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Fuel Distribution Optimization in Malang: A Hybrid Routing Approach

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ABSTRACT

Fuel distribution optimization is essential for reducing costs, minimizing travel distances, and improving supply efficiency. In Indonesia, increasing fuel demand and shifting policies necessitate an optimized Pertamax distribution strategy. However, existing routing methods remain inefficient, leading to higher operational costs. This study addresses this gap by applying a hybrid optimization approach, integrating Clarke-Wright Savings (CWS) for route grouping, Nearest Neighbour (NN) for delivery sequencing, and Goal Programming (GP) for vehicle allocation, cost, and time optimization. The dataset includes 60 Pertashop locations and weekly Pertamax demand, with distance matrices derived from Google Maps. MATLAB is used for GP model computation. Results show that the optimized routes reduce total travel distance from 1,121.8 km to 981.8 km (12.5%), while GP minimizes distribution costs by 59.68% and delivery time by 48.68%. This integrated approach enhances fuel supply chain efficiency, outperforming conventional routing through structured clustering and optimized delivery sequencing. These findings contribute to logistics optimization by integrating heuristic and mathematical programming, offering a scalable solution for fuel distribution and broader supply chain networks.

Keywords: Clarke-Wright Savings; Fuel Distribution Optimization; Goal Programming; Nearest Neighbour; Vehicle Routing Problem (VRP)

INTRODUCTION

Fuel distribution is a critical component of energy logistics, ensuring a stable supply for both economic activities and daily life. An efficient distribution system not only ensures a stable energy supply but also helps reduce operational costs and improve the effectiveness of the supply chain [1]. In Indonesia, PT Pertamina is responsible for the production and distribution of fuel across the country [2]. As the number of motor vehicles continues to rise, particularly in high-mobility regions such as East Java, the demand for fuel has also increased significantly [3].

However, this growing fuel consumption presents new challenges, regarding cost efficiency and environmental impact [4]. Carbon emissions from motor vehicles continue to rise, leading to a decline in air quality in major cities. One of the key contributing factors is the use of low-octane fuel, such as Pertalite, which produces higher emissions compared

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to higher-octane alternatives like Pertamax [5]. To address this issue, the Indonesian government has implemented restrictions on Pertalite purchases [6]. This policy aims to reduce environmental impact while encouraging consumers, particularly those in the middle-to-upper economic class, to transition to Pertamax, which is more environmentally friendly. This shift in fuel policy requires an optimized distribution strategy to ensure an efficient and cost-effective supply of Pertamax, particularly in high-demand regions.

The primary challenge in fuel distribution is determining an optimal route that minimizes total travel distance, delivery time, and operational costs while ensuring demand fulfillment. One of the key factors influencing this efficiency is the selection of an optimal distribution route. This challenge is commonly framed as a Vehicle Routing Problem (VRP) [7], where inefficient routes can lead to increased operational costs, higher fuel consumption, and delivery delays [8]. Studies have shown that optimizing distribution routes can reduce costs by up to 28% [9], making it a crucial aspect of improving energy distribution efficiency.

One of the widely used methods for solving VRP is the Clarke-Wright Savings (CWS) algorithm [10], which focuses on reducing travel distances by merging routes with potential distance savings [11]. This method has been applied in various sectors, including optimizing postal distribution routes in the Czech Republic [12] and steel distribution in Thailand [13]. While CWS is effective in reducing travel distance, it does not explicitly optimize the sequence of deliveries within a route, which can further improve efficiency. To address this, the Nearest Neighbour (NN) algorithm is employed as a complementary method to systematically arrange distribution points, not only shortening travel distances but also accelerating the delivery process [14]. Further explanations regarding NN can be found in [15].

Despite these advancements, fuel distribution involves additional complexities beyond distance and time, such as vehicle capacity constraints, cost efficiency, and delivery schedules. Traditional VRP approaches primarily focus on minimizing distance but often overlook multi-objective optimization factors, such as balancing the number of vehicles, reducing total costs, and ensuring equitable fuel distribution. A more comprehensive approach is required, which integrates multiple objectives into the optimization process. One such method is Goal Programming (GP) [16], which enables the simultaneous optimization of multiple criteria, making it well-suited for complex distribution problems. GP has been successfully applied in various domains, including production scheduling [17] and transportation network management [18], yet its application in fuel distribution remains underexplored. Further details on GP can be found in [19].

Although previous studies have explored individual applications of CWS, NN, and GP in logistics and transportation, their combined implementation in fuel distribution has not been thoroughly investigated. Most prior research has primarily focused on either minimizing transportation costs or optimizing route selection, without integrating delivery sequencing and multi-objective cost efficiency into a single model [20]. To address this gap, this study aims to develop a comprehensive approach to fuel distribution by integrating CWS algorithm to determine optimal routes grouping, NN algorithm to arrange delivery sequences, and GP to enhance efficiency based on multiple strategic objectives. Through this approach, the study is expected to enhance the efficiency of Pertamax fuel distribution by reducing operational costs, minimizing travel distances, accelerating delivery times, and ensuring a more equitable fuel supply for the public, while also supporting Indonesia's carbon emission reduction policies. This research contributes to the advancement of fuel distribution optimization by integrating route optimization, delivery sequencing, and multi-objective cost minimization into a unified model, providing a practical solution for improving fuel logistics in Indonesia.

METHODS

The method used in this study integrates the Clarke-Wright Savings (CWS) algorithm, the Nearest Neighbour (NN) algorithm, and the Goal Programming (GP) approach to optimize fuel distribution in Malang City. The study specifically focuses on the distribution of Pertamax fuel, ensuring efficient routing and scheduling to meet demand at Pertashop stations. The combination of these three methods is justified as follows: CWS minimizes total travel distance by grouping delivery routes based on the highest savings values, NN determines the optimal delivery sequence within each route to further reduce travel distance, and GP optimizes the number of vehicles, distribution costs, and total delivery time to achieve an efficient distribution strategy.

The dataset used in this study includes the geographical locations of 60 Pertashop stations and one central depot, along with the weekly demand for Pertamax fuel at each Pertashop. The vehicle fleet consists of fuel tankers, each with a maximum capacity of 8,000 liters, dedicated solely to Pertamax distribution. Distance data between all locations are obtained from Google Maps and compiled into a distance matrix.

The CWS algorithm is applied to group routes based on the highest savings values. This process includes constructing a distance matrix, calculating the savings matrix, sorting savings values in descending order, and forming delivery routes by selecting Pertashop combinations with the highest savings values until the vehicle's capacity is reached. Once the routes are established, the NN algorithm is used to determine the optimal delivery sequence within each route by sequentially selecting the nearest unvisited Pertashop from the depot until all deliveries are completed.

The results from the CWS and NN algorithms serve as input for the GP method, which optimizes the number of vehicles used, distribution costs, and total delivery time. The GP model is formulated by defining decision variables, operational constraints, and objective functions aligned with the company's efficiency targets. The model is solved using MATLAB software. The entire research process is illustrated in Figure 1. This approach ensures that fuel distribution is conducted efficiently in terms of distance, time, and cost.

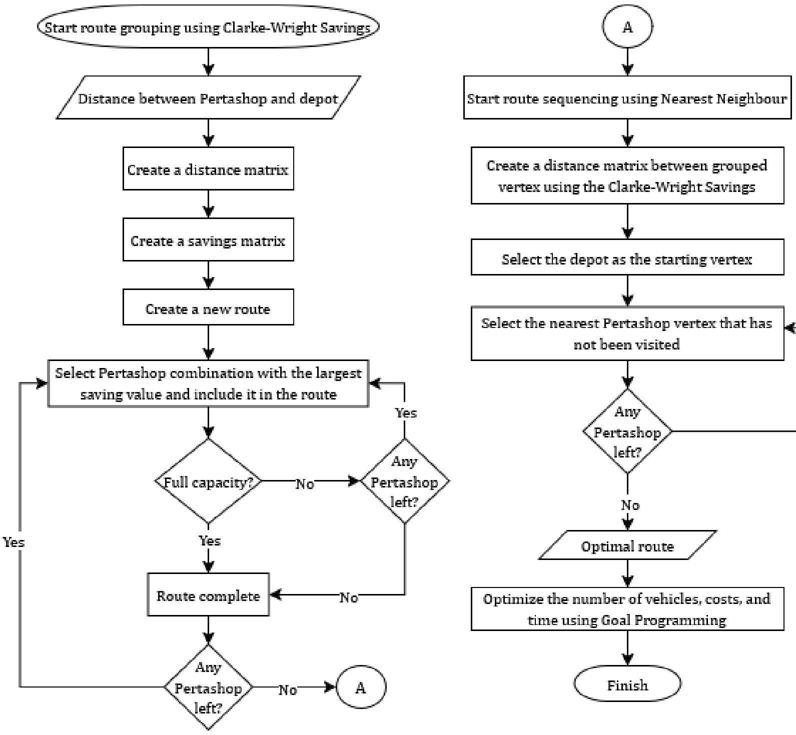

Figure 1. Research Flowchart

RESULTS AND DISCUSSION

Route Optimization

A weighted graph is constructed to represent the fuel distribution network, consisting of one depot and 60 Pertashop locations. Each location, including the depot and Pertashops, is represented as a vertex in the set of vertices $V = \{v_0, v_1, v_2, \ldots, v_{60}\}$ where v_0 represents the depot, and v_1 to v_{60} represent the Pertashop locations. The complete set of vertices is presented in Table 1 below.

Table 1. List of vertex

Vertex	Pertashop	Vertex	Pertashop	Vertex	Pertashop
$\boldsymbol{v_0}$	Pagak	v_{21}	Sarangan	v_{42}	Sumberejo
$\boldsymbol{v_1}$	Depot	v_{22}	Dampit	v_{43}	Buring
$\boldsymbol{v_2}$	Kalisongo	v_{23}	Blayu	v_{44}	Ngabab
$\boldsymbol{v_3}$	Purwosekar	v_{24}	Madyopuro	v_{45}	Candirenggo
$\boldsymbol{v_4}$	Kebobang	v_{25}	Sanankerto	v_{46}	Jeru
$\boldsymbol{v_5}$	Sumbergesing	v_{26}	Tawangrejeni	v_{47}	Pringu
$\boldsymbol{v_6}$	Parangargo	v_{27}	Jatimulyo	v_{48}	Kedungsalam
$\boldsymbol{v_7}$	Sidorenggo	v_{28}	Karangsuko	v_{49}	Srimulyo
$\boldsymbol{v_8}$	Bululawang	v_{29}	Ngajum	v_{50}	Dinoyo
$\boldsymbol{v_9}$	Karangnongko	v_{30}	Baturetno	v_{51}	Argosuko
$\boldsymbol{v_{10}}$	Bumirejo	v_{31}	Sumbersuko	v_{52}	Tamanharjo
$\boldsymbol{v_{11}}$	Sukolilo	v_{32}	Karangwidoro	v_{53}	Kedungpedaringan
$\boldsymbol{v_{12}}$	Ngijo	v_{33}	Gampingan	v_{54}	Punten
$\boldsymbol{v_{13}}$	Curungrejo	v_{34}	Wajak	v_{55}	Sumberbrantas
$\boldsymbol{v_{14}}$	Tawangargo	v_{35}	Landungsari	v_{56}	Ngroto
$\boldsymbol{v_{15}}$	Wonokerto	v_{36}	Gadungsari	v_{57}	Gading Kasri
$\boldsymbol{v_{16}}$	Dengkol	v_{37}	Tumpang	v_{58}	Sidorejo
$\boldsymbol{v_{17}}$	Gubukklakah	v_{38}	Ardimulyo	v_{59}	Dadapan
$\boldsymbol{v_{18}}$	Saptorenggo	v_{39}	Kromengan	v_{60}	Karangpandan
$\boldsymbol{v_{19}}$	Ngadirejo	v_{40}	Tlogomas		

Vertex	**Pertashop**	**Vertex**	