

# Large neighborhood search for route and fleet optimization in frozen food distribution

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## ABSTRACT

This study develops an optimization model to enhance the distribution efficiency of a frozen food distributor. The company faces operational inefficiencies due to excessive fleet capacity and conventional route assignment methods, which increase travel distances and overall distribution costs. To address these challenges, an extended Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) model is proposed, which integrates heterogeneous fleet characteristics and prioritizes customer service constraints. The model is solved using the Large Neighborhood Search (LNS) metaheuristic to determine optimal routing and fleet allocation strategies. The optimized model achieves a 15.95% reduction in total travel distance and a 21.84% decrease in total distribution costs compared with the company's current operations. The findings confirm the effectiveness of the LNS-based CVRPTW approach in improving logistics performance and provide practical insights for companies seeking to minimize distribution costs through strategic route planning and fleet management.

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## 1. INTRODUCTION

Efficiency in the distribution process is a cornerstone of modern supply chain management, directly impacting operational costs, resource utilization, and customer satisfaction [1], [2]. In the pursuit of a competitive advantage, companies continually seek methods to optimize their logistics operations, particularly in the realm of vehicle routing, also known as the Vehicle Routing Problem (VRP) [3]. The VRP constitutes a class of optimization problems aimed at determining a set of optimal routes for a vehicle fleet. This challenge remains central to both academic research and industrial practice [4].

The state of the art in VRP research is extensive, with foundational models like the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) providing a basis for numerous modern variants that address complex, real-world scenarios [5]. The field is rapidly evolving to tackle emerging challenges such as sustainability through green VRPs [6], the integration of autonomous vehicles like drones, and dynamic routing in response to real-time disruptions [7]–[9]. While these models are powerful, a core hypothesis of this study is that their standard formulations are often insufficient to address unique business rules. A critical

research gap exists where many models do not explicitly integrate strategic constraints such as the presence of priority customers who require differentiated service levels, a topic of growing importance in today's customer-centric, last-mile logistics environment [10]–[12]. In this study, the priority customer mechanism is modeled as a hard scheduling constraint rather than a soft penalty, ensuring that priority customers are always served earlier regardless of distance or route geometry. The development of powerful heuristics and metaheuristics to find high-quality solutions for these complex VRP instances has therefore been a major focus of contemporary research [13].

This study specifically addresses the challenges faced by a frozen food distributor. The company utilizes a diverse (*heterogeneous*) fleet and implements a strategic policy to prioritize service for certain customers, a factor that introduces additional complexity into route determination. The significance of this research lies in its effort to bridge the gap between existing VRP theory and actual business practice through the development of a tailored model for the Heterogeneous Fleet VRP [14], [15]. This study also contributes a practical Excel-based VBA optimization tool that makes advanced routing methods accessible to SMEs. In addition, the model provides a clear managerial insight by showing that the fleet can be reduced from four to three vehicles, resulting in measurable cost savings.

The primary objective of this research is to design and develop an extension of the classic CVRPTW model, originally built by Solomon [16], by modifying its formulation to accommodate the priority customer constraint. Priority customers are modeled using a hybrid mechanism that combines strict ordering constraints, and modified time-window logic. To achieve this, the Large Neighbourhood Search (LNS) algorithm is employed, with the model's implementation and solution process carried out using Visual Basic for Applications (VBA) within Microsoft Excel [17]. LNS and its adaptive variants remain state-of-the-art metaheuristics, frequently implemented to solve complex VRPs due to their flexibility and effectiveness in exploring vast solution spaces [18]–[20]. The algorithm's efficacy relies on a 'destroy and repair' mechanism, where the strategic choice of removal and insertion operators is critical to its success, with ongoing research continuously proposing more sophisticated operator designs [21]. This methodology has proven robust in a wide range of logistics applications, affirming its suitability for this study [22]. As its main conclusion, the study validates the model's efficacy by revealing a pathway to major operational improvements. The results show a significant optimization of the vehicle fleet, leading to a marked reduction in the total distance traveled and a considerable decrease in overall distribution expenditures [23].

