater than the FLV, position relocation is done for all the players.

Table 8. Position relocation of player 1

Player to be Relocated	Player in CM	Distance
1	**1**	**0**
	2	**40.81**

The process above is performed for each player and the results are as follows.

Xnearest-best of player 1 = Player 2
Xnearest-best of player 2 = Player 1
Xnearest-best of player 3 = Player 1

The next step is calculating the new position of each player using Equation 5, where the values of α and ε are given in Table 9.

Table 9. Values of α and ε

Player	α	ε
1	15	[0.9 0.5 -0.9 0.2 0.7 -0.9]
2	15	[-0.9 0.2 -0.6 0.1 0.4 -0.2]
3	15	[0.6 -0.2 0.9 0.7 -0.1 0.5]

The results of the new positions are as follows.

Position of player 1:
46.10 39.51 33.18 61.17 63.51 44.67
Position of player 2:
43.24 45.26 33.10 33.49 69.76 42.69
Position of player 3:
65.74 39.26 55.60 42.49 62.26 53.19

Because there are no coordinates that lie outside the allowable range (33 to 90), normalization is not necessary for these coordinates. After the players' new positions are obtained, decoding is conducted and the algorithm moves to the next iteration. When the number of iterations has reached the predetermined limit, the final solution is returned.

III. Result and Discussion

We conducted research at a bottled water company. The company has one depot as a distribution center and three vehicles. The research was conducted during four working days, starting from September 7 until September

10 2021 (Monday-Thursday). During this period, the company received orders from 23 customers on the first day, 18 customers on the second day, 20 customers on the third day, and 18 customers on the fourth day. Hence, a total of 78 customers was visited in four days.

Transportation cost data consists of fuel cost which is Rp. 9400/liter or Rp 1,044/km; maintenance and tire replacement costs of Rp. 60/km; oil cost Rp. 54/km; and the cost of replacing brake fluid and brake lining is Rp. 4.5/km. So, the total transportation cost for each vehicle is Rp. 1,162.5/km. We also constructed a distance matrix and collected data on demands and the initial routes used by the company. Tables 10 and 11 present the initial routes and total transportation cost on these routes.

Table 10. Initial route

Day	Vehicle	Route	Loading (cm^3)
Mon	1	D-P23-P19-P15-P11-P2-P69-P35-P3-P38-D	3260304
	2	D-P7-P26-P43-P47-P72-P65-P32-D	2911788
	3	D-P49-P4-P52-P57-P30-P76-P67-D	2947104
Tue	1	D-P13-P50-P46-P40-P56-P27-D	2218428
	2	D-P16-P6-P59-P29-P73-P78-D	2801466
	3	D-P22-P12-P20-P66-P37-P77-D	2061828
Wed	1	D-P58-P63-P14-P53-P21-P39-33-D	2800980
	2	D-P10-P1-P18-P54-P60-P25-P68-D	2810592
	3	D-P8-P17-P51-P34-P31-P75-D	2667276
Thu	1	D-P24-P55-P5-P61-P44-P36-D	2317788
	2	D-P71-P9-P64-P62-P74-D	2984364
	3	D-P48-P7-P45-P41-P42-P28-D	2365524

Table 11. Total transportation cost of the initial route

Day	Vehicle	Distance	Tansporta-tion costs	Total Cost
Mon	1	107.35	Rp 124,794	
	2	90.1	Rp 104,741	Rp 364,269
	3	115.9	Rp 134,734	
Tue	1	119.8	Rp 139,268	
	2	118.5	Rp 137,756	Rp 379,732
	3	88.351	Rp 102,708	
Wed	1	115.4	Rp 134,153	Rp 390,368
	2	98.6	Rp 114,623	
	3	121.8	Rp 141,593	
Thu	1	79.9	Rp 92,884	
	2	103	Rp 119,738	Rp 298,530
	3	73.9	Rp 85,909	

Implementation of FGA is done by running a program that has been created using the NetBeans IDE 8.2 software. NetBeans software is an IDE (Integrated Development Environment) application based on the Java programming language. The proposed route and the total transportation cost is presented in Tables 12 and 13. We present the example of the initial route on day 1 with the proposed route using the Google Maps layout in Figures 5 and 6.

Table 12. Proposed route

Day	Vehicle	Route
Mon	1	D-P32-P76-P30-P35-P67-P69-P43-D
	2	D-P23-P15-P19-P7-P4-P47-P72-P49-P65-D
	3	D-P3-P57-P38-P52-P11-P2-P26-D
Tue	1	D-P22-P56-P29-P77-P27-P73-P78-P37-D
	2	D-P59-P66-P46-P40-P6-P20-P12-P50-D
	3	D-P16-P13-D
Wed	1	D-P14-P53-P54-P60-P39-P51-P21-D
	2	D-P10-P17-P18-P8-P1-D
	3	D-P25-P33-P75-P68-P34-P31-P63-P58-D
Thu	1	D-P61-P28-P74-P36-P62-P64-P55-D
	2	D-P24-P5-P42-P41-P45-P44-P70-D
	3	D-P9-P48-P71-D

Table 13. Total transportation cost of the proposed route

Day	Vehicle	Distance	Tansportati-on costs	Total Cost
Mon	1	85.3	Rp 99,161	Rp 218,550
	2	30.9	Rp 35,921	
	3	71.8	Rp 83,468	
Tue	1	103.65	Rp 120,493	Rp 199,021
	2	59.05	Rp 68,647	
	3	8.5	Rp 9,881	
Wed	1	51	Rp 59,288	Rp 209,541
	2	17.05	Rp 19,821	
	3	112.2	Rp 130,433	
Thu	1	103.5	Rp 120,319	Rp 194,729
	2	49.51	Rp 57,554	
	3	14.5	Rp 16,856	

The main objective of the routing problem with capacity constraints is to minimize vehicle distance by using a minimum number of vehicles to balance routes and vehicle loads. The decrease in vehicle distance will in turn reduce the transportation cost. The cost savings obtained by the football game algorithm is shown in Table 14.

