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Optimizing Vehicle Routing with Soft Time Windows Using a Hybrid Genetic Algorithm

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***Abstract*—Determining delivery routes that minimize total cost is a key issue in goods distribution. This study focuses on a bottled drinking water (AMDK) company in City X that distributes its products to multiple retail outlets with different service time requirements. Such conditions fall within the scope of the Vehicle Routing Problem with Time Windows (VRPTW). In this study, a soft time windows approach is adopted, allowing vehicles to serve retailers beyond their specified time limits at the expense of penalty costs. The main objective is to identify optimal delivery routes under the soft time windows policy while minimizing total cost. The results demonstrate that the Hybrid Genetic Algorithm outperforms the initial solution in terms of total cost reduction. The initial routes are generated using the Nearest Insertion Heuristic and subsequently refined through mutation processes within the genetic algorithm framework.**

***Index Terms*—Distribution Routing Optimization; VRPTW; Nearest Insertion Heuristic; Hybrid Genetic Algorithm; Soft Time Windows; Total cost minimization.**

I. Introduction

Minimizing distribution costs for goods or services is a primary objective in logistics and distribution systems. Distribution efficiency is a critical lever for improving operational performance and cost effectiveness, and the absence of structured routing methods often results in inefficient travel distances and increased distribution costs [1]. Accordingly, determining optimal vehicle routes becomes essential, as reflected in cold-chain logistics studies where optimized distribution path design can reduce costs while maintaining customer satisfaction [2].

The Vehicle Routing Problem (VRP) concerns serving a set of customers from a depot using a fleet of vehicles subject to operational constraints such as travel distance, time, and vehicle capacity. A prominent variant is the Vehicle Routing Problem with Time Windows (VRPTW), which incorporates service- availability constraints at the customer level. In VRPTW, routes are scheduled for a limited number of vehicles with fixed capacities and travel times originating from a depot to serve geographically dispersed customers, while respecting customer- specific time windows for service initiation. Because the service windows may differ across customers, routing decisions must jointly consider travel efficiency and schedule feasibility to produce implementable routes [3]. In this context, prior work also indicates that hybrid solution strategies, such as combining genetic algorithms with other heuristics, including Ant Colony Optimization (ACO) and Tabu Search (TS), can provide promising trade-offs between time feasibility and cost efficiency [4].

In VRPTW, time-window constraints may be categorized as hard or soft. Under hard time windows, vehicles must arrive before a specified deadline to be considered feasible [3]. By contrast, soft time windows allow deviations from the specified interval but impose penalty costs that directly influence the total cost objective. Three time-related components are particularly influential in this setting: waiting time, service time, and tardiness. Waiting time arises when a vehicle arrives before the service window opens and must wait, whereas tardiness occurs when service begins after the latest allowable time and typically incurs lateness penalties [5]. However, many VRPTW studies simplify the treatment of these time deviations by assuming equivalent penalty costs for waiting time and tardiness, which eases

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modeling and computation [6]. This simplifying assumption can be limiting in applications where the operational consequences of tardiness may be more severe than waiting, thereby shifting the optimal routing decisions. Consequently, practical VRPTW implementations benefit from approaches that explicitly balance travel efficiency with the cost impacts of both waiting and tardy conditions as part of the total cost minimization objective [7]

A wide range of metaheuristics has been employed to address VRPTW, including Simulated Annealing (SA), Tabu Search (TS), Ant Colony Optimization (ACO), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO), and these methods are recognized for producing high-quality solutions. Yudong, et al. [8] demonstrated the effectiveness of such metaheuristics across multiple VRP scenarios, while Chai, et al. [9] emphasized their robustness relative to traditional heuristics. Comparative findings also suggest that different metaheuristics exhibit complementary strengths, ACO can outperform SA and GA in certain routing contexts [10], and hybridizing GA with PSO can improve performance beyond using either method alone [11]. These results support the broader view that hybrid approaches are attractive for complex VRPTW settings because they can integrate fast constructive mechanisms with powerful global search behavior.

In this research, a Genetic Algorithm (GA) is utilized to resolve the VRPTW. GA is inspired by biological evolution, in which a population of candidate solutions (individuals) evolves through selection and variation operators. In GA, chromosomes represent solution structures and are composed of genes that encode specific traits, and improved solutions emerge through iterative evolution [12, 13]. Crossover combines genetic material from parent chromosomes to generate offspring and promote the propagation of beneficial traits [12, 14]. Mutation introduces random gene changes to maintain diversity and mitigate premature convergence, where search may otherwise become trapped in suboptimal regions [15]. In addition, adaptive mechanisms that adjust crossover and mutation rates according to population fitness have been shown to enhance GA effectiveness [13, 16].

