Genetic algorithm to optimize green vehicle routing and allocation planning for perishable products

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ABSTRACT

This paper introduces a novel approach to the Green Vehicle Routing Problem (GVRP) by integrating multiple trips, heterogeneous vehicles, and time windows, specifically applied to the distribution of bakery products. The primary objective of the proposed model is to optimize route planning and vehicle allocation, aiming to minimize transportation costs and carbon emissions while maximizing product quality upon delivery to retailers. Utilizing a Genetic Algorithm (GA), the model effectively achieves near-optimal solutions that balance economic, environmental, and quality-focused goals. Empirical results reveal a total transportation cost of IDR 856,458.12, carbon emissions of 365.43 $kgCO_2e$, and impressive average product quality of 99.90% across all vehicle trips. These findings underscore the capability of the model to efficiently navigate the complexities of real-world logistics while maintaining high standards of product delivery. The proposed GVRP model serves as a valuable tool for industries seeking sustainable and cost-effective distribution strategies, with implications for broader advancements in supply chain management.

1. Introduction

In today's globalized economy, the efficient transportation of perishable products has become a critical concern. The increasing distance between production centers and consumers necessitates robust and reliable logistics systems to ensure the timely delivery and quality preservation of sensitive products, such as pharmaceuticals [1], food [2]–[4], and beverages [5]. This challenge is particularly evident in the bakery industry, where freshness is paramount to customer satisfaction and business success [6].

Consider, for instance, a large-scale bakery enterprise that supplies a variety of bread products to numerous retail outlets across a wide geographical area. This company faces the dual challenge of maintaining product freshness while simultaneously optimizing its distribution network to minimize costs [6], [7]. Such a scenario highlights the complexities inherent in managing supply chains for perishable products and underscores the necessity for advanced logistics solutions [8]. Within this context, time windows emerge as a critical constraint in the distribution of perishable goods, as demonstrated in studies examining the integration of time constraints within cold chain logistics [9]. This issue is particularly significant in the bakery industry, where the freshness of products is directly linked to their quality and marketability, making effective time management essential for maintaining consumer satisfaction.

Moreover, the operational challenges are further compounded by the need for multiple trips and the utilization of heterogeneous vehicles. The complexity of multiple trips allows for greater flexibility in route planning but also requires careful coordination to ensure that product freshness is maintained throughout each delivery cycle [10]. Heterogeneous vehicle fleets, which consist of different types of vehicles with varying capacities and characteristics, introduce additional logistical intricacies [11], [12], [13]. Effectively managing these vehicles can optimize delivery routes and reduce costs while ensuring that perishable items, like baked goods, are transported under optimal conditions [14]. Therefore, addressing these complexities through advanced routing models and logistics strategies is crucial for enhancing efficiency and preserving product quality in the bakery supply chain.

The Vehicle Routing Problem (VRP) serves as a fundamental concept in operations research, encompassing diverse issues, including the optimization of distribution routes [15], [16], management of heterogeneous vehicle fleets [17], [18], and sustainable cold chain logistics [17]. Its versatility extends to various applications such as improving waste collection efficiency [19], coordinating emergency supply distribution [15], [20], and planning winter road maintenance [16], [21]. Traditional VRP models often prioritize cost minimization or time efficiency; however, few adequately consider the delivery's perishability. In the context of perishable products, the VRP becomes significantly more complex due to their time-sensitive nature [22], [23]. Recent scholarly work has illuminated the evolving landscape of VRP research, particularly concerning perishable products. A comprehensive review by Utama *et al.* [21] analyzed 59 studies published between 2001 and 2020, focusing on route optimization for quality-sensitive goods and revealing a prevalence of metaheuristic algorithms that address single and multi-objective optimization problems, with cost minimization as a predominant objective. Alkaabneh *et al.* [24] introduced a comprehensive approach combining inventory routing with environmental costs, highlighting the importance of minimizing fuel consumption alongside traditional delivery costs. Furthermore, Zhu *et al.* [25] explored the inclusion of freshness-keeping costs in cold chain logistics, optimizing routes to minimize product spoilage and overall distribution costs. These approaches demonstrate that modern VRP models must evolve to include multi-objective frameworks, balancing cost, time, and product quality to address the unique challenges perishable goods pose. In light of growing environmental concerns, the logistics industry faces increased scrutiny regarding its impact on sustainability. The emergence of the Green Vehicle Routing Problem (GVRP) integrates sustainability parameters into traditional VRP models [19], [26]. A thorough review by Moghdani *et al.* [19] encompassing 309 papers published from 2006 to 2019 highlighted the increasing emphasis on environmental considerations in transportation logistics. As the GVRP field continues to evolve, researchers recognize the need to incorporate realistic constraints and objectives to address the complexities of modern logistics operations.

This study aims to contribute to this field by developing a comprehensive GVRP model tailored to the bakery industry, considering product deterioration, multiple trips, heterogeneous fleets, and time windows. The overarching goals include minimizing operational transport costs, reducing carbon emissions, and maximizing product quality. By addressing these interrelated objectives, this research provides a holistic approach to green logistics management in perishable goods distribution. Integrating multiple trips, heterogeneous fleets, time windows, cost minimization, emission reduction, and quality maximization into a single GVRP model reflects the real-world complexities logistics managers face, aligning with the broader societal goals of sustainable development and environmental stewardship. The intersection of perishable product logistics and environmental sustainability presents fertile ground for research and innovation, particularly in the bakery industry. This translates to a multifaceted challenge, primarily centered on designing an efficient distribution route network that ensures timely delivery of fresh bread products to various stores, each with specific receiving time windows [23], [27]. This time sensitivity is crucial for meeting contractual obligations and maintaining the quality of baked goods, which deteriorate rapidly [28]–[30]. The routing solution must also minimize transportation costs, a significant component of operational expenses, while reducing carbon emissions associated with the distribution process [31]–[33].

To address these challenges, this paper develops a GVRP model tailored to the bakery industry, determining the optimal routing strategy and vehicle allocation that minimizes operational costs and environmental impact while ensuring the timely delivery of fresh products. This research employs a Genetic Algorithm (GA) to solve this complex optimization problem, leveraging its robustness in handling multi-objective scenarios and its capacity to find near-optimal solutions in large search spaces.

The choice of GA is particularly well-suited to the GVRP due to its adaptive heuristic approach, which excels in addressing non-linear, multi-objective problems. Unlike exact methods such as linear programming, which may struggle with large-scale and highly constrained problems, GA dynamically explores the solution space, avoiding local optima and enhancing solution diversity. Compared to other metaheuristic techniques like tabu search and simulated annealing, GA offers greater flexibility in handling dynamic constraints and overlapping objectives, making it particularly effective for real-world logistics applications [34]–[36]. While metaheuristic methods like tabu search and simulated annealing can perform well under certain conditions, they often require extensive parameter tuning to achieve optimal results. In contrast, GA consistently provides high-quality solutions with improved computational efficiency, making it a robust approach for optimizing vehicle routing and allocation planning [37].

The novelty of this research lies in three key contributions. First, it develops a GVRP model that uniquely integrates perishability constraints with eco-friendly considerations, addressing a significant gap in the literature [38], [39]. Second, it demonstrates the effectiveness of GA in solving real-world logistics problems, particularly those that struggle with dynamic and large-scale scenarios [40]–[44]. Lastly, it offers actionable insights through a case study on bakery logistics, providing managers with a robust framework for balancing economic and environmental priorities.

The remainder of this paper is structured as follows: Section 2 details our proposed method, including the specifics of our mathematical model and solution approach. Section 3 presents the results of our computational experiments and offers a thorough analysis of the findings. Finally, Section 4 concludes the paper by summarizing key insights and suggesting directions for future research in this critical area of logistics and supply chain management.

2. Model Development

2.1. Problem Descriptions

An illustration of this complex bakery distribution problem is presented in Fig. 1. The bakery industry faces a complex VRP characterized by the delivery of perishable products with declining quality over time. Based on Fig. 1, fresh bread must be distributed to various retail stores, each with specific morning time windows for receiving deliveries. This time sensitivity is crucial for maintaining product freshness and meeting contractual obligations with retailers. In addition to the challenge of optimizing delivery schedules, multiple trips are considered if the load of the first trip exceeds the vehicle's capacity.

In such cases, vehicles must return to the bakery hub for reloading before embarking on a second trip to complete the remaining deliveries. This adds complexity to route planning, as the need for additional trips impacts overall delivery time, vehicle utilization, and resource allocation. The problem becomes even more challenging due to the need to optimize the number and capacity of delivery vehicles and their routing to meet strict morning delivery schedules. Vehicle speed is critical, especially during morning rush hours when increased human activity leads to traffic congestion, potentially causing delays and affecting delivery times. This optimization challenge goes beyond logistical efficiency; it directly influences transportation costs and carbon emissions. The objective is to develop routing strategies and vehicle allocations that effectively meet time-window constraints while minimizing economic and environmental costs, all while maintaining the quality of bread products. The flow of this research is presented in Fig. 2 to illustrate the overall approach.

The research flow in Fig. 2 outlines a systematic approach to solving the VRP problem. It begins with problem descriptions, where the key challenges and objectives are identified. Next, model development involves formulating a comprehensive framework to address the VRP problem. Data collection follows, ensuring that relevant and accurate data are gathered to test the model. Finally, the model solution-based GA phase applies optimization techniques to find efficient solutions.

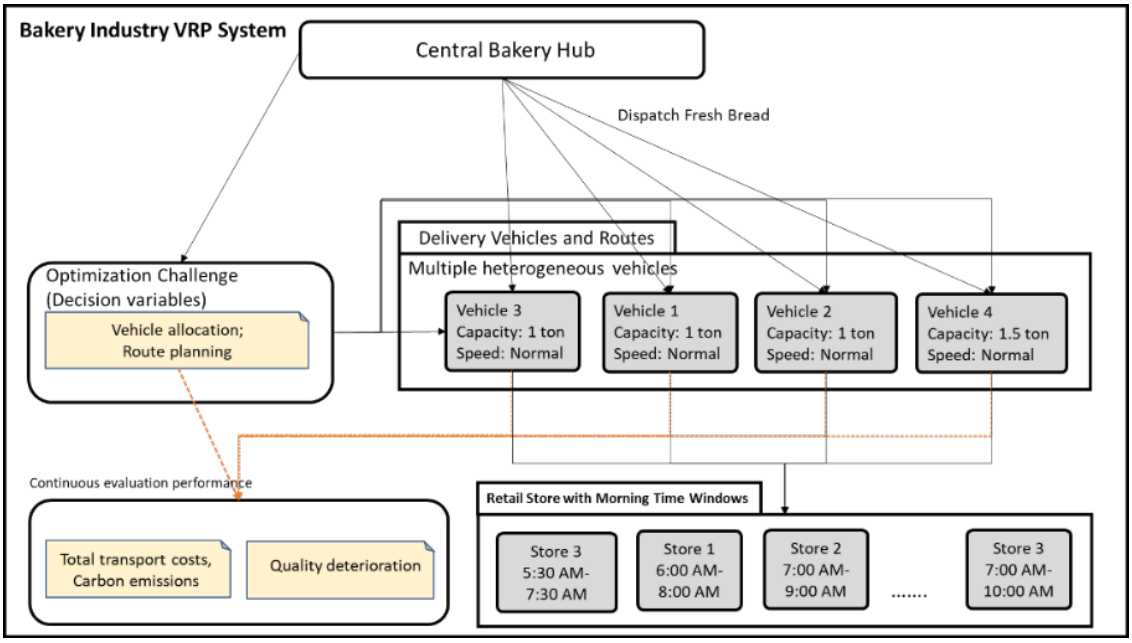


Fig. 1. Bakery product distribution network

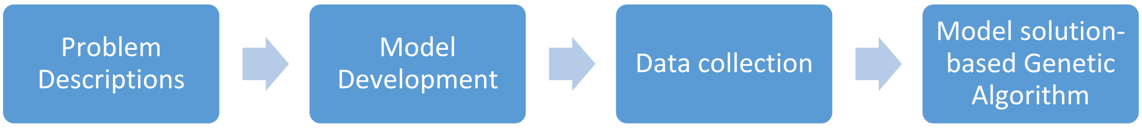


Fig. 2. Research flowchart

2.2. Model Formulation

We can first use the notations to develop a mathematical model for this VRP that accounts for perishable product quality, delivery time windows, and carbon emissions.

2.2.1. Notations

- Indices and sets
  N : Set of locations, including the bakery hub (0) and retail stores (1 to n), {0, 1, 2, 3,...,n}.
  k : Index for vehicles, $k \in K$, where K is the set of vehicles.
  i, j : Indices for locations (nodes), where $i, j \in N$.
  r : Number of trips for each vehicle k.
  S : A subset of nodes from the complete set of retailer nodes N in the VRP

- Parameter
  D_i : Demand at retail store i.
  $W_{ij}^{k,r}$: Total initial weight (in kg) of cargo at the start of a trip r for vehicle k, calculated as the sum of demands for all nodes in that trip.
  w : Weight per unit product in kg.
  B_{truck} : The empty weight of the truck.
  T_{ik}^{r} : Arrival time at node i for vehicle k during trip r.
  T_{jk}^{r} : Arrival time at node j for vehicle k during trip r.

T_i^{start} : Start of the delivery time window at store i.
T_i^{end} : End of the delivery time window at store i.
$T_{loading}$: Loading time at the bakery hub.
$T_{unloading}$: Unloading time at each retail store.
α_{early} : Penalty cost for early delivery (before T_i^{start}).
α_{late} : Penalty cost for late delivery (after T_i^{end}).
d_{ij} : Distance between locations i and j (in kilometers)
v_k : Speed of vehicle k (in km/h).
C_k : Capacity of vehicle k (in units of bread).
c_{km} : Transportation cost per kilometer for vehicle k (in monetary units).
Q_i : Initial quality of the product at node i, assumed to be 100% at the depot.
$\delta_i(T_{ik}^r)$: Quality decay function at time t for bread delivered to store i.
e^c : The emission factor for CO_2
e^m : The emission factor for CH_4
e^n : The emission factor for NO_2
GWP_c : The global warming potential for CO_2.
GWP_m : The global warming potential for CH_4.
GWP_n : The global warming potential for NO_2.

- Decision variables

$z_{ij}^{k,r}$: A binary decision variable that represents whether 1 if vehicle v is allocated to travel from the station i to station j, and $z_{ij}^v = 0$ otherwise.
$N^{k,r}$: The sequence of nodes visited by a vehicle k per trip r, for example $[0, n_1, n_2, n_3, \dots, n_m, 0]$.

2.2.2. Assumptions

We used some basic assumptions to ensure the model's suitability for operational conditions in the field, simplify calculations, and improve modelling accuracy. The following are the assumptions used in this study: 1) The demand at each retailer is known and constant; 2) Each retail store is visited exactly once by one vehicle; 3) The distances between all pairs of nodes are known and remain constant; 4) The quality of the bread decreases over time according to a predefined decay function $\delta_i(t)$; 5) Each vehicle travels at a constant speed v_k and the travel time between any two locations i and j is calculated based on this fixed speed. 6) Each retail store has a specified time window for delivery; 7) The model assumes that the time required for loading at the bakery hub and unloading at each retail store is fixed and known; 8) Each vehicle has a fixed capacity C_k, which limits the amount of bread it can carry. The total demand fulfilled by each vehicle must not exceed its capacity.

2.2.3. Mathematical model

This model aims to minimize operational costs and emissions while ensuring that the bread quality remains high upon delivery to customers by optimizing the route planning $N^{k,r}$ and vehicle allocation $z_{ij}^{k,r}$. The model prioritizes operational efficiency and customer satisfaction, emphasizing the importance of delivering fresh, high-quality bread.

- Objective 1: Minimize transport costs

$$Z_1(N_k, z_{ij}^{k,r}) = \sum_{k\in K}\sum_{r\in R_k}\sum_{i\in N}\sum_{j\in N} z_{ij}^{k,r}(c_{km}\cdot d_{ij}) + \sum_{k\in K}\sum_{r\in R_k}\sum_{i\in N}\left(\alpha_{early}\cdot \max(T_i^{start} - T_{i,k}^r, 0) + \alpha_{late}\cdot \max(T_{i,k}^r - T_i^{end}, 0)\right) \quad (1)$$

- Objective 2: Minimize carbon emissions

$$Z_2(N_k, z_{ij}^{k,r}) = \sum_{k\in K}\sum_{r\in R}\sum_{j\in N} z_{ij}^{k,r}\, d_{ij}\,(W_i^{k,r} + B_{truck})(\mathrm{GWP_c}\cdot e^c + \mathrm{GWP_m}\cdot e^m + \mathrm{GWP_n}\cdot e^n) \quad (2)$$

- Objective 3: Maximize bread quality at delivery

$$Z_3(N_k, z_{ij}^{k,r}) = \frac{1}{|K|}\sum_{k\in K}\sum_{r\in R}\sum_{i\in N}\left(Q_i - \delta_i\left(T_{ik}^r(N_k, z_{ij}^k)\right)\right) \tag{3}$$

- Subject to

$$\sum_{j\in N} z_{0j}^{k,r} = 1, \sum_{i\in N} z_{i0}^{k,r} = 1, \forall k \in K, \forall r \in R \tag{4}$$

$$\sum_{k\in K}\sum_{j\in N} z_{ij}^{k,r} = 1, \quad \forall i \in N \tag{5}$$

$$\sum_{j\in N} z_{ij}^{k,r} = \sum_{j\in N} z_{ji}^{k,r}, \quad \forall i \in N, \forall k \in K, \forall r \in R \tag{6}$$

$$\sum_{i\in N}\sum_{j\in N} D_i^r z_{ij}^{k,r} \le C_k, \quad \forall k \in K, \forall r \in R \tag{7}$$

$$T_i^{start} \le T_{ik}^r \le T_i^{end} \tag{8}$$

$$T_{jk}^r \ge T_{loading} + \frac{d_{0j}}{v_k} + T_{unloading}, \ \forall j \in N, \forall k \in K, \forall r \in R \tag{9}$$

$$T_{jk}^r \ge T_{ik}^r + \frac{d_{ij}}{v_k} + T_{unloading}, \qquad \forall i,j \in N, \forall k \in K, \forall r \in R \tag{10}$$

$$Penalty_{early}^i = \max(T_i^{start} - T_{ik}^r, 0), \ \forall i \in N, \forall k \in K, \forall r \in R \tag{11}$$

$$Penalty_{early}^i = \begin{cases} \alpha_{early}(T_i^{start} - T_{ik}^r, 0), & If\ T_i^{start} - T_{ik}^r > 1\ hour \\ 0, & Otherwise \end{cases} \tag{12}$$

$$Penalty_{late}^i = \max\left(T_{ik}^r - T_i^{end}, 0\right), \forall i \in N, \forall k \in K, \forall r \in R \tag{13}$$

$$Penalty_{late}^i = \begin{cases} \alpha_{late}\left(T_{ik}^r - T_i^{end}, 0\right), & If\ T_{ik}^r - T_i^{end} > 1\ hour \\ 0, & Otherwise \end{cases} \tag{14}$$

$$W_i^{k,r} = W_{initial}^{k,r} - \sum_{l\in N}\left(D_l^r w\, z_{li}^{k,r}\right), \forall i \in N, \forall k \in K, \forall r \in R \tag{15}$$

$$W_{initial}^{k,r} = \sum_{l\in N} D_l^r w \tag{16}$$

$$\sum_{i,j\in S} z_{ij}^{k,r} \le |S| - 1, \quad \forall S \subset N, S \ne \emptyset, \forall k \in K \tag{17}$$

The objective of the GVRP model is to optimize three key functions. The first function, represented in Eq. (1), focuses on minimizing transportation costs. The second, as shown in Eq. (2), aims to reduce carbon emissions, while the third function, expressed in Eq. (3), addresses quality decay resulting from transportation time. Constraint (4) defines each vehicle must depart from the bakery hub and return to the bakery hub. Constraint (5) ensures each store must be visited exactly once by one vehicle for all trips. Constraint (6) states that the number of vehicles arriving at a node i is equal to the number of vehicles departing from the same node i on each trip r. Constraint (7) ensures that the total demand (i.e., the quantity of goods) delivered by vehicle k during trip r does not exceed the vehicle's maximum capacity C_k. Moreover, Constraint (7) also ensures that when the total demand for a route exceeds the vehicle's capacity, the vehicle must make multiple trips. Constraint (8) ensures that the delivery times respect the time windows for each node. Arrival time calculation for the first leg (from the bakery hub to the first retailer) is computed in Constraint (9). Constraint (9) accounts for the loading time at the bakery hub, the travel time from the bakery hub to the first retailer, and the unloading time at that retailer. Meanwhile, for subsequent legs (from one retailer to another) defined in constraint (10). It accounts for the travel time between two retailers and the unloading time at the destination retailer. Constraints (11) and (13) specify the penalty for arriving before the start time and for late arrival at the store i, respectively. However, Constraints (11) and (13) are influenced by the conditions in Constraints (12) and (14), where if the penalty exceeds 1 hour, the cost should include a higher penalty rate. Since carbon emissions are calculated based on transportation distance and weight, then constraint (15) defines the total weight of the cargo carried by a vehicle k on trip r from node i to node j, which decreases progressively as deliveries are made. Constraint (16) total initial weight of cargo loaded onto the truck for trip r. Constraint (17) ensures that no subtours are formed by restricting the number of routes within any subset of nodes S to be less than the size of the subset, thereby preventing vehicles from circulating among nodes without returning to the central hub.

2.3. Solution approach

In this section, the development of a GA tailored for the GVRP with multi-objective optimization, which consists of: minimizing both costs (Z_1) and emissions (Z_2) and maximizing bread quality upon delivery (Z_3). The GVRP is an NP-hard problem, and metaheuristic approaches like GA are well-suited for finding near-optimal solutions within a reasonable timeframe. The chromosome structure is crucial to the success of the GA. Each chromosome is encoded as a binary string where the length corresponds to the number of possible routes between stations in the network. For instance, if there are n stations and k vehicles, each chromosome will have a length of $k \times (n^2 - n)$, reflecting all potential vehicle-route combinations. Each gene in the chromosome is a binary decision variable $z_{ij}^{k,r}$ which takes the value of 1 if the vehicle v is assigned to the route from the station i to station j, and 0 otherwise. Then, the pseudocode of GA for this problem is presented in Algorithm 1 (Fig. 3).

```
1: Initialize Population: Randomly generate an initial population of chromosomes.
2: Evaluate Fitness:
   For each chromosome in the population, calculate its fitness based on the
   objective function (i.e., minimizing both costs Z_1 and emissions (Z_2) and
   maximizing bread quality upon delivery (Z_3)).
3: While stopping criterion not met (i.e., the maximum number of generations or
   convergence):
4: Selection:
   Select chromosomes based on a roulette wheel mechanism, where the probability
   of selection is proportional to the fitness of each chromosome.
5: Crossover (Two-Point Crossover):
   For each selected pair of parent chromosomes:
   With a certain probability, perform a two-point crossover by randomly selecting
   two crossover points on the parent chromosomes. Swap the genes between these
   two points to create two offspring chromosomes.
6: Mutation (Jump and Creep Method):
   For each offspring chromosome:
   With a certain probability, apply one of the two mutation techniques:
   Jump mutation: Randomly select and replace a gene with a randomly chosen
   value from the permissible range.
   Creep Mutation: Select a gene and increment or decrement its value by a small
   predefined amount to introduce slight variations.
7: Evaluate Fitness:
   Calculate the fitness of each new offspring chromosome.
8: End While
9: Output: Return the best chromosome found as the optimal route planning N^{k,r} and
   vehicle allocation z_{ij}^{k,r} for vehicle routing.
```

Fig. 3. The pseudocode of GA

The following provides a step-by-step outline of the GA process:

Step 1. Initialize Population

GA begins by initializing a population of potential solutions (Pop), referred to as chromosomes. In this context, each chromosome is divided into two key components: route node planning N_k and vehicle allocation $z_{ij}^{k,r}$ as shown in Fig. 4. The route node planning chromosome represents a possible sequence of customer visits, starting and ending at a bakery hub, effectively encoding the order in which customers are visited. The vehicle allocation chromosome, on the other hand, assigns specific vehicles to the planned routes, ensuring that each route has the appropriate vehicle based on capacity or other constraints. This dual representation allows the GA to simultaneously optimize both the route planning and vehicle assignment for efficient vehicle delivery in the context of the GVRP. The diversity of this initial population, containing variations in both route sequences and vehicle allocations, is crucial as it forms the basis for the subsequent search for an optimal solution.

Node	Vehicle			
	1	2	3	4
1	1	0	0	0
2	0	1	0	0
3	0	1	0	0
4	0	0	1	0
5	1	0	0	0
Service route:	0-1-5-0	0-2-3-0	0-4-0	0

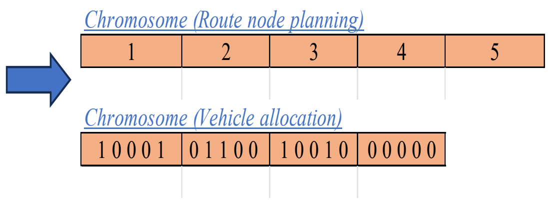


Fig. 4. Chromosome representation

Step 2. Evaluate Fitness

After initializing the population, the fitness of each chromosome is evaluated using the fitness function F to assess the quality of each solution. In this formulation, Z_1 represents the cost of the route, Z_2 accounts for carbon emissions, and Z_3 reflects the quality of the bread upon delivery (to be maximized). The fitness function is designed to minimize the overall fitness value, which combines these objectives through a weighted sum approach, along with a penalty term P for constraint violations. The fitness function is formulated as:

$$F = w_1 \cdot Z_1 + w_2 \cdot Z_2 + w_3 \cdot -Z_3 + P \tag{18}$$

where w_1, w_2, and w_3 are the weights assigned to the respective objectives. Z_1 and Z_2 are to be minimized (cost and emissions). Z_3 is to be maximized, so we use $-Z_3$ to convert it into a minimization objective. P represents any penalty for constraint violations.

In this case, the weights reflect the relative importance of each objective, with w_1= 0.4, w_2=0.3, $w_3 = 0.3$. This weighting emphasizes the minimization of costs slightly more than emissions and quality. A lower fitness value indicates a more optimal solution, signifying reduced costs and emissions while maintaining high product quality and adhering to constraints.

Step 3. Selection

In this phase, the roulette wheel selection method selects chromosomes to contribute to the next generation. In this approach, each chromosome is assigned a probability of selection proportional to its fitness value, with fitter chromosomes having a higher chance of being selected. The metaphor of a roulette wheel is used, where sections of the wheel are allocated based on fitness, and chromosomes are chosen based on where the "wheel" lands. Unlike elitism, which directly preserves the best solutions, roulette wheel selection maintains diversity by allowing all chromosomes to contribute to the next generation, thus balancing exploration and exploitation and preventing premature convergence to suboptimal solutions.

Step 4. Crossover

The selected chromosomes undergo a two-point crossover, combining genetic material from two parents to produce offspring, as shown in Fig. 5.

Step 5. Mutation

A mutation process is applied with a specified probability to maintain genetic diversity and avoid premature convergence. The mutation is performed using the jump and creep method in this context. Jump mutation involves making large, random changes to a chromosome by replacing a gene with a completely different value, while creep mutation makes smaller, incremental adjustments by slightly altering the value of a gene within its allowable range, as shown in Fig. 6.

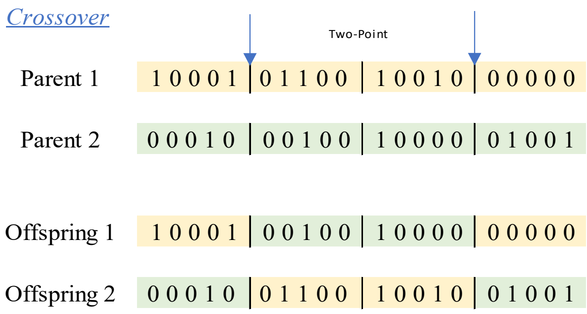


Fig. 5. Crossover

The mutation probability (P_m) controls the frequency of both types of mutations. This combination allows the algorithm to explore a broader range of solutions, with jump mutations introducing significant diversity and creep mutations fine-tuning solutions to avoid local optima, ultimately enhancing the search for the global optimum.

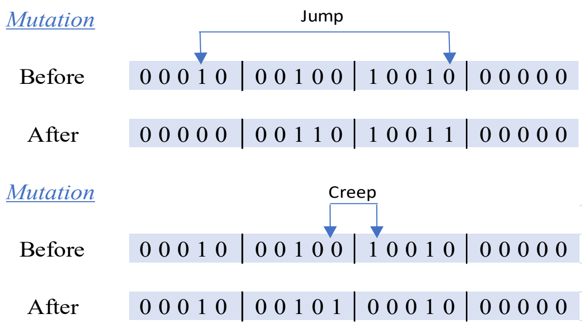


Fig. 6. Mutation

Step 6. Evaluate Fitness

After crossover and mutation, the fitness of the newly generated chromosomes is re-evaluated. The algorithm then determines which chromosomes will advance to the next generation, using strategies like elitism to preserve the best-performing individuals or additional selection methods. This process aims to retain high-quality solutions while promoting continued exploration and refinement within the population across successive generations.

Step 7. Termination

The algorithm continuously cycles through the processes of selection, crossover, mutation, and re-evaluation until a specified stopping condition—namely, the number of generations G_n,—is met. Once this condition is satisfied, the algorithm terminates, and the most optimal solution identified during the process is selected.

Step 8. Set the best solution

The chromosome with the best fitness value in the final population represents the optimal solution to the GVRP. This solution corresponds to a vehicle route that minimizes costs and emissions while maximizing bread quality during delivery.

3. Results and Discussion

In this section, we address the GVRP in the bread industry by developing a mathematical model encoded in Microsoft Excel, optimized using a GA approach. The GA was executed through the XL Optimizer, an Excel add-in that facilitates optimization tasks. By using this add-in, the GA generated robust initial solutions, improving the efficiency and accuracy of route planning and vehicle allocation for bread distribution. To evaluate the effectiveness of the proposed method, numerical experiments were conducted on a PC with an Intel(R) Core™ i5 10500H CPU at 2.5 GHz, 8 GB RAM, running Windows 10 Professional. The outcomes of the model were then compared to the existing distribution data in the bread industry to assess the performance improvements achieved through the GA-based optimization:

3.1. Test instances

To evaluate the proposed VRP model, we conducted numerical experiments using a large-scale scenario with 40 nodes. The demand data for each node D_i, the distances between nodes d_{ij}, as well as time windows (T_i^{start} and T_i^{end}) for each node can be seen from this link (https://bit.ly/3Y1gxb6). Additionally, the operational logistics data, including vehicle capacities, speed, cost parameters, and emission, are summarized in Table 1 and Table 2.

Table 1. Data related to delivery operations

k	C_k (Units)	v_k (km/hr)	B_{truck} (kg)	c_{km} (Rupiah/km)	w (kg)	α_{early}& α_{late} (Rupiah/hr)	$T_{loading}$ (minutes)	$T_{unloading}$ (minutes)	Q_i
1	5200	50	800	581.20	0.07	10000	20	15	100
2	5200	50	800						
3	5200	50	800						
4	5200	50	1588						

Table 2. Data related to emission

Global Warming Potential			Emission Factor		
GWP_c	GWP_m	GWP_n	e^c	e^m	e^n
1	28	265	0.297	0.0035	0.0027

These tables provide the foundational inputs necessary for testing the model's performance across different scales, allowing us to analyze its effectiveness in optimizing routing strategies while maintaining product freshness and minimizing transportation costs.

3.2. Computational results

The computational results of the GVRP model using GA with demand data for 40 nodes and four vehicles were tested using four parameter combinations. Each combination was evaluated three times to account for the stochastic nature of the GA, which can produce varying results depending on the initial random population. Testing each combination multiple times ensures that the results are consistent and not influenced by random outliers, providing a more robust evaluation of the parameter settings.

Based on the experimental results in Table 3, several key insights emerge regarding the performance of the GA in evaluating fitness values across three trials with different parameter combinations. The best-performing combination was found to be Pop = 150, P_c = 0.9, P_m = 0.02, and G_n =500, which yielded the lowest average fitness value of 371,877.04. This indicates that a larger population size, a high crossover rate, a moderate mutation rate, and a higher number of generations contribute to a more optimal fitness outcome. Furthermore, this parameter setting demonstrated good consistency across trials, with relatively small differences between the first, second, and third trials, showcasing its reliability in consistently achieving robust solutions.

In contrast, the combination Pop = 100; P_c = 0.8; P_m = 0.01; G_n = 300 resulted in the highest average fitness value of 415,954.27, indicating that smaller population sizes and fewer generations hinder the algorithm's ability to explore the solution space effectively, leading to suboptimal outcomes. The Pop = 125; P_c =0.75; P_m = 0.025; G_n = 400 combinations produced a slightly better average fitness value of 404,791.18, but it exhibited greater variability between trials. The lower crossover probability and higher mutation rate might have caused this variability, with one trial showing a significant improvement while the others performed less favorably.

Table 3. Experimental result for 40 nodes and 4 Vehicles

Experiment	Trial 1	Trial 2	Trial 3	Average
$Pop = 100$; $P_c = 0.8$; $P_m = 0.01$; $G_n = 300$	478,263.89	391,361.08	378,237.85	415,954.27
$Pop = 125$; $P_c = 0.75$; $P_m = 0.025$; $G_n = 400$	434,769.94	429,744.14	349,859.48	404,791.18
$Pop = 150$; $P_c = 0.9$; $P_m = 0.02$; $G_n = 500$	383,841.41	389,126.82	342,662.90	371,877.04
$Pop = 175$; $P_c = 0.85$; $P_m = 0.03$; $G_n = 200$	437,121.39	395,817.79	371,812.75	401,583.97

Lastly, the combination $Pop = 175$; $P_c = 0.85$; $P_m = 0.03$; $G_n = 200$ delivered a decent average fitness value of 401,583.97, but again showed larger variations between trials, particularly in the third trial. This suggests that while a larger population and higher mutation rate can be beneficial, the relatively low number of generations restricted the algorithm's ability to converge on optimal solutions. Overall, the parameter combination with $Pop = 150$; $P_c = 0.9$; $P_m = 0.02$; $G_n = 500$ proved to be the most effective, striking a good balance between exploration and exploitation in the solution space and leading to the most consistent and optimal results across trials. Building upon the previous analysis of the GA parameter combination $Pop = 150$; $P_c = 0.9$; $P_m = 0.02$; $G_n = 500$, which produced the best average fitness value, further investigation into the specific objectives reveals even more insightful results. Table 4 reflects the performance of this parameter set across three trials, evaluating three key objectives: costs (Rp), carbon emissions (kgCO_2e), and average quality of bread (%).

Table 4. Summary of optimization results for vehicle routing problem across multiple trials

Objectives	Trial 1	Trial 2	Trial 3	Average
Costs (IDR)	959,381.20	972,581.20	856,458.12	929.473,50
Carbon emission (kgCO_2e)	396.36	414.42	365.43	392,07
Average Quality of Bread (%)	99.89	99.89	99.90	99.89

From the results, Trial 3 stands out as the most effective trial, achieving the most favorable outcomes across all evaluated objectives. Transportation costs, calculated based on total travel distance, were minimized most efficiently in Trial 3, achieving the lowest cost of IDR 856,458.12, compared to IDR 959,381.20 in Trial 1 and IDR 972,581.20 in Trial 2. This significant cost reduction indicates that the third trial effectively optimized route planning, resulting in superior cost efficiency while maintaining operational feasibility.

Similarly, in terms of carbon emissions, calculated following the GHG protocol standards, Trial 3 achieved the lowest emissions at 365.43 kgCO_2e, outperforming Trial 1 and Trial 2, which recorded emissions of 396.36 kgCO_2e and 414.42 kgCO_2e, respectively. The reduction in emissions in Trial 3 highlights the model's ability to align economic and environmental objectives effectively. This emphasizes the model's capability to identify more sustainable routing solutions without significantly compromising cost efficiency, simultaneously addressing financial and environmental concerns.

Regarding product quality, measured based on the adherence to delivery time windows to ensure freshness upon arrival, all trials demonstrated consistent results with minimal variation. Trial 3 maintained a slightly higher quality score of 99.90%, compared to 99.89% in both Trial 1 and 2. This consistency indicates that, despite focusing on optimizing cost and emissions, the algorithm effectively maintained high product quality standards. The findings reaffirm the reliability of the model in balancing economic efficiency, environmental impact, and product quality throughout the delivery process.

Overall, the results from Trial 3 demonstrate the effectiveness of the proposed model in optimizing the distribution process by minimizing transportation costs and emissions while ensuring product quality, making it a viable solution for sustainable logistics operations.

Building on the selection of Trial 3 as the best performer from Table 4, a deeper analysis of the solution search process using the GA reveals interesting insights, as illustrated in Fig. 7. The optimization process in Trial 3 demonstrates a clear convergence pattern, where the algorithm reaches an optimal or near-optimal solution by generation 321. From this point onward, no further improvements were observed in the fitness value up until generation 500, indicating that the algorithm had effectively explored and exploited the solution space by generation 321.

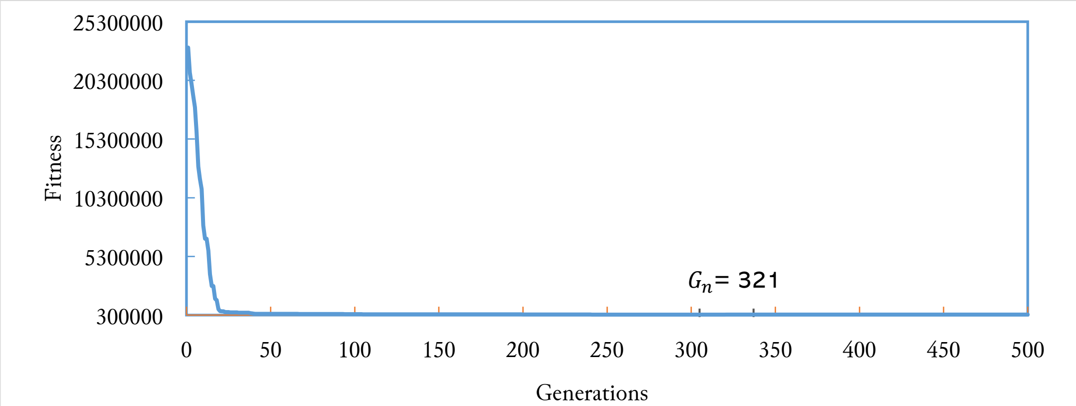


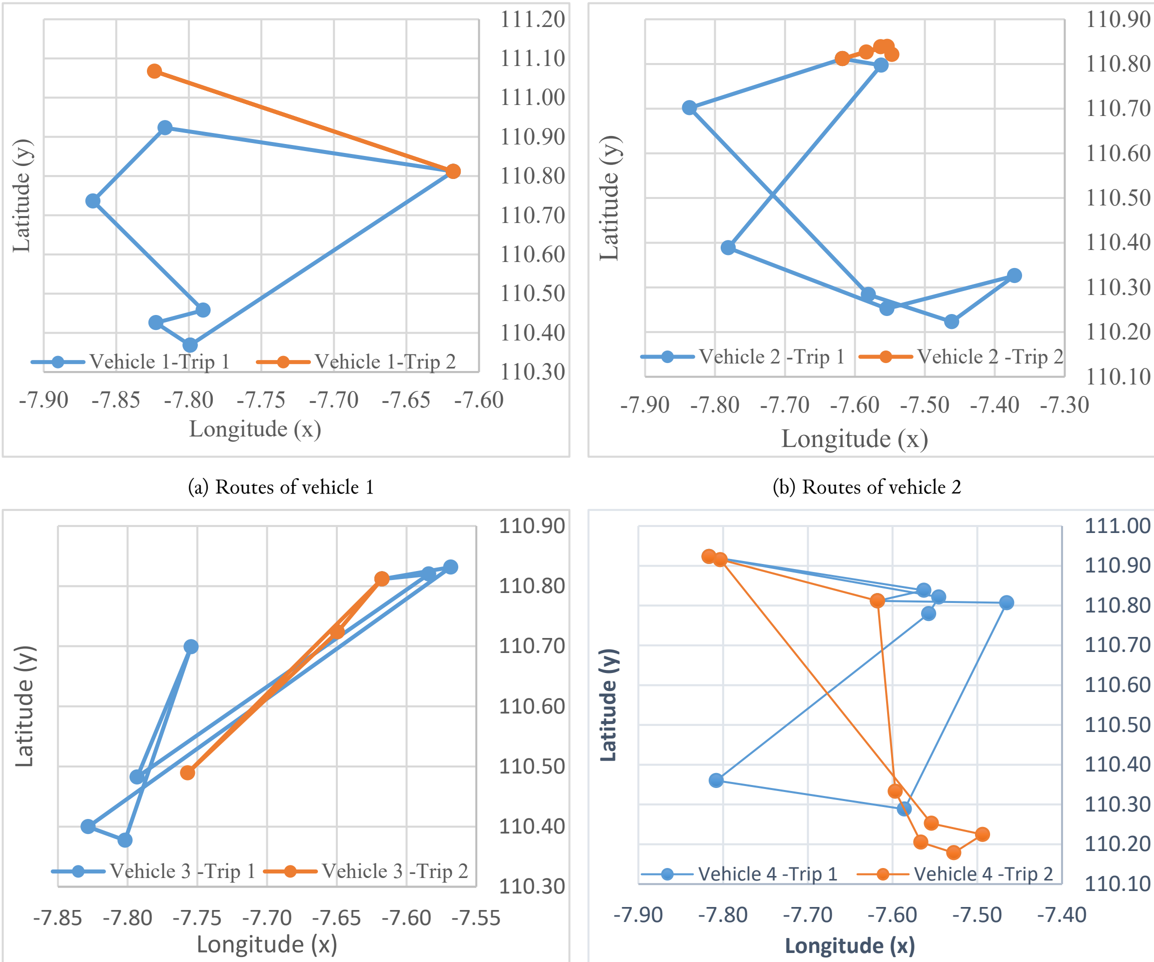
Fig. 7. Graphs illustrating the convergence path of solutions reached by the GA

The results from Trial 3 in Table 4 demonstrate the significant impact of optimized route planning and vehicle allocation on the overall performance of the GA solution, as shown in Fig. 8. Each vehicle route was strategically designed to minimize transportation costs and carbon emissions, and maintain high product quality. Vehicle 1, with its shorter routes totaling 281.90 km, achieved the lowest costs (IDR 163,839.32) and emissions (53.47 kgCO_2e), while also delivering the highest quality of 99.94%. Similarly, Vehicles 2 and 3 maintained efficient routes, resulting in moderate costs and emissions while preserving product quality close to the optimal level. On the other hand, Vehicle 4, with a significantly longer route covering 547.40 km, contributed the highest costs (IDR 318,147.01) and emissions (194.68 kgCO_2e). Despite this, the overall system balanced the performance, allowing for cost-effective and environmentally sustainable operations without compromising on high-quality product delivery, as seen in the 99.85% quality for Vehicle 4.

The optimized routing strategy led to a total transportation cost of IDR 856,458.12 and total carbon emissions of 365.43 kgCO_2e, while maintaining an impressive 99.90% average product quality across all vehicles. This showcases the effectiveness of the GA in simultaneously addressing multiple objectives and finding an optimal balance. By minimizing emissions for most vehicles, the algorithm successfully reduced the environmental impact while ensuring delivery costs were kept low. Furthermore, the consistent product quality reflects the robustness of the solution, even when handling longer and more complex routes. Overall, the trial exemplifies the capability of the GA to deliver near-optimal solutions that prioritize sustainability, cost-efficiency, and product integrity in real-world logistics operations.

Interestingly, the analysis of route planning for all four vehicles reveals that careful consideration of distance and delivery sequence can lead to notable efficiencies. By ensuring that vehicles are allocated to routes that optimize their total travel distance and align with delivery requirements, achieving substantial reductions in operational costs and carbon emissions is possible while maximizing product quality. The strategic trip planning, which prioritizes shorter routes with fewer stops for each vehicle, minimizes costs and emissions and enhances the overall service quality, as reflected in the high-quality scores across all vehicles. This indicates that a well-structured routing and allocation strategy is paramount for balancing economic viability and environmental responsibility, showcasing the effectiveness of the applied optimization model in enhancing supply chain performance.

The results of this study have significant implications for industry applications and sustainability goals, offering a practical tool for optimizing logistics in sectors such as bakery product distribution. The proposed GVRP model effectively addresses real-world complexities, such as heterogeneous vehicle fleets and dynamic delivery time windows, demonstrating its adaptability and utility across various industries dealing with perishable goods or time-sensitive deliveries. By minimizing transportation costs and carbon emissions while maintaining high average product quality (99.90%), the model enables businesses to achieve operational efficiency without compromising environmental and customer satisfaction standards. From a sustainability perspective, the model supports efforts to reduce carbon footprints in supply chain operations, aligning with global environmental regulations and corporate social responsibility initiatives. Additionally, it contributes to the United Nations' Sustainable Development Goals (SDG 12 and SDG 13) by promoting responsible production and consumption and advancing climate action. By integrating economic, environmental, and quality objectives, this model serves as a valuable strategy for industries to enhance competitiveness and sustainability in an increasingly eco-conscious and demanding marketplace.



(a) Routes of vehicle 1

(b) Routes of vehicle 2

(c) Routes of vehicle 3

(d) Routes of vehicle 4

Notes: (a) **Routes of vehicle 1**, total distance 281.90 km, total costs IDR 163839.32, total emission: 53.47 kgCO_2e, and Quality 99.93% (Trip 1: 0→17→14→33→34→38→38→ 0, Trip 2: 0→20→0); (b) **Routes of vehicle 2**, total distance 303.30 km, total costs IDR 176276.92, total emission: 58.88 kgCO_2e, and Quality 99.90% (Trip 1: 0→9→36→22→25→26→21→15→0, Trip 2: 0→2→3→4→10→0); (c) **Routes of vehicle 3**, total distance 306.60 km, total costs IDR 178194.87, total emission: 58.41 kgCO_2e, and Quality 99.92% (Trip 1: 0→1→32→13→35→40→6→0, Trip 2: 0→12→31→0); (d) **Routes of vehicle 4**, total distance 547.40 km, total costs IDR 318147.01, total emission: 194.68 kgCO_2e, and Quality 99.85% (Trip 1: 0→10→17→7→8→37→30→5→0, Trip 2: 0→29→28→27→24→22→16→17→0)

Fig. 8. Delivery routes optimized for four vehicles, illustrating efficient path selection

While the proposed GVRP model has demonstrated significant strengths, there are some limitations and challenges that should be acknowledged to provide a balanced perspective. First, the model relies on specific input data from a real-world bakery distribution system, which may limit its generalizability to other industries or regions without customization. Additionally, the computational complexity of GA, particularly for large-scale datasets, can lead to extended processing times, requiring careful parameter tuning to balance solution quality and computational efficiency. Finally, external factors such as fluctuating traffic conditions or unforeseen delays, which are difficult to model precisely, may impact the practical implementation of the proposed approach. Addressing these limitations in future work could further enhance the robustness and applicability of the model across diverse scenarios

4. Conclusion

In conclusion, this paper presents a novel GVRP model that incorporates multiple trips, heterogeneous vehicles, and time windows, applied to a real-world bakery product distribution case. The primary objective of the proposed model is to optimize route planning and vehicle allocation to minimize transportation costs and carbon emissions while maximizing product quality upon delivery to retailers. Through a series of comprehensive GA experiments, the model demonstrates its capability to find near-optimal solutions that effectively balance economic, environmental, and quality-focused objectives. The results highlight the success of the proposed GVRP model, where the best trial achieved a total transportation cost of IDR 856,458.12, carbon emissions of 365.43 $KgCO_2e$, and an average product quality of 99.90% across all vehicle trips. These outcomes showcase the algorithm's efficiency in optimizing multiple objectives while considering real-world constraints such as heterogeneous vehicle fleets and varying delivery windows. By integrating these complex factors, the model supports more sustainable and cost-effective distribution strategies and ensures the high quality of products during delivery. This makes the model a valuable tool for industries seeking to improve their operational efficiency and environmental impact in a competitive marketplace. Further research could explore the testing of alternative metaheuristic algorithms to enhance solution robustness and efficiency. In addition, incorporating the complexity of dynamic lot sizing into the model could provide deeper insights into inventory management alongside vehicle routing. This integration would allow for better alignment of production and distribution strategies, accommodating fluctuating demand patterns while optimizing resource utilization.

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Declarations

Author contribution. Conceptualization, Hayati Mukti Asih and Raden Achmad Chairdino Leuveano; Data curation, Hayati Mukti Asih and Raden Achmad Chairdino Leuveano; Investigation, Hayati Mukti Asih, Raden Achmad Chairdino Leuveano, Dhimas Arief Dharmawan, and Ardiansyah Ardiansyah; Methodology, Raden Achmad Chairdino Leuveano; Resources, Hayati Mukti Asih; Software, Raden Achmad Chairdino Leuveano; Visualization, Hayati Mukti Asih and Raden Achmad Chairdino Leuveano; Writing, Hayati Mukti Asih and Raden Achmad Chairdino Leuveano.
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