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Application of K-Means Clustering and OR-Tools to Optimize Rice Distribution: A Case Study of Perum Bulog Indonesia

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***Abstract*—Food security is a key priority for the Indonesian government, essential for maintaining economic and political stability. To meet the nation's nutritional needs, the government must ensure stable, affordable food availability across the country. Rice, Indonesia's primary staple, is consumed at an average of 139 kilograms per capita annually, with a dependency rate of 97%. To address food security challenges, the government has tasked Perum BULOG, a State-Owned Enterprise, with managing the Food Supply and Price Stabilization Program (SPHP) for rice. This paper proposes a method to optimize the distribution to Perum BULOG's retailers, known as Rumah Pangan Kita (RPK), using the Heterogeneous Capacitated Vehicle Routing Problem (HCVRP). The study employs the K-Means algorithm for clustering RPK addresses and Guided Local Search via OR-Tools to determine optimal transportation types. The results indicate a 21% reduction in delivery costs, significantly enhancing the efficiency of the SPHP rice distribution process, thereby supporting food security in Indonesia.**

***Keywords*— Heterogeneous capacitated vehicle routing problem (HCVRP), k-means algorithm, transportation.**

I. Introduction

Indonesia is currently facing food security issues, as a policy priority for the nation's leaders [1], [2]. Strategic management policies have been established to ensure a sustainable food supply and facilitate public access to affordable food [3]. Rice, the primary staple consumed by Indonesians, sees an average annual consumption of 139 kilograms per capita, with a dependency rate of 97% [2], [4], [5], [6]. To address these food security issues, the Indonesian government, through the National Food Agency, has implemented the Rice Supply and Price Stabilization Program (SPHP) in collaboration with Perum BULOG, a State-Owned Enterprise specializing in food logistics [7], [8], [9], [10].

Perum BULOG plays a crucial role in stabilizing rice prices at the consumer level so that price increases can be curbed during lean seasons [11], through distribution channels like *Rumah Pangan Kita* (RPK) [12]. However, the current distribution process to RPKs is inefficient, as it relies on customer order queues without considering optimal routing and vehicle capacity, leading to increased costs and slower delivery times [13]. To address these inefficiencies, this research focus on optimizing the distribution of SPHP rice by Perum BULOG to the RPKs in the Greater Jakarta area (JABODETABEK). The study employs the Heterogeneous Capacitated Vehicle Routing Problem (HCVRP) to determine the most efficient routes and appropriate vehicle types, thereby reducing shipping costs and enhancing delivery efficiency [14], [15].

In previous studies, distribution optimization was conducted with the aid of linear programming based on decision variables such as distance and cost [2], [16]. Additionally, other studies have discussed route optimization using the saving matrix method [17]. The Traveling Salesman Problem (TSP) is one of the distribution issues frequently addressed in past studies; however, TSP does not account for vehicle capacity, a critical factor given that each RPK order averages up to 2 tons per delivery. This study builds on this literature by applying K-Means clustering and Guided Local Search via OR-Tools to optimize rice distribution, ultimately contributing to improved food security in Indonesia.

II. Related Work

A. Supply Chain Management

Supply Chain Management (SCM) plays an important role in increasing distribution efficiency and reducing shipping costs [20], [21]. Recent research highlights the importance of SCM integration in achieving cost efficiency and competitive advantage through effective distribution strategies [22]. They found that close collaboration between manufacturers, suppliers, and logistics service providers can significantly reduce shipping costs by consolidating shipments, optimizing routes, and improving vehicle utilization [23]. Additionally, the importance of technologies such as transportation management systems and supply chain visibility to enhance efficiency and reduce waste in the distribution process [24], [25]. By

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effectively integrating the flow of information, materials, and finances, SCM enables companies to optimize their distribution networks, reduce logistics costs, and improve customer service, thereby enhancing overall competitiveness [24]. Recent advancements in metaheuristic algorithms, such as hybrid genetic algorithms and particle swarm optimization, have shown promising results in solving complex CVRP instances within SCM, enabling more efficient distribution planning for large-scale supply chains [25].

B. Transportation Problem

The Transportation Problem (TP) is an optimization problem related to the efficient shipping or distribution of goods [26]. In the context of logistics, TP is used to determine the routes and quantities of goods to be delivered from sources to destinations at minimum cost [27]. According to a study published in the European Journal of Operational Research, TP can be applied in various industries, such as freight shipping, public transportation, and supply chain management, to improve operational efficiency and reduce costs [28]. In recent years, research related to TP has evolved using various approaches, such as metaheuristics and genetic algorithms [29]. The study's results indicated that the metaheuristic approach could enhance delivery efficiency and reduce costs [30]. Additionally, another study used genetic algorithms to solve TP with distance and cost constraints [31]. The results showed that the genetic algorithm approach could improve delivery efficiency and reduce costs [32].

C. K-Means Clustering

K-Means Clustering is a highly popular data clustering algorithm widely applied in various fields, such as customer segmentation, transportation infrastructure planning, and natural resource demand analysis. According to [33], the K-Means algorithm was used to classify the number of clean water customers in Indonesia from 1995 to 2015 based on their province of residence. Meanwhile, [34] revealed that K-Means is also utilized for customer segmentation based on their RFM (Recency, Frequency, and Monetary) values, and compared its performance with the Fuzzy C-Means algorithm. On the other hand, [35] proposed a modification to the K-Means algorithm by combining it with a noise algorithm to automatically detect urban hotspots and determine the optimal number of clusters.

Although K-Means Clustering has been widely adopted in various cases, the algorithm has weaknesses in determining the number of clusters and initializing the initial centroids accurately [36]. To address these shortcomings, several studies, discussed new methods for better initial centroid determination and compare these with other approaches such as Fuzzy C-Means [34], [35]. Additionally, the evaluation of clustering results is conducted using various evaluation indices like DB, PBM, SC, and SSE [35]. With appropriate modifications and evaluations, K-Means Clustering has the potential to become a highly effective algorithm for clustering data and uncovering patterns within it more accurately and reliably. Furthermore, recent research has explored the integration of K-Means with other techniques to enhance its performance and applicability in complex scenarios. For instance [37], proposed a novel approach combining K-Means with spectral clustering and manifold learning, demonstrating improved accuracy and robustness in handling high-dimensional data and non-convex cluster shapes.

D. Heterogeneous Capacitated Vehicle Routing Problem

The Heterogeneous Capacitated Vehicle Routing Problem (HCVRP) is an extension of the Capacitated Vehicle Routing Problem (CVRP) that reflects real-world situations where the vehicle fleet used has different characteristics, particularly in terms of each vehicle's carrying capacity [38]. The objectives of HCVRP can vary, such as minimizing the longest travel time of all vehicle routes (min-max objective) or minimizing the total travel time of all vehicle routes (min-sum objective) [39]. Additionally, HCVRP may involve additional constraints like delivery time limits that must be met, so delivery delays need to be considered in solving the problem [40]. To address the complexity of HCVRP, various exact and heuristic methods have been developed by researchers. Some of the latest proposed methods include a deep reinforcement learning approach using an attention mechanism [39], a mixed integer programming formulation solved with Memetic Algorithm and Simulated Annealing methods [40], and a branch-and-cut algorithm based on Benders decomposition [41]. Computational results show that these methods can produce better solutions compared to previous conventional methods and perform very well in solving HCVRP.

E. Linear Programming

Linear programming is an optimization technique used in solving the Capacitated Vehicle Routing Problem (CVRP) [42]. CVRP is typically formulated as a linear program with the objective of minimizing the total travel distance by reducing transportation costs while considering vehicle capacities [43]. The decision variables in the linear programming model are binary variables representing the vehicle routes between locations. Previous research modeled the electric vehicle routing problem with time windows as a multi-objective mixed-integer linear programming problem [44]. Additionally, there is a combination of variable neighborhood search with linear programming to solve the multi-product green VRP [45]. These studies demonstrate that linear programming can be used to model issues in CVRP, such as assigning product deliveries to customers with the aim of optimizing costs [46], distance, number of vehicles, time, and emissions.

III. Research Method

The research begins with direct field observations at the headquarters and warehouse of Perum BULOG, where various types of data essential for processing, optimization, and analysis were collected. The data includes a comprehensive list of RPKs (Retail Outlets) that serve as customers of Perum BULOG. For each RPK, the quantity of orders placed was recorded, along with the corresponding delivery addresses. Additionally, the distance from the Perum BULOG warehouse to each RPK was measured, and shipping costs were calculated based on the transportation mode used. Furthermore, the capacity of each available transportation mode for delivering goods was documented. The primary sources of this data were BULOG's internal logistics records, transportation cost

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schedules, and operational staff reports gathered during site visits.

After collecting the raw data, the RPK address data was processed to group the RPKs into delivery clusters using the K-Means Clustering algorithm. The clustering was implemented in Python, with the primary parameter for K-Means being the geographical coordinates, such as latitude and longitude of each RPK, which allowed for spatial grouping of outlets into clusters. This method aimed to reduce total delivery distances by creating clusters of geographically close RPKs. Each cluster was then optimized for delivery routes to reduce costs and time spent on transportation.

Once the RPKs were grouped into clusters, the next step involved calculating the distances between each RPK within a cluster to form a distance matrix. This distance matrix served as a crucial input for solving the delivery route optimization problem. The Heterogeneous Capacitated Vehicle Routing Problem (HCVRP) method was used to optimize the delivery routes. This problem was solved using the Guided Local Search algorithm from the OR-Tools library, also implemented in Python. OR-Tools was chosen for its robust capabilities in handling vehicle routing problems and its flexibility in integrating real-world constraints such as vehicle capacity and varying transportation costs..

The next stage of this research involves determining all sets, parameters, and variables used to solve the delivery route optimization problem.

Table 1.
Sets, Parameter, and Variables

Sets	Description
V	Set of Customer Points or RPK and Depots, denoted by i and j
K	Set of Vehicles Used
Parameter	**Description**
R_{ij}	Distance from point i to point j
C_k	Cost or shipping cost per km for vehicle k
Q_k	Vehicle k's capacity
d_i	Demand or request from customer RPK
Variables	**Description**
X_{ij}^{k}	1, if there is a journey from point i to point j with vehicle k 0, if there is no journey from point i to point j with vehicle k
Y_i^k	1, if point i is visited by vehicle k 0, if point i is not visited by vehicle k

This research aims to optimize the delivery routes from Perum BULOG warehouse locations to each RPK site to achieve equitable distribution of SPHP rice products to every RPK location, thereby enhancing food security in Indonesia, particularly in the JABODETABEK region. In line with the study's objective, equation (1) is formulated as the optimization process goal, aiming to determine the most efficient routes with the minimum distance, where $X_{i,j}$ represents the distance that delivery vehicles must travel from point i to point j.

$$Minimize \sum_{k\in K}\sum_{i\in V}\sum_{j\in V} c_k\, r_{ij}\, X_{ij}^{k} \tag{1}$$

Besides determining the objectives of the optimization process, to solve the route optimization problem using HCVRP, it is also necessary to establish the constraints of this study based on real-life cases in the field. The first constraint refer to (2), that each customer location is visited exactly once by only one type of vehicle.

$$\sum\nolimits_{k\in K}^{n} y_i^k = 1, \forall i \in V \tag{2}$$

The second constraint refer to (3), that for each vehicle k, the number of vehicles leaving the depot must be equal to the number of vehicles returning to the depot, and for each vehicle k that performs deliveries, it will always originate or start from the depot, where the depot is represented by 0.

$$\sum_{j\in V}^{n} x_{0jk} = \sum_{j\in V}^{n} x_{j0k} = 1,\ k \in K \tag{3}$$

The third constraint refer to (4), that each vehicle will visit one point or location RPK i. Afterward, the vehicle must leave that RPK location to proceed to the next RPK location or return to the BULOG warehouse or depot.

$$\sum_{j\in V}^{n} x_{ijk} - \sum_{j\in V}^{n} x_{jik} = 0, \forall i \in V,\ k \in K, i \neq j \tag{4}$$

The fourth and final constraint refer to (5), that vehicles have a maximum capacity limit of Q_k which means that the delivery routes for customer orders (RPK) must not exceed the capacity of the vehicle used.

$$\sum\nolimits_{i\in V}^{n} d_i\, y_i^k \leq Q_k, \forall k \in K \tag{5}$$

This comprehensive approach, combining K-Means Clustering for initial grouping and HCVRP optimization with specific constraints, aims to provide an efficient and practical solution for Perum BULOG rice distribution challenges in the JABODETABEK region. By minimizing total travel distance while respecting vehicle capacities and ensuring each RPK is served, this method strives to enhance the overall efficiency and effectiveness of the food distribution system, ultimately contributing to improved food security in Indonesia.

IV. RESULT

Customer RPK data from Perum BULOG is grouped based on clustering results from K-Means processing, as shown in Fig. 1. There are 71 RPK address points, which are then divided into 5 cluster groups. This clustering approach allows for more efficient route planning by grouping geographically proximate RPKs together, enabling better utilization of vehicle capacities and reducing overall travel distances. The detailed results of the cluster assignments using the K-Means algorithm are presented in Table 2 through Table 6.

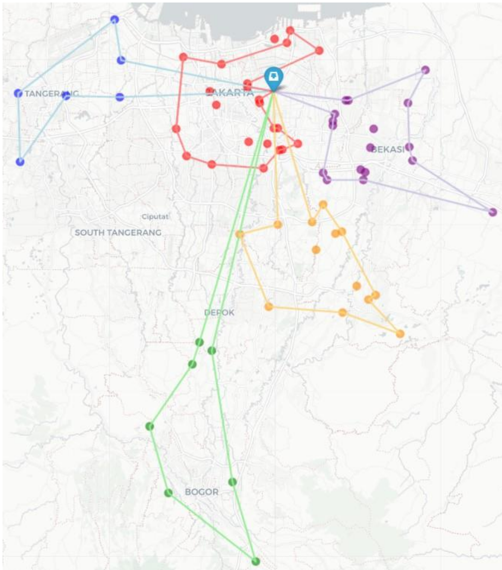

Fig. 1. Clustering visualization using k-means.

Table 2.
Results of K-Means Clustering for Cluster 0

Cluster 0	
No	RPK
1	RPK - AS-SYIFA
2	RPK - YPP
3	DKI RPK PD PADI SUBUR
4	RPK - DENI BERKAH
5	RPK - ARA MURNI
6	RPK - BERKAH TANGERANG
7	RPK - TOKO KITA

Table 3.
Results of K-Means Clustering for Cluster 1

Cluster 1	
No	RPK
1	RPK - TOKO RIZKY
2	RPK - AGEN BERAS SUMBER JAYA ABADI
3	RPK - PT MULTI RASA BINTANG
4	DKI RPK LAZUARDI GEMILANG
5	DKI RPK YUNI TRI
6	RPK - SUKSES SEJAHTERA
7	RPK - BERKAH FAMILY
8	DKI RPK ENYA
9	RPK - M ADAM
10	RPK - MAJU JAYA LOGISTIK
11	RPK - TOKO AL HADID
12	RPK - DEWI SRI

Table 3 Continued.
Results of K-Means Clustering for Cluster 1

Cluster 1	
No	RPK
13	RPK - REVA
14	RPK - SUMBER REZEKI
15	RPK - WARUNG PAKPAHAN
16	RPK - KIOS BERAS HANIFAH
17	DKI RPK HARAPAN ELIM
18	RPK - HABEEL FOOD
19	RPK - TOKO BERAS DHIA
20	RPK - TOKO ANUGERAH
21	RPK - RAHMATAN II
22	RPK - THEO JAYA
23	RPK - TOKO PODOMORO
24	RPK - JELITA BERAS

Table 4.
Results of K-Means Clustering for Cluster 2

Cluster 2	
No	RPK
1	RPK - PRATAMA
2	RPK - SAWUNG JANUR KUNING
3	RPK - ABRAL JAYA
4	RPK - LARIS MANIS
5	RPK - MURNI JAYA
6	RPK - TOKO JEMBATAN BOLA PURI
7	RPK - ABI FROZEN FOOD
8	RPK - BUDE LALA

Table 5.
Results of K-Means Clustering for Cluster 3

Cluster 3	
No	RPK
1	DKI RPK AKU DAN KAMU
2	DKI RPK IMAM DAN UMAM
3	DKI RPK MAJU TIGA SEKAWAN
4	DKI RPK PURNABAKTI LOGISTIK
5	DKI RPK SEJAHTERA (KEN RICK)
6	RPK - KHANSA
7	RPK - KOPERASI KONSUMEN GUYUB RUKUN SANB
8	RPK - NURAZ GERAI SEMBAKO
9	RPK - TOKO SEMBAKO "SUMBER PANGAN SEHAT"
10	RPK - TOKO SEMBAKO SUMBER PANGAN SUKSES
11	RPK - TOKO USAHA BARU DUA
12	RPK - WARUNG HANAN
13	RPK - NANDA
14	RPK - SUMBER KONDANG
15	RPK - TOKO BERAS PURNAMA
16	RPK - TOKO ONJ
17	RPK - RIANG MARKET
18	DKI RPK TOKO BAROKAH JAYA ROROTAN

Table 6.
Results of K-Means Clustering for Cluster 4

Cluster 4	
No	RPK
1	DKI RPK BAKTI
2	DKI RPK HUSNA II
3	DKI RPK RATNA
4	RPK - HUSNA 1
5	RPK - TOKO PUDING
6	RPK - ALMEERA
7	DKI RPK RAVENALA 327
8	RPK - BENHIL SEMBAKO
9	RPK - SAMARA
10	RPK - TOKO BERAS "RANIA"
11	RPK - SWASEMBADA
12	RPK - ADE RAHMAT APENDI
13	RPK - TOKO RANURA SHOP
14	RPK - VIAN SEMBAKO

The results of processing the Heterogeneous Capacitated Vehicle Routing Problem (HCVRP), focusing on minimizing distance and the number of orders per RPK, are analyzed using OR-Tools to determine optimal routes for each vehicle and vehicle type selection within each cluster. This sophisticated approach takes into account the varying capacities of different vehicle types, ensuring that the most appropriate vehicle is assigned to each route based on the demand and geographical distribution of the RPKs within each cluster. Each proposed route for every cluster can be viewed in Table 7, detailing the total distance and total cost, providing a comprehensive overview of the optimized distribution plan.

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Table 7.
Proposed Routes in each Cluster

Cluster	Proposed Truck	Proposed Route	Demand (ton)	Total Distance (km)	Total Cost (IDR)
Cluster 0	Truck B	0-6-0	4	73.30	1,308,387.15
	Truck C	0-3-4-0	8	76.80	2,380,738.00
	Truck C	0-1-2-0	8	70.52	2,186,058.00
	Truck C	0-5-7-0	8	107.59	3,335,383.00
Cluster 1	Truck A	0-8-0	2	20.78	220,289.20
	Truck A	0-17-0	2	23.61	250,234.20
	Truck A	0-18-0	2	20.06	212,604.20
	Truck A	0-22-0	2	22.83	241,976.80
	Truck A	0-24-0	2	10.16	112,996.00
	Truck A	0-3-0	2	12.14	128,715.80
	Truck B	0-1-0	4	20.76	370,583.85
	Truck B	0-10-0	4	18.70	333,795.00
	Truck B	0-13-0	4	21.19	378,259.35
	Truck B	0-15-0	4	17.86	318,818.85
	Truck B	0-16-0	4	11.84	211,254.75
	Truck B	0-9-0	4	6.69	119,470.05
	Truck B	0-14-0	4	41.97	749,093.10
	Truck B	0-23-19-0	4	18.45	329,243.25
	Truck B	0-7-0	4	19.75	352,555.35
	Truck C	0-4-0	6	6.88	213,156.00
	Truck C	0-6-5-0	8	10.43	323,299.00
	Truck C	0-2-12-11-0	8	46.81	1,451,203.00
	Truck C	0-20-21-0	8	19.53	605,523.00
Cluster 2	Truck A	0-5-0	2	119.44	1,266,106.40
	Truck C	0-4-1-0	8	124.92	3,872,427.00
	Truck C	0-8-7-0	8	94.01	2,914,434.00
	Truck C	0-6-2-3-0	8	122.01	3,782,155.00
Cluster 3	Truck B	0-11-0	4	77.17	1,377,430.95
	Truck B	0-17-0	4	22.17	395,734.50
	Truck C	0-6-0	6	30.59	948,383.00
	Truck C	0-14-12-0	8	32.02	992,527.00
	Truck C	0-4-3-7-0	8	58.22	1,804,913.00
	Truck C	0-16-13-0	8	24.21	750,541.00
	Truck C	0-2-9-10-0	8	46.81	1,451,203.00
	Truck C	0-18-5-1-0	8	56.91	1,764,241.00
	Truck C	0-8-15-0	8	39.13	1,212,875.00
Cluster 4	Truck A	0-2-0	2	51,94	550,595.80
	Truck B	0-9-10-0	4	77.31	1,380,037.05
	Truck B	0-8-0	4	62.36	1,113,143.85
	Truck B	0-7-0	4	87.43	1,560,536,25
	Truck B	0-13-0	4	38.46	686,475.30
	Truck C	0-4-3-0	8	51.74	1,603,847.00
	Truck C	0-11-6-0	8	75.20	2,331,324.00
	Truck C	0-1-5-0	8	51.68	1,602,111.00
	Truck C	0-14-12-0	8	54.18	1,679,518.00
	Total		244	2097.05	51,174,196.00

The results of processing using OR-Tools show that there are 3 types of trucks: Single Cab Pick Up with a capacity of 2-ton capacity (Truck A), CDD Bak/Box with a 4-ton capacity (Truck B), and Fuso with an 8-ton capacity (Truck C). Table 1 indicates that there are 2 types of trucks scheduled for delivery to cluster 0: one unit of Truck B and three units of Truck C. Delivery to cluster 1 is conducted using 3 types of trucks: 6 units of Truck A, 9 units of Truck B, and 4 units of Truck C. Vehicles used for delivery to cluster 2 include 2 types of trucks: 1 unit of Truck A and 3 units of Truck C. Furthermore, delivery to cluster 3 is carried out using 2 types of trucks: 2 units of Truck B and 7 units of Truck C. Finally, delivery to cluster 4 is done using 3 types of trucks: 1 unit of Truck A, 4 units of Truck B, and 4 units of Truck C. The total distance required for delivering SPHP rice products to each RPK customer location after optimization based on HCVRP (Heterogeneous Capacitated Vehicle Routing Problem) is 2,097.05 km, with a total delivery cost amounting to Rp51,174,196.00. Detailed distance and cost calculations for each cluster based on OR-Tools are presented in Table 8.

Table 8.
Distance and Cost Calculations Based on OR-Tools Optimization

Cluster	Total Distance (km)	Total Cost (IDR)
Cluster 0	328.208	9,210,566.15
Cluster 1	370.931	6,923,070.75
Cluster 2	460.380	11,835,122.40
Cluster 3	387.230	10,697,848.45
Cluster 4	550.300	12,507,588.25

Solving the Heterogeneous Capacitated Vehicle Routing Problem (HCVRP) for the delivery of SPHP rice by Perum BULOG to RPKs has demonstrated significant cost savings, as shown in Table 9. The total delivery cost incurred by Perum BULOG before optimization was Rp61,804,487.20, while the total cost after optimization is Rp51,174,196.00. This represents a 21% reduction in costs, highlighting the efficiency of optimizing delivery routes using the HCVRP model.

Table 9.
Decision Cost

	Total Distance (km)	Total Cost (IDR)
Before Optimization	3352.56	61,804,487.20
After Optimization	2097.05	51,174,196.00
Savings	1255.51	10,630,291.20
Savings (%)		**-21%**

In addition to cost savings, the optimization enhances operational efficiency, potentially improving service quality by facilitating more timely and efficient deliveries. A key finding of this study is the substantial reduction in total travel distance, which can lead to faster delivery times, reduced fuel consumption, and decreased vehicle wear and tear. These factors contribute not only to immediate cost reductions but also to long-term operational sustainability and environmental benefits. Moreover, by improving vehicle utilization and reducing overall transportation effort, the optimized routing supports BULOG's broader goals of resource efficiency and service excellence

V. CONCLUSION

This study demonstrates the significant impact of applying the Heterogeneous Capacitated Vehicle Routing Problem (HCVRP) method in optimizing the delivery routes of SPHP rice by Perum BULOG. By analyzing data from 71 RPK customer points and clustering them into 5 groups using the K-Means algorithm, followed by route optimization through Guided Local Search with OR-Tools, we achieved a notable reduction in total travel distance to 1,255.51 km and a 21%

decrease in delivery costs, from Rp61,804,487.20 to Rp51,174,196.00. These results highlight the crucial role of HCVRP-based route optimization in enhancing logistics efficiency.

The reduction in shipping costs directly contributes to the government's efforts to improve food security by ensuring that rice remains accessible and affordable for the population. The efficiency gains from this study not only support stable food prices but also have the potential to minimize food spoilage and reduce consumer prices, ultimately bolstering Indonesia's food security framework.

Future research could enhance the HCVRP model by integrating green logistics principles to further optimize environmental sustainability in delivery routes. This could involve using low-emission vehicles, optimizing fuel usage, and selecting routes that minimize carbon footprints. Additionally, incorporating considerations of road infrastructure conditions, such as road quality and traffic congestion, would provide deeper insights into balancing efficiency with sustainability. These enhancements would support the development of logistics strategies that are not only cost-effective but also environmentally friendly, contributing to climate change mitigation and environmental preservation.

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