Building on these foundations, this study proposes a Hybrid Genetic Algorithm that combines GA with the Nearest Insertion Heuristic. The Nearest Insertion Heuristic is used to construct an initial solution efficiently, which is then refined through GA-based evolutionary search to improve solution quality. By leveraging a constructive heuristic for initialization and GA operators for exploration and exploitation, the proposed hybrid approach is expected to produce vehicle routes that minimize total cost while accounting for the operational implications of time-window deviations under soft time windows. Contributions of this study are as follows: (1) it addresses VRPTW in a cost-oriented setting where time-window deviations are represented through penalty mechanisms embedded in the objective function; (2) it develops a Hybrid Genetic Algorithm that integrates Nearest Insertion for initial solution generation with GA-based improvement; and (3) it targets route solutions that reduce overall distribution cost while maintaining feasibility with respect to vehicle and scheduling constraints.

II. METHODS

This section describes the methodology (Figure 1) used to solve the Vehicle Routing Problem with Time Windows (VRPTW) under a soft time windows policy using a Hybrid Genetic Algorithm. It outlines the problem context, the mathematical formulation, the required input data, and the procedure for generating an initial solution and subsequently improving it through evolutionary optimization.

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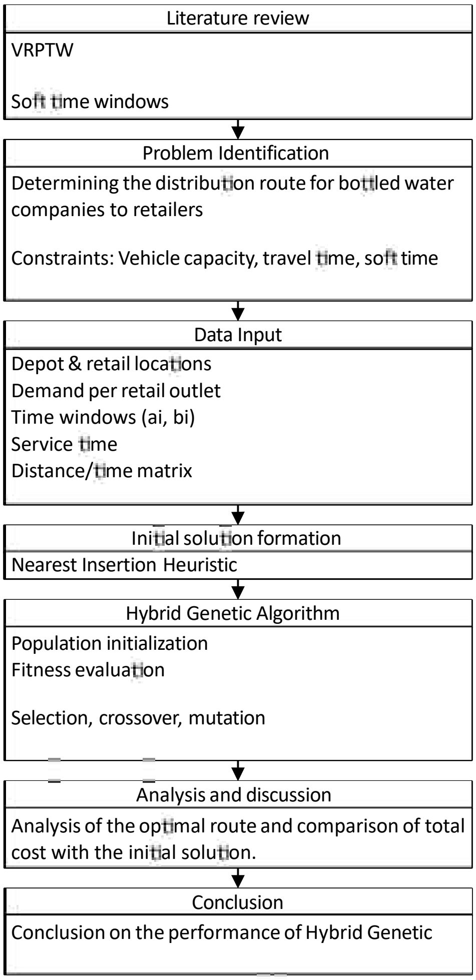

Figure 1. Hybrid Genetic Algorithm for VRPTW with Soft Time Windows Flowchart

A. Problem Identification

This study addresses the problem of determining delivery routes for bottled drinking water (AMDK) distribution from a depot to retailers in City X. The objective is to obtain routing plans that minimize the total distribution cost, which consists of travel-related costs and time-window–related penalty costs, while ensuring that operational constraints (e.g., vehicle capacity and service schedules) are satisfied.

B. Mathematical Formulation of VRPTW

The VRPTW is an extension of the Capacitated Vehicle Routing Problem (CVRP) in which the service at each customer must start within a specified time interval (time window). Under a soft time windows policy, arriving earlier than the allowed service start time may produce waiting-related costs, while arriving later than the service deadline leads to penalty costs for tardiness.

Notation:

T_{ik} : service start time at customer i using vehicle k .

C_{ij}: Travel cost from i to k (source: i" to k").

S_i: Service time at customer i

t_{ij}: Travel time required from i to j

a_i: earliest time customer i

b_i: latest time customer i

q_i: Quantity of goods (demand) to be picked up from customer i

Q: Capacity of vehicle k

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Mathematical Formulation [17]:

Objective Function:

$$Min \sum_{k \in K} \sum_{(i,j) \in A} C_{ij} X_{ij} \tag{1}$$

Subject to:

$$\sum_{k \in K} \sum_{j \in \sigma-(i)} X_{ij} = 1 \quad \forall i \in N, \tag{2}$$

$$\sum_{j \in \sigma+(v)} X_{0jk} = 1 \quad \forall k \in K, \tag{3}$$

$$\sum_{i \in \sigma-(j)} X_{0jk} - \sum_{i \in \sigma+(j)} X_{ijk} = 0 \quad \forall k \in K, j \in K, \tag{4}$$

$$\sum_{j \in \sigma-(n+1)} X_{i,n+1,k} = 1 \quad \forall k \in K, \tag{5}$$

$$X_{ijk}(T_{ik} + S_i + t_{ij} - T_{jk}) \leq 0 \quad \forall k \in K, (i,j) \in A, \tag{6}$$

$$a_i \leq T_{ik} \leq b_i \quad \forall k \in K, i \in V, \tag{7}$$

$$\sum_{i \in N} q_i \sum_{j \in \sigma+(1)} X_{ijk} \leq Q \quad \forall k \in K \tag{8}$$

$$X_{ijk} \in \{0,1\} \quad \forall k \in K, (i,j) \in A, \tag{9}$$

The objective function in Equation (1) minimizes the total cost. The constraint in Equation (2) ensures that each customer is assigned to exactly one route. Equation (3) enforces that service begins from the depot, ensuring that customers are visited as part of feasible delivery routes originating from the depot. Constraints in Equations (4) and (5) define flow conservation for each vehicle route, such that the number of incoming arcs equals the number of outgoing arcs for each visited customer, thereby constructing valid source-to-sink paths. Equations (6) and (7) maintain schedule feasibility by regulating the service start time at each customer with respect to the specified time windows, including early-arrival waiting and late-arrival tardiness under the soft time windows setting. Finally, Equation (8) ensures capacity feasibility by requiring that the total demand served on each route does not exceed the vehicle capacity.

C. *Hybrid Genetic Algorithm*

Genetic Algorithms (GA) were first introduced by John Holland in the 1960s and later formalized in Adaptation in Natural and Artificial Systems (1975) [18]. GA is inspired by evolutionary principles in which individuals with better “fitness” have a higher probability of surviving and reproducing, while less fit individuals are gradually eliminated. In the GA framework, each candidate solution is encoded as a chromosome and evaluated using a fitness function. Through repeated generations, the population is improved by applying genetic operators—parent selection, crossover, and mutation—so that new offspring can inherit advantageous traits and achieve better fitness values.

In this study, GA is combined with the Nearest Insertion Heuristic to form a Hybrid Genetic Algorithm The hybridization is introduced primarily at the initialization stage to avoid starting from purely random solutions. The Nearest Insertion Heuristic is known to be efficient for vehicle routing problems [19], and embedding heuristic-based initialization within GA can accelerate the search process because the initial population is closer to promising regions of the solution space [20]. As a result, the subsequent evolutionary search is expected to require fewer generations to reach high-quality routing plans.

. The initial population consists of a set of chromosomes, each representing a candidate routing plan for the VRPTW. In this representation, each chromosome encodes customer visit sequences that form vehicle routes; genes correspond to customers, and the gene order determines the service order. The number of chromosomes in the population (popsize) is determined according to the scale of the problem being solved. After the population is formed, each chromosome is evaluated using the fitness function defined in this study, namely total cost. Chromosomes with better fitness values are then more likely to be chosen as parents to generate the next generation.

New solutions are generated by recombining parent chromosomes through crossover. This tudy employs Heuristic Crossover as a local-search-oriented recombination operator [21]. Rather than

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exchanging genes randomly, Heuristic Crossover constructs offspring by selecting genes while considering inter- customer distances and route structure inherited from the parents, with the aim of producing coherent routes that preserve good building blocks from both solutions. To maintain diversity and prevent premature convergence, the offspring produced by crossover are subsequently modified through mutation. Mutation changes the gene sequence within a chromosome (i.e., within the same route representation), thereby introducing new customer orderings that may yield alternative and potentially better routing configurations. The mutated chromosomes constitute the offspring population, which is then evaluated again using the same fitness measure.

Finally, offspring are compared against their parents or the current population based on fitness value. Because the fitness in this study is total cost, solutions with lower total cost are preferred and retained to form the population for the next generation. This iterative process continues until the termination condition defined for the experiment is met, producing a set of vehicle routes that minimizes total cost under the given operational constraints.

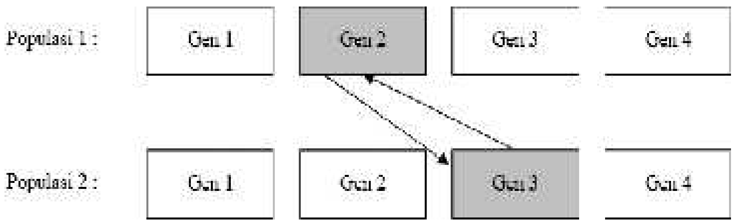

Figure 2. Illustration of the crossover process

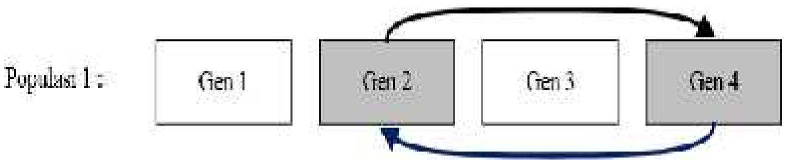

Figure 3. Illustration of the mutation process

III. Result And Discussion

This section describes how the solution is calculated to determine the route with the minimum total cost by optimizing total travel time. The distribution of bottled drinking water (AMDK) to retailers in City X involves several cost components, which are incorporated into the objective function to minimize total cost. Penalty costs for earliness and tardiness are treated as equivalent in prior work [22]; however, in this study tardiness is assumed to be twice as costly as waiting (earliness) to reflect the higher operational and service impact of late deliveries.

The average vehicle speed is set at 43 km/h, which is equivalent to 0.72 km/min. Fuel consumption while driving is assumed to be 1 liter per 9 km, and the diesel price is Rp 9,800.00 per liter. Therefore, the fuel cost per kilometer is Rp 9,800.00/9 = Rp 1,088.9 per km. The transportation cost per minute is then obtained by multiplying the cost per kilometer by the distance traveled per minute (0.72 km/min), resulting in Rp 1,088.9 × 0.72 = Rp 780.4 per minute.

In addition to travel-related fuel costs, fuel consumption during idling is also considered. Idling fuel consumption is assumed to be 1.5 liters per hour, or 0.03 liters per minute. Based on the same diesel price, the waiting cost is calculated as Rp 9,800.00 × 0.03 = Rp 245 per minute. The tardiness cost is assumed to be twice the waiting cost, yielding Rp 245 × 2 = Rp 490 per minute.

The first stage of the hybrid Genetic Algorithm is the construction of an initial population as the starting set of feasible solutions. This study uses the Nearest Insertion Heuristic to generate the initial routes by iteratively inserting the next

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customer based on the shortest incremental travel time from the partially constructed route. With respect to time windows, this study adopts soft time windows, meaning that vehicles may arrive before the opening time or after the closing time of each retail outlet; such violations are permitted but incur penalty costs corresponding to earliness (waiting) and tardiness (late arrival), respectively.

A. Formation of the initial population using the Nearest Insertion Heuristic method

The Nearest Insertion Heuristic is a route determination method that inserts the selected route into the previously created initial route. This route insertion is done by considering the closest travel time. The initial vehicle will depart from the warehouse and return to the warehouse. From the distance matrix, the retail location with the closest travel time from the warehouse will be searched for. For the first vehicle route, the selected retailer is SB. After obtaining the G-SB-G route, the next step is to select a retailer to be inserted between G- SB or SB-G. The selected retailer BJ is inserted into SBG, so that retailer BJ is placed after SB. When the vehicle capacity is full, if there are still retailers that have not been included in the route, a new route is created.

In Table 1 the vehicle will depart from the warehouse at 7:00 a.m., then it will search for the retailer with the closest travel time from the warehouse, which is SB. Retailer SB has a travel time of 27 minutes from the warehouse, with a demand of 176.6 kg. The retailers selected in the route will be checked in advance to see if they meet the specified restrictions. The first restriction is that the total demand for each retailer must be less than the vehicle's capacity, which is 1200 kg. In addition to considering capacity, it is necessary to have opening hours from 7:00 a.m. to 12:00 p.m. Because the time windows in this study are soft time windows, vehicles can pass through the time windows owned by retailers but will be subject to additional costs (penalty costs). For SB retailers, vehicles will arrive at 7:27 a.m. and no penalties will be incurred. Penalties occur at retailers S1 and LM. At these two retailers, vehicles arrive late. The total delay is 210 minutes. If the first route has met the capacity limit, create a new route for other retailers that have not considered the time windows of each retailer. Each retail outlet has different time windows. For retail outlet SB, the vehicle will arrive at 7:27 a.m. and there will be no penalty. Penalties occur at retail outlets S1 and LM. At these two retail outlets, the vehicle arrives late. The total delay is 210 minutes. If the first route has reached its capacity limit, create a new route for the other retail outlets that have not yet been selected.

The following results present the routes obtained for the two vehicles and the corresponding total cost calculation for each route. For Vehicle 1, the selected route is $G \rightarrow S \rightarrow B \rightarrow L \rightarrow M \rightarrow S \rightarrow A \rightarrow S1 \rightarrow L \rightarrow G$. The transportation cost is computed based on a total travel time of 179 minutes and a unit transportation cost of Rp 780.370 per minute, yielding 179×780.370 =Rp 139,686.296. The penalty cost consists of waiting and tardiness components. In this route, the waiting time is 0 minutes, so the waiting cost is 0×245 =Rp 0. The tardiness is 210 minutes, and with a tardiness cost of Rp 490 per minute, the tardiness cost is 210×490 =Rp 102,900.0. Therefore, the total cost for Vehicle 1 is the sum of transportation and penalty costs, resulting in Rp 242,586.296.

For Vehicle 2, the selected route is $G \rightarrow P \rightarrow G \rightarrow B \rightarrow S \rightarrow H \rightarrow B \rightarrow P \rightarrow S \rightarrow G$.

The transportation cost is calculated using a total travel time of 248 minutes and the same unit transportation cost of Rp 780.370 per minute, resulting in 248×780.370 =Rp 193,531.852. The penalty cost is then determined in the same manner. The waiting time is 0 minutes, producing a waiting cost of 0×245 =Rp 0. The tardiness is 275 minutes, and thus the tardiness cost is 275×490 =Rp 134,750.0. Consequently, the total cost for Vehicle 2 is Rp 328,281.851.

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Table 1. Determining Route 1 for Vehicles using the NI method

R	D	CD	DP	TT (Min)	UT (Min)	AT (WIB)	OT (WIB)	CT (WIB)	FT (WIB)	EP	LP	TP
G												
SB	176.6	176.6	0	00.27.00	00.30.00	07.27.00	07.00.00	12.00.00	07.57.00	0	0	0
BJ	105.1	281.7	0	00.25.00	00.30.00	08.22.00	07.00.00	14.00.00	08.52.00	0	0	0
LA	112.2	393.9	0	00.19.00	00.30.00	09.11.00	08.00.00	14.00.00	09.41.00	0	0	0
MM	140.6	534.5	0	00.32.00	00.30.00	10.13.00	08.00.00	15.00.00	10.43.00	0	0	0
SC	158.7	693.2	0	00.11.00	00.30.00	10.54.00	08.00.00	11.00.00	11.24.00	0	0	0
AJ	96.9	790.1	0	00.12.00	00.30.00	11.36.00	08.00.00	14.00.00	12.06.00	0	0	0
S1	128.5	918.6	0	00.17.00	00.30.00	12.23.00	08.00.00	11.00.00	12.53.00	0	1	1
LM G	153.2	1071.8	0	00.14.00 00.22.00	00.30.00	13.07.00 13.59.00	08.00.00	11.00.00	13.37.00	0	1	1
			Total	02.59.00		Tardy	03.30.00	Waiting	0.00.00			
			Minute	179.00		Minute	210.00	Minute	0.00			

B. Crossover

After the initial solution (initial population) is generated, the subsequent step is to apply crossover using the Heuristic Crossover method. The initial population constructed in the previous stage serves as the set of parent solutions for this operation. In genetic algorithms, crossover is generally defined as the process of exchanging genetic information (genes) between two parent chromosomes to produce new offspring solutions. In this study, the heuristic crossover is performed using two parent vehicle routes.

The two parent routes are defined as follows: the first parent route (RK 1) is $G \rightarrow S \rightarrow B \rightarrow L \rightarrow M \rightarrow S \rightarrow A \rightarrow S1 \rightarrow L \rightarrow G$, and the second parent route (RK 2) is $G \rightarrow P \rightarrow G \rightarrow B \rightarrow S \rightarrow H \rightarrow B \rightarrow P \rightarrow S \rightarrow G$. Because each route contains eight customer nodes (i.e., eight genes, excluding the depot), a random integer is generated within the interval from 1 to 8 to determine the gene position used in the crossover process. In this case, the selected random number is 1.

Next, the inter-gene distances required for the heuristic decision rules are retrieved from the distance matrix. Based on these distance values, the crossover operation is then performed between the two vehicle routes to generate offspring solutions, which can be seen in Tables 2 and 3. The same procedure is applied in both directions, meaning that Vehicle 1 is crossed with Vehicle 2 and, conversely, Vehicle 2 is crossed with Vehicle 1, to ensure that the heuristic exchange mechanism is consistently evaluated across the two parent structures. Table 2 and 3 show select the genes with the minimum distance and Table 4 show crossover result.

Table 2. Crossover RK 1 with RK 2

From	To	Distance
G	PA	00.29.00
G	GM	00.43.00
G	**BD**	00.20.00
G	SM	00.59.00
G	HB	00.52.00
G	BG	00.39.00
G	PB	00.39.00
G	SR	00.46.00

Table 3. Crossover RK 2 with RK 1

From	To	Distance
G	SB	00.27.00
G	BJ	00.40.00
G	LA	00.27.00
G	MM	00.24.00
G	SC	00.39.00
G	AJ	00.33.00
G	S1	00.50.00
G	**LM**	00.22.00

Table 4. Crossover result

	Crossover							
C1	**BD**	SR	LA	MM	SC	AJ	A1	**PA**
C2	**LM**	GM	SB	SM	HB	BG	PB	SR

C. Mutation

The crossover operation produces two intermediate solutions (i.e., two crossover outputs which can be seen in Table 4), which are subsequently subjected to mutation in order to generate offspring. In genetic algorithms, mutation is generally defined as an operation that modifies a chromosome by altering the arrangement of genes within the same individual solution (i.e., within the same

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route). In this study, mutation is implemented as an intergenic exchange guided by distance-based considerations. The procedure is performed as follows.

First, one gene position is selected at random from a chromosome consisting of eight genes (excluding the depot). A random integer between 1 and 8 is generated, and in this case the selected value is 3 which shown in Table 5. Next, the distance between gene 2 and gene 3 is computed using the distance matrix. Based on the matrix, the distance from retail SR (gene 2) to LA (gene 3) is 33. After that, in Table 6 the shown distance from gene 2 to all other genes in the same chromosome is evaluated. From these candidate distances, select one gene that has the minimum distance from gene 2 and must be less than the distance from gene 2 to gene 3. Based on the calculation, gene 3 is selected because it has a distance of 20 from gene 2, which satisfies the selection rule. The intergenic mutation is then executed as shown in Table 7, by exchanging the relevant gene positions according to the defined mutation mechanism. The same mutation procedure is applied to the second offspring (offspring 2) to obtain its mutated form, can be seen in Table 8. Following crossover and mutation, the resulting offspring solutions are compared against the parent solutions. If an offspring yields a better objective value (i.e., a lower total cost), the solution is updated by replacing the corresponding parent with the improved offspring. In this study, the crossover and mutation operators were applied for three iterations. Although this setting is sufficient to demonstrate the procedure, additional iterations may be performed to potentially obtain better solutions.

Table 5. Random Integer Selection (value = 3)

Crossover 1							
BD	SR	**LA**	MM	SC	AJ	A1	PA

Table 6. Distances from Gene 2 to Other Genes

Crossover 1		
From	To	Distance
SR	BD	00.21.00
SR	**MM**	00.20.00
SR	SC	00.35.00
SR	AJ	00.41.00
SR	S1	00.35.00
SR	PA	00.34.00

Table 7. Intergenic mutation for offspring 1

Offspring 1							
BD	SR	LA	MM	SC	AJ	A1	PA

Table 8. Intergenic mutation for offspring 2

Offspring 2							
HB	GM	SB	SM	LM	BG	PB	SR

D. Evaluation of fitness values for each mutation route

Fitness value evaluation is conducted to ensure that the offspring routes satisfy the problem constraints and can be considered feasible solutions. The primaryfeasibility constraint evaluated in this stage is vehicle capacity. An offspring route is acceptable only if the total demand served across the assigned retail outlets does not exceed the vehicle's capacity.

Beyond feasibility, the fitness measure used in this study is the total cost which can be seen in Table 9. This fitness measure serves as the basis for comparing candidate solutions and selecting the best route. The total cost consists of transportation cost and penalty cost (waiting and tardiness). For offspring 1, the evaluation indicates that waiting occurs at retail BD. The vehicle arrives at 07:20, whereas BD opens at 08:00, requiring the vehicle to wait for 40 minutes before service can begin. For offspring 2, the evaluation shows waiting at retail LM. The vehicle arrives at 07:49, while LM opens at 08:00, resulting in an 11-minute waiting time. After completing service at LM, the vehicle continues to the next retail outlet according to the route schedule.

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Table 9. Fitness evaluation for offspring 1

	R	D	CD	DP	TT (Min)	UT (Min)	AT (WIB)	OT (WIB)	CT (WIB)	FT (WIB)	EP	LP	TP
Offspring 1	G												
	BD	136.6	136.6	0	00.20.00	00.30.00	07.20.00	08.00.00	15.00.00	07.50.00	1	0	1
	SR	100.9	237.5	0	00.21.00	00.30.00	08.11.00	07.00.00	10.00.00	07.30.00	0	0	0
	MM	140.6	378.1	0	00.20.00	00.30.00	07.50.00	08.00.00	15.00.00	08.30.00	1	0	1
	LA	112.2	490.3	0	00.32.00	00.30.00	09.02.00	08.00.00	14.00.00	08.30.00	0	0	0
	SC	158.7	649	0	00.28.00	00.30.00	08.58.00	08.00.00	11.00.00	08.30.00	0	0	0
	AJ	96.9	745.9	0	00.12.00	00.30.00	08.42.00	08.00.00	14.00.00	08.30.00	0	0	0
	S1	128.5	874.4	0	00.17.00	00.30.00	08.47.00	08.00.00	11.00.00	08.30.00	0	0	0
	P	147.8	1022.2	0	00.30.00	00.30.00	09.00.00	07.00.00	11.00.00	07.30.00	0	0	0
	A				00.29.00		.						
	G												
				Total	03.29.00		Tardy	00.00.00	Waiting	00.50.00			
				Minute	209.00		Minute	0.00	Minute	50.00			

Note. R: Retail; D: Demand; CD: Cumulative Demand; DP: Demand Penalty; TT: Travel Time; UT: Unloading Time; AT: Arrival Time; OT: Open Time; CT: Close Tme; FT: Finish Time; EP: Early Penalty; LP: Late Penalty; TP: Total Penalty

The total cost for offspring 1 is calculated based on its transportation and penalty components. The transportation cost is derived from the total travel time of 209 minutes, multiplied by the transportation cost rate of Rp 780.370 per minute, resulting in 209 × 780.370 = Rp 163,097.407. In addition to transportation cost, the penalty cost arises from time window considerations. Offspring 1 incurs a waiting time of 50 minutes, which corresponds to a waiting cost of 50 × 245 = Rp 12,250.0, while no tardiness is observed, leading to a tardiness cost of Rp 0. Consequently, the total cost for offspring 1 amounts to Rp 175,347.407. The results indicate that although offspring 1 achieves a relatively short total travel time, the waiting penalty contributes noticeably to the overall cost. This suggests that the delivery sequence generated for offspring 1 arrives earlier than the allowable service time at several retail locations, leading to increased waiting time. Nevertheless, the absence of tardiness penalties implies that the route successfully complies with the upper bounds of the time windows. Overall, the cost structure of offspring 1 reflects a trade-off between efficient travel time and early arrival, highlighting the importance of balancing route efficiency and time window compliance in minimizing total distribution cost.

Table 10. Fitness evaluation for offspring 2

	R	D	CD	DP	TT (Min)	UT (Min)	AT (WIB)	OT (WIB)	CT (WIB)	FT (WIB)	EP	LP	TP
Offspring 1	G												
	HB	210	210	0	00.52.00	00.30.00	07.52.00	07.00.00	11.00.00	08.22.00	0	0	0
	GM	210	420	0	00.50.00	00.30.00	09.12.00	07.00.00	14.00.00	07.30.00	0	0	0
	SB	176.6	596.6	0	01.00.00	00.30.00	08.30.00	07.00.00	12.00.00	07.30.00	0	0	0
	SM	110	706.6	0	00.31.00	00.30.00	08.01.00	08.00.00	09.00.00	07.30.00	0	0	0
	LM	153.2	859.8	0	00.19.00	00.30.00	07.49.00	07.00.00	11.00.00	08.30.00	1	0	1
	BG	130.5	990.3	0	00.27.00	00.30.00	08.57.00	07.00.00	13.00.00	07.30.00	0	0	0
	PB	105.2	1095.5	0	00.30.00	00.30.00	08.00.00	07.00.00	12.00.00	07.30.00	0	0	0
	SR	100.9	1196.4	0	00.39.00	00.30.00	08.09.00	07.00.00	10.00.00	07.30.00	0	0	0
	G				00.46.00		.						
				Total	05.54.00		Tardy	00.00.00	Waiting	00.11.00			
				Minute	354.00		Minute	0.00	Minute	11.00			

Note. R: Retail; D: Demand; CD: Cumulative Demand; DP: Demand Penalty; TT: Travel Time; UT: Unloading Time; AT: Arrival Time; OT: Open Time; CT: Close Tme; FT: Finish Time; EP: Early Penalty; LP: Late Penalty; TP: Total Penalty

Similarly, the total cost for offspring 2, as presented in Table 10, is calculated based on a total travel time of 354 minutes. The transportation cost is obtained by multiplying the total travel time by the transportation rate, resulting in 354 × 780.370 = Rp 276,251.111. In addition to transportation cost, the penalty cost is derived from time window violations. As shown in the table, offspring 2 experiences a waiting time of 11 minutes, which leads to a waiting penalty of 11 × 245 = Rp 2,695.0, while no tardiness is observed, resulting in a

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tardiness penalty of Rp 0. Consequently, the total cost incurred by offspring 2 amounts to Rp 278,946.111. The results in Table 10 indicate that the delivery route generated for offspring 2 satisfies most of the time window constraints, as reflected by the absence of tardiness penalties and the relatively small waiting penalty. This suggests that the routing sequence produced by the Hybrid Genetic Algorithm is able to balance travel efficiency and service time compliance, leading to a lower overall penalty cost while maintaining an acceptable transportation cost.

Overall, the Hybrid Genetic Algorithm produces a lower total cost compared to the initial routes generated using the Nearest Insertion Heuristic, as summarized in Table 11. The comparison clearly shows that the offspring solutions consistently outperform the parent routes in terms of total cost. The most significant improvement is primarily attributed to a substantial reduction in penalty costs, especially the elimination of tardiness penalties across all offspring solutions. This indicates that the Hybrid Genetic Algorithm is effective in generating delivery routes that better comply with time window constraints while maintaining efficient travel times.

Furthermore, although the transportation costs of some offspring routes are comparable to or slightly higher than those of the parent routes, the absence of tardiness penalties results in a considerably lower overall cost. As a consequence, the offspring routes are able to replace the parent routes as the updated best solutions in the evolutionary process. Among the evaluated offspring candidates, offspring 3 and offspring 4 achieve the minimum total cost, demonstrating the best balance between transportation cost and penalty cost. Therefore, these two offspring routes are selected as the final solutions in this study.

Table 11. Comparison of total route costs for parents and offspring

Parent	Transportation Cost	Penalty cost		Total cost	Ttot Cost
		Waiting cost	Tardy cost		
RK 1	Rp 139686.296	Rp -	Rp 102900.0	Rp 242586.29	Rp 570868.148
RK 2	Rp 193531.852	Rp -	Rp 134750.0	Rp 328281.852	
Offspring - i					
Offspring -1	Rp 163097.407	Rp 12250.0	Rp -	Rp 175347.407	Rp 454293.519
Offspring - 2	Rp 276251.111	Rp 2695.0	Rp -	Rp 278946.111	
Offspring - 3	Rp 156074.074	Rp 2450.0	Rp -	Rp 158524.074	Rp 357872.407
Offspring - 4	Rp 196653.333	Rp 2695.0	Rp -	Rp 199348.333	
Offspring - 5	Rp 163877.778	Rp 5880.0	Rp -	Rp 169757.778	Rp 369260.370
Offspring - 6	Rp 195092.593	Rp 4410.0	Rp -	Rp 199502.593	

IV. CONCLUSION

This section summarizes the conclusions of the study by presenting the selected distribution routes for bottled drinking water (AMDK) in City X and highlighting the cost implications of applying the Hybrid Genetic Algorithm (HGA) in comparison with the initial solution generated using the Nearest Insertion Heuristic. The findings demonstrate that incorporating retailer time windows into routing decisions leads to substantial changes in the overall cost structure when compared with approaches that focus solely on minimizing travel time. In particular, penalty costs emerge as a dominant component of the total cost, with tardiness penalties contributing significantly higher costs than waiting (earliness) penalties. This emphasizes that minimizing late arrivals plays a critical role in achieving a minimum-cost distribution solution.

Furthermore, although the HGA framework allows for a larger number of iterations that could potentially enhance solution quality, this study implemented only three iterations. Despite this limitation, the results indicate that the HGA effectively improves route selection by consistently replacing higher-cost parent routes with lower-cost offspring routes. This outcome suggests that the evolutionary search mechanism embedded in the HGA is capable of efficiently exploring and exploiting the solution space, even with a limited number of iterations, and is well suited for handling routing problems with soft

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time window constraints.

Based on the best-performing offspring, the final routes recommended for implementation are as follows: RK 1 is $G \rightarrow S \rightarrow B \rightarrow S \rightarrow B \rightarrow S1 \rightarrow A \rightarrow S \rightarrow L \rightarrow G$, and RK 2 is $G \rightarrow P \rightarrow G \rightarrow M \rightarrow H \rightarrow L \rightarrow B \rightarrow P \rightarrow S \rightarrow G$

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