Figure 5. Initial route day 1

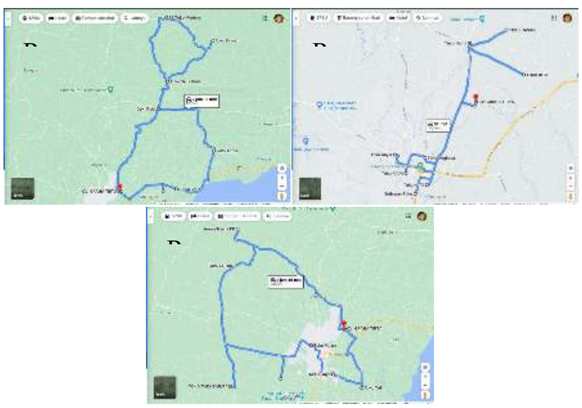

Figure 6. Proposed route day 1

Table 14. Transportation cost saving

Day	Iniatial cost	Fixed cost	Gap	Saving
Mon	Rp364,269	Rp218,550	Rp145,719	40%
Tue	Rp379,732	Rp199,021	Rp180,711	48%
Wed	Rp390,368	Rp209,541	Rp180.827	46%
Thu	Rp298,530	Rp194,729	Rp103,801	35%
Saving average				42%

Figure 7 illustrates that the proposed route succeeds in reducing the transportation cost. Compared to the initial costs, the proposed route provides an average daily savings of 42%. This is because in the initial routes, three customers were located near one another but were served by three different vehicles. Meanwhile, in the proposed route generated by the football game algorithm, the three customers can be served on one route using only one vehicle.

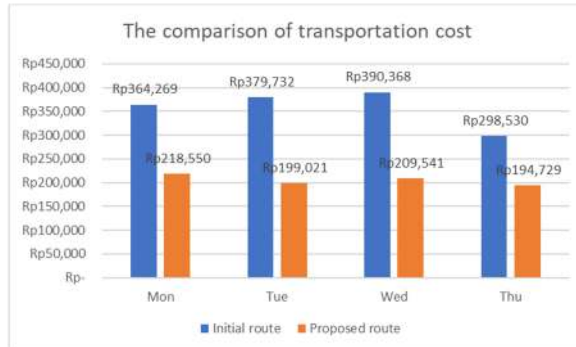

Figure 7. The comparison of transportation cost

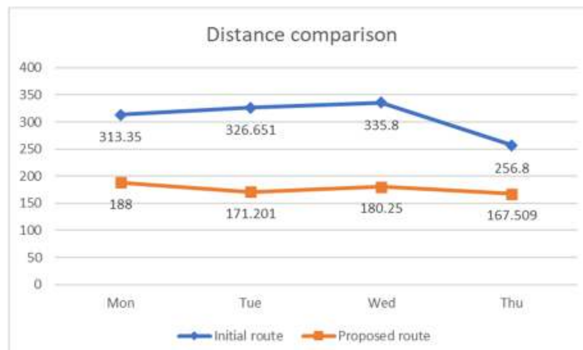

Figure 8. Distance comparison

Figure 8 compares the total distance of the initial and proposed routes on each day. On Monday, the distance of the initial routes is 313.35 km while the total mileage of the proposed route is 188 km, making a reduction of 125.35 km. As for Tuesday, Wednesday, and Thursday, the proposed route provides distance savings of 155.45 km, 155.55 km, and 89.29 km than the initial route. Thus, the average distance savings obtained with the proposed route is 131.41 km.

From Figures 7 and 8, it can be concluded that distance has a positive linear effect on transportation cost. The smaller the distance traveled, the smaller the resulting transportation cost. The transportation cost generated on Monday on the proposed route is IDR 218,550 with a total distance of 188 km. In contrast, the transportation cost for the initial route on Monday is IDR 364,269 with a total distance of

313.35km. This means that the algorithm saved 40% of the transportation cost on Monday. Moreover, across all observed days, it provided an average daily savings of 42%.

Because there are many customers to serve, it is suitable to choose a metaheuristic method to solve the capacitated vehicle routing problem. Computational time and robustness are the main consideration of researchers in the optimization field. FGA was implemented to construct the route of the delivery of goods. The result shows that the football game algorithm can provide transportation routes with low transportation cost. Additionally, it is confirmed that the parameter values proposed by Djunaidi & Juwono (2018) can be implemented in the solving of real case study.

IV. CONCLUSION

This paper applied a relatively new metaheuristic method to solve a routing problem. The Football Game Algorithm was conducted for constructing optimized routes for a bottled drinking water company. The algorithm finds better routes with less distance which results in significant reductions in the transportation cost. The results show that the proposed route obtained using the football game algorithm can provide an average daily transportation cost savings of more than 42%. The results of this proposed route can be considered by the company in determining the next transportation route. In this case, transportation cost are only determined based on the cost of fuel which is proportional to the distance travelled. As a result, we suggest that several factors, such as load weight, congestion level, delivery time, and others, be considered when calculating the total transportation cost.

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