## 2. MODEL DEVELOPMENT

This section describes the characteristics of the system, notations and assumptions, the mathematical model, and the proposed solution procedure.

### 2.1. System Description

The system analyzed in this study represents the distribution process of a frozen food distributor operating in the Solo Raya region, Indonesia. The company serves a diverse range of customers, including supermarkets, minimarkets, and hotels. Distribution activities are carried out using a heterogeneous fleet of four vehicles, consisting of two light trucks (each with a capacity of 300 boxes) and two light commercial vans (each with a capacity of 120 boxes). Every vehicle is operated by a two-person crew comprising one driver and one assistant.

Daily operations are conducted between 08:00 and 16:30, with a maximum working duration of eight hours per crew, including a 30-minute break. The service time at each customer location consists of a variable unloading component—approximately 30 seconds per box—and a fixed administrative component ranging from five to fifteen minutes, depending on the customer category. A key operational constraint is the company's strategic policy to prioritize early deliveries to customers classified as Local Modern Trade (LMT) supermarkets to maintain high service levels and strengthen customer satisfaction.

### 2.2. Notations and Assumptions

The following notations are used in this model.

Decision variables:

$X_{ijk}$  : Vehicle  $k$  traveling from node  $i$  to node  $j$

$Y_k$  : The type of vehicle  $k$  employed

Sets:

$V$  : Set of customers

$K$  : Set of vehicles

$A$  : Set of arcs  $(i, j)$

$P$  : Set of priority customers

$N$  : Set of non-priority customers

Parameters:

$d_{ij}$  : Distance between the customer  $i$  and customer  $j$ .

$q_i$  : Demand/service quantity at the customer  $i$ .

$S_i$  : Service time at the customer  $i$ .

$F_k$  : Fixed operational cost of the vehicle  $k$ .

$c_k$  : Variable transportation cost per kilometer for the vehicle  $k$ .

$Q_k$  : Maximum capacity of the vehicle  $k$ .

$T^*$  : Maximum allowable working time of the vehicle  $k$ .

$P_v$  : Priority service cut-off time; Priority status (1 = priority customer, 0 otherwise).

The following assumptions were adopted in developing the model:

1. The travel distance and travel time for each vehicle are obtained from Google Maps data and are assumed to accurately represent real-world traffic conditions.
2. The service time at each customer location comprises two components: unloading time and administrative time.
3. The total working duration for all distribution activities is assumed to remain constant across each operational day.

### 2.1 Mathematical Model

This study proposes an extended CVRPTW model that integrates heterogeneous fleet characteristics, time window constraints, and a priority customer logic. Unlike simply assigning an early TW, our model forces priority customers to be served earlier via an arrival-time ordering constraint, ensuring they appear earlier in the route even if travel time or geography indicates otherwise. The model is developed based on an empirical case study at a frozen food distribution company in Indonesia. Its formulation is adapted and expanded from the foundational CVRPTW framework originally proposed by Solomon [16].

The decision variables in the model represent the optimal vehicle routing paths and the selection of vehicle types. The objective function aims to minimize the total distribution cost per planning period. The total distribution cost comprises both fixed and variable components: fixed costs include driver and assistant wages, vehicle taxes, and depreciation, while variable expenses cover fuel consumption and vehicle maintenance.

To determine the optimal values of these decision variables, the LNS metaheuristic is employed due to its proven effectiveness in solving complex combinatorial optimization problems. The algorithm is implemented using VBA in Microsoft Excel. LNS was selected because it provides a strong solution quality for medium-sized VRPTW instances, offers flexible destroy–repair operators compatible with heterogeneous fleet and priority constraints, and can be efficiently implemented in Excel VBA, making it suitable for SMEs. The model development process is structured to align with the research objectives and is guided by the characteristics and constraints identified in the case study system. The general formulation of the model is presented as follows.

$$\min Z = \sum \left( F_k Y_k + \sum_i \sum_j c_k d_{ij} X_{ijk} \right) \quad (1)$$

The total transportation cost is composed of two main components: fixed costs and variable costs. The fixed cost component includes driver and assistant wages, vehicle taxes, and depreciation expenses. In contrast, the variable cost component consists of fuel consumption and vehicle maintenance expenses. These cost components collectively form the objective function of the model, which aims to minimize the overall distribution cost. Based on these cost definitions, the model is subject to the following constraints:

1. This constraint ensures that each customer is visited exactly once by a single vehicle, preventing both unserved customers and duplicate visits, and thereby guaranteeing complete demand fulfillment without routing redundancy

$$\sum_{j \in V} \sum_{k \in K} X_{ijk} = 1, \forall i \in V \tag{2}$$

2. The constraint enforces that each vehicle route starts at the depot, reflecting the operational condition in which all distribution activities originate from a centralized facility.

$$\sum_{i \in V_0} X_{0jk} = 1, \forall k \in K \tag{3}$$

3. The constraint requires that every active vehicle return to the depot after completing its route, ensuring that all routes are closed and operationally feasible within a daily planning horizon.

$$\sum_{i \in V} X_{i0k} - \sum_{j \in V} X_{0jk} = 0, \forall k \in K \tag{4}$$

4. The constraint restricts the total customer demand served by a vehicle not to exceed its maximum load capacity, and represents the physical limitations of the vehicles, ensuring that the routing solution is feasible in practice

$$\sum_{i \in V} q_i \sum_{j \in V} X_{ijk} \leq Q_k Y_k \tag{5}$$

5. The constraint ensures that the combined travel time and service time of each vehicle route does not exceed the maximum allowable working time, thereby maintaining compliance with daily operational and labor regulations.

$$\sum_{i \in V} S_i Y_k + \sum_{i,j \in A} d_{ij} X_{ijk} \leq W_k, \forall k \in K \tag{6}$$

6. This constraint defines the binary nature of the routing decision variables, indicating whether a vehicle travels from node  $i$  to node  $j$ , and ensures logical consistency in route selection.

$$X_{ijk} \in \{0,1\} \forall i, j \in V, \forall k \in K \tag{7}$$

7. The constraint links route selection to vehicle activation, ensuring that a vehicle is considered active only if it is assigned to at least one route segment, and enables accurate accounting of fixed fleet-related costs.

$$Y_k \in \{0,1\} \forall k \in K \tag{8}$$

8. Priority customer service time constraint. Both constraints enforce that priority customers are served before a predefined cut-off time, regardless of route geometry or travel distance. This mechanism models priority service as a hard scheduling constraint, ensuring that priority customers are consistently served earlier within each delivery route.

$$t_i \leq T^*, \forall i \in P \tag{9a}$$

$$t_i > T^*, \forall j \in N \tag{9b}$$

### 3. RESULTS

#### 3.1. Development of the VBA tool

The first stage involves the development of a VBA-based computational tool designed to support parameter calculation and solution search processes. The tool integrates several key worksheets, including a custom user interface (ribbon), an initial configuration sheet, a location database, a distance–time matrix, a vehicle data sheet, and a solution output sheet. Each component was developed to ensure seamless interaction between data input, computation, and result visualization.

The construction of the VBA tool represents the foundation of the model’s solution procedure. It provides a structured environment that mirrors the operational characteristics of the distribution system while enabling automation of route optimization and cost evaluation tasks. [Figure 1](#) to [Figure 5](#) illustrate the structure and interface of the developed VBA tool, demonstrating its functionality and alignment with the modeled system characteristics. [Figure 1](#) explains the initial configuration worksheet, which is used to verify that all initial





3.2. Model Execution through Replications

Following the development of the VBA-based tool, the model was executed through a series of replications to determine the optimal routing and fleet allocation solutions. The replications were conducted over a specified period corresponding to the week with the highest customer demand within a given month. This approach was adopted to ensure that the model was tested under the most operationally demanding conditions.

The results of these replications are summarized in Table 1 to Table 3, which present the daily run summaries and the corresponding costs incurred by each fleet. In the summary of the simulation results over a six-day replication period, the cost incurred by each vehicle is reported; a zero cost indicates that the vehicle was not utilized. The summarized results include the total travel distance along with the number of iterations (Table 1). Based on these results, the total distance traveled by all fleets using the optimized model amounts to 2,271.02 km.

Table 1. Summary of distance traveled for all replications

Day	Distance Traveled Vehicle 1 (km)	Distance Traveled Vehicle 2 (km)	Distance Traveled Vehicle 3 (km)	Distance Traveled Vehicle 4 (km)	Total Distance Traveled (km)
1	131.19	169.55	114.41	0	415.15
2	202.56	151.02	165.48	0	519.06
3	124.06	0	100.81	0	224.87
4	179.56	163.77	35.51	0	378.84
5	180.98	129.05	115.47	0	425.50
6	194.34	113.26	0	0	307.60
<b>TOTAL</b>					2,271.02

Meanwhile, the comparison of the total distance traveled per day between the actual system and the modified model is presented in the Figure 6.

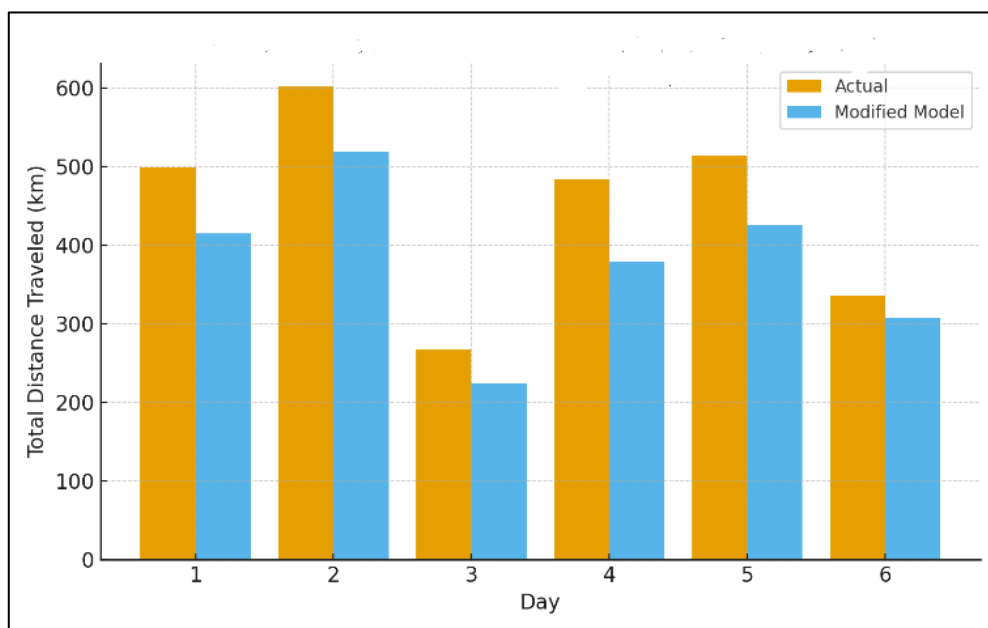
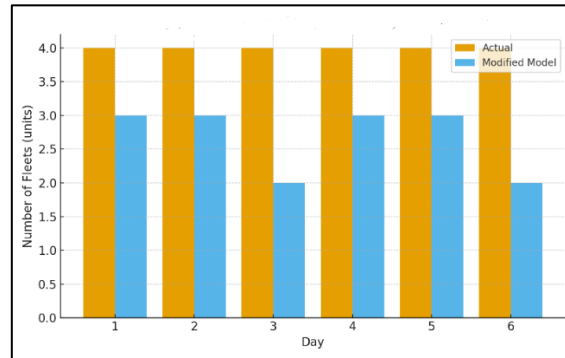


Figure 6. Total distance traveled per day: Actual vs. modified model

The second set of results includes the fleet travel time summary, in which Fleet 4 was not utilized in any replication, resulting in a working time of zero (Table 2). Based on these results, a comparison of the number of fleets used per day between the actual system and the modified model can be made, as shown in the Figure 7.

**Table 2.** Summary of travel time for all replications

Day	Travel Time Vehicle 1 (H:Mn)	Travel Time Vehicle 2 (H:Mn)	Travel Time Vehicle 3 (H:Mn)	Travel Time Vehicle 4 (H:Mn)
1	6:03	6:27	6:56	0:00
2	7:53	7:45	7:57	0:00
3	6:13	0:00	5:40	0:00
4	7:21	6:33	2:51	0:00
5	7:36	6:44	7:09	0:00
6	7:45	6:51	0:00	0:00

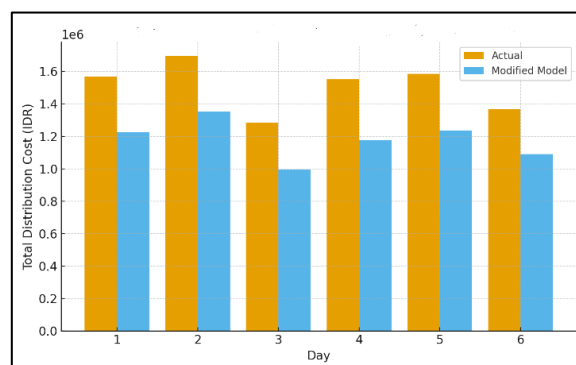


**Figure 7.** Number of fleets used per day: Actual vs. modified model

Based on the total cost across all replications, the total distribution cost amounts to IDR 8,498,627. Furthermore, Fleet 4 was not utilized; therefore, its total cost reflects only the fixed cost of IDR 236,865 (Table 3). Meanwhile, Figure 8 illustrates a comparison of the total daily distribution cost between the actual system and the modified model.

**Table 3.** Summary of total cost for all replications

Day	Cost Vehicle 1 (Rp)	Cost Vehicle 2 (Rp)	Cost Vehicle 3 (Rp)	Cost Vehicle 4 (Rp)	Total Cost (Rp)
1	399,554	445,698	379,528	236,865	1,461,645
2	485,415	423,411	443,224	236,865	1,588,915
3	390,981	241,734	362,570	236,865	1,232,150
4	457,747	438,747	281,151	236,865	1,414,510
5	459,458	396,975	380,861	236,865	1,474,159
6	475,527	377,991	236,865	236,865	1,327,248
<b>TOTAL</b>					<b>8,498,627</b>



**Figure 8.** Total distribution cost per day: Actual vs. modified model.

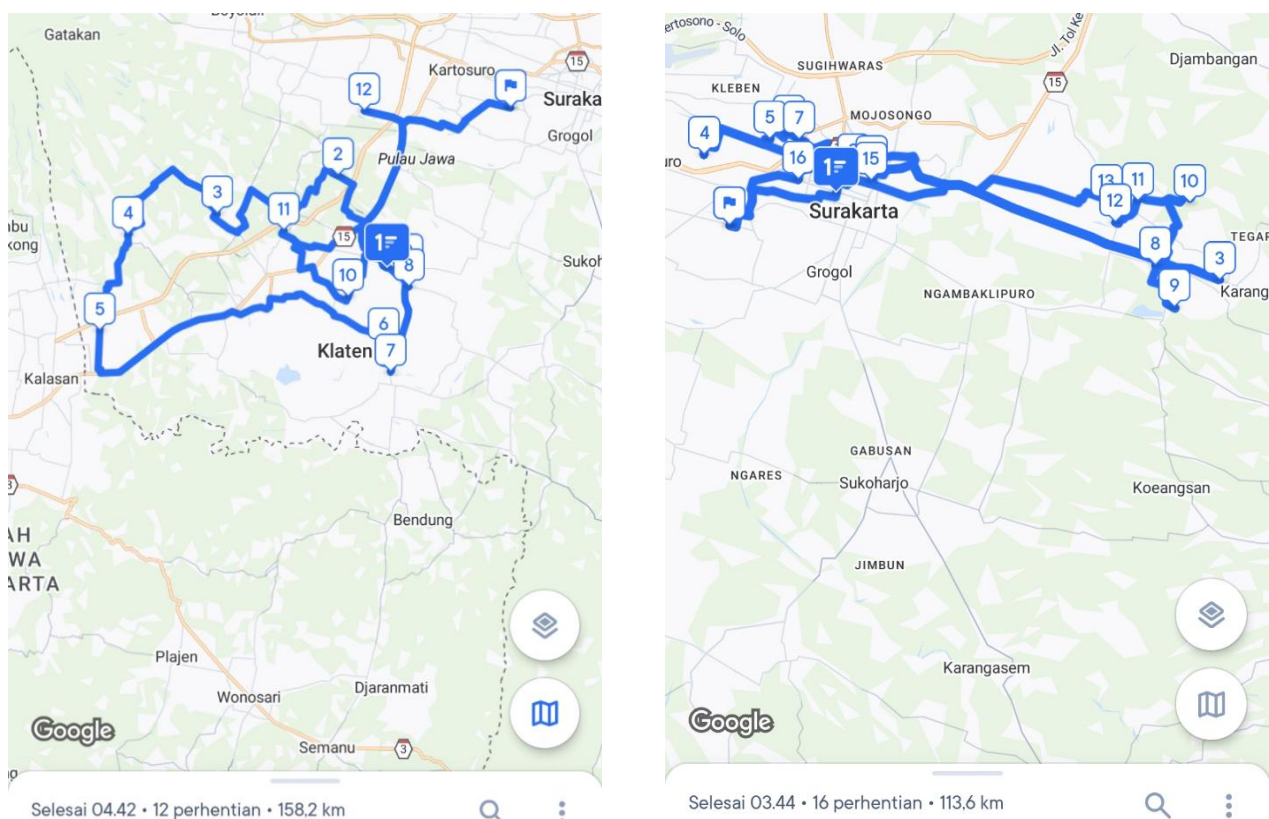


3.3. Model validation

The third stage validates the model outputs to ensure that all constraints are satisfied and that the total travel distance generated by the VBA model aligns with actual distances obtained from Google Maps. This validation step confirms the accuracy and reliability of the model implementation.

The validation process was conducted to assess the realism and feasibility of the routes generated by the developed model. The results from the model runs indicate that all routing solutions are feasible and comply with the applied operational constraints. Specifically, the working time for each active vehicle adheres to the eight-hour daily limit and remains within the operational window of 08:00–16:30. Additionally, vehicle load levels do not exceed the respective maximum capacities. For the first day of operation, the model dispatched Fleets 1, 2, and 3, while Fleet 4 remained unused.

Route validation was further performed by comparing the total distances generated by the VBA model with the corresponding distances obtained from Google Maps (Figure 9). This comparison confirms that the distances computed by the model closely align with real-world conditions, demonstrating high consistency between simulated and actual route data. Table 4 presents a detailed comparison between the actual distances and the model-generated distances for each vehicle used on the first day of delivery. The close correspondence between the two validates the model’s accuracy and applicability for real distribution operations.



(a) Actual route

(b) Route generated by the proposed model

Figure 9. Actual route on the first day for Fleet 3 (GM Blind Van 1).

Table 4. Validation of actual and model-generated route distances

No.	Vehicle Type	Calculated Distance (km)		Validated Distance (km)	
		Actual	Modified Model	Actual	Modified Model
1	Hino LT 1	221,4	131,19	225,8	128,8
2	Hino LT 2	59,4	169,55	57,6	171,2
3	GM Blind Van 1	151,5	114,41	158,2	113,6
4	GM Blind Van 2	65,1	0	64	0

3.4. Sensitivity analysis

The final stage performs sensitivity analysis on the vehicle load capacity parameter to assess the model’s responsiveness to parameter changes. The analysis examines scenarios with capacity variations of ±5% and ±10% to evaluate the stability and scalability of the proposed model.

In this study, a sensitivity analysis was conducted to evaluate the model’s responsiveness to changes in vehicle load capacity. The analysis examined variations of -10%, -5%, +5%, and +10% in the load capacity parameter during the third day of the delivery period. Under the baseline scenario, the total distribution cost was IDR 995,285 (derived from IDR 1,232,150 after subtracting the fixed cost of the fourth vehicle), with a total travel distance of 224.87 km. The results of the sensitivity analysis are summarized in Table 5 and Table 6.

**Table 5.** Summary of sensitivity analysis for vehicle load capacity (-5% and -10%)

Vehicle Type	Capacity Change (%)	Load Capacity (boxes)	Distance Traveled (km)	Cost per Fleet (IDR)	Total Cost (IDR)
GM Blind Van 1	-5	114	73.48	328,495	
Hino LT 1	-5	285	155.73	429,077	
Hino LT 2	-5	285	0	241,734	999,306
GM Blind Van 1	-10	108	73.51	328,532	
Hino LT 1	-10	270	162.47	437,185	
Hino LT 2	-10	270	0	241,734	1,007,451

**Table 6.** Summary of sensitivity analysis for vehicle load capacity (+5% and +10%)

Vehicle Type	Capacity Change (%)	Load Capacity (boxes)	Distance Traveled (km)	Cost per Fleet (IDR)	Total Cost (IDR)
GM Blind Van 1	+10	132	52.72	302,607	
Hino LT 1	+10	330	167.63	443,393	
Hino LT 2	+10	330	0	241,734	987,734
GM Blind Van 1	+5	126	84.15	338,098	
Hino LT 1	+5	315	140.37	410,599	
Hino LT 2	+5	315	0	241,734	990,431

The analysis reveals that variations in vehicle load capacity have a substantial influence on both total travel distance and overall distribution cost. An increase in fleet capacity enables the model to generate more efficient routing solutions, thereby reducing total travel distance and, consequently, overall distribution expenditures. In contrast, a reduction in vehicle capacity limits feasible routing combinations and may compel vehicles to travel longer distances to meet all customer demands, which increases variable costs and total distribution expenses. These findings confirm that the model is highly sensitive to changes in vehicle capacity, emphasizing the strategic importance of optimal fleet configuration and capacity planning in enhancing logistics efficiency.

In addition, a sensitivity analysis was conducted to examine how the routing results change when the priority rule is relaxed. Three scenarios were compared: strict priority enforcement, a relaxed priority window, and the absence of priority constraints. The findings show that relaxing the rule increases routing flexibility and reduces both distance and cost, while the strict-priority case yields the highest operational cost due to limited routing freedom.

4. DISCUSSION

The application of the proposed LNS-based CVRPTW model to the case study of a frozen food distributor demonstrates its effectiveness in addressing the company’s complex distribution planning challenges. The simulation results for the peak demand period reveal that the required fleet can be optimized from four to

three vehicles, indicating that the current capacity is sufficient without additional resources. The optimized configuration results in a significant reduction in total travel distance—from 2,702.1 km to 2,271.02 km over six operational days—leading to notable operational cost savings. Under the optimized policy, the total distribution cost decreases, corresponding to a 21.84% reduction (Table 7). These improvements highlight the model's ability to enhance resource utilization and overall distribution efficiency.

**Table 7.** Comparative analysis of actual and optimized model results

Day	Total Distance Traveled (km)		Number of Fleets (units)		Total Distribution Cost (IDR)	
	Actual	Modified Model	Actual	Modified Model	Actual	Modified Model
1	499.5	415.15	4	3	1,567,627	1,224,780
2	602	519.06	4	3	1,696,544	1,352,050
3	267.3	224.87	4	2	1,285,869	995,285
4	484.2	378.84	4	3	1,552,538	1,177,645
5	513.5	425.5	4	3	1,584,815	1,237,294
6	335.6	307.6	4	2	1,367,463	1,090,383
<b>TOTAL</b>	<b>2,702.1</b>	<b>2,271.02</b>	<b>4</b>	<b>3</b>	<b>9,054,856</b>	<b>7,077,437</b>

Compared with existing models in the literature, such as those presented by Adi and Kusniawati [24], Fadjriani, et al. [25], which primarily considers homogeneous fleets, the proposed model provides additional value by simultaneously integrating two key dimensions of real-world distribution systems: heterogeneous fleet composition and priority customer service. While prior CVRPTW formulations offer strong methodological foundations, their simplifying assumptions often restrict their applicability in practice. By relaxing these assumptions, the present model achieves greater realism and applicability for distributors managing mixed fleets and differentiated customer segments. From an implementation perspective, the use of an Excel-based VBA optimization tool aligns with prior work by Erdogan [26], who demonstrated that spreadsheet-based VRP solvers can effectively support real-world decision making for small and medium-sized enterprises. This supports the practical relevance of the proposed model, particularly in environments where access to specialized optimization software is limited.

A further strength of the model lies in its explicit incorporation of the priority customer policy. Instead of assuming uniform service among all customers, the model prioritizes high-value clients, thereby aligning distribution decisions with corporate service-level objectives and customer retention strategies. From a managerial perspective, the developed framework serves as an effective decision-support tool that enables planners to transition from experience-based routing toward data-driven optimization. It provides quantitative evidence for both daily operational planning and long-term strategic decisions, such as fleet sizing, allocation, and investment planning. Moreover, the results emphasize the critical role of accurate data acquisition—particularly for travel time and service parameters—in sustaining optimization performance. The reduction in total distance traveled under the modified model also implies lower fuel use and consequently reduced CO<sub>2</sub> emissions. Because vehicle emissions are strongly correlated with distance, the improved routing contributes directly to a smaller carbon footprint even without calculating exact emission values.

The sensitivity analysis further validates the model's robustness. Variations of -10%, -5%, +5%, and +10% in vehicle load capacity were examined to assess the model's responsiveness to parameter changes. This parameter was selected because of its dual physical and financial significance. The analysis reveals that moderate adjustments in capacity substantially affect total distance and cost outcomes, underscoring the importance of optimal fleet utilization. These findings highlight a key managerial insight: even small improvements in capacity planning can generate measurable efficiency gains, reinforcing the value of continuous fleet assessment in logistics operations.

## 5. CONCLUSION

Based on the data processing and analysis presented in the preceding sections, several key conclusions can be drawn regarding the developed optimization model and its operational impact. This study successfully developed and implemented an LNS-based model for determining optimal routing and fleet allocation in

frozen food distribution. A major contribution of the model lies in its capability to incorporate priority customer service constraints, ensuring that high-priority clients are served earlier within each delivery route. The proposed model provides a systematic framework that minimizes total distribution costs through the simultaneous optimization of fleet configuration and routing decisions. A key contribution of this research is the VBA-based optimization tool, which offers a practical solution for firms without specialized software. The model also delivers a direct managerial insight by identifying that only three vehicles are required, reducing operational costs significantly.

The results indicate that a strategic reduction in the company's fleet size enhances distribution efficiency without compromising service performance. Specifically, the analysis suggests the removal of one Grand Max Blind Van (Fleet 4), which remained unused throughout the VBA-based simulations. Consequently, an optimal fleet configuration consists of three operational units: two Hino Light Trucks and one Grand Max Blind Van.

The application of the model yields substantial improvements in operational performance. The optimized routing configuration reduces the total travel distance from 2,702.1 km under actual operating conditions to 2,271.02 km, representing a 15.95% reduction in distance. Correspondingly, the total distribution cost decreases from IDR 9,054,856 to IDR 7,077,437, resulting in a cost saving of 21.84%. These findings validate the effectiveness of the LNS-based CVRPTW approach in enhancing distribution efficiency and demonstrate its practical applicability for logistics systems that employ heterogeneous fleets and prioritize service requirements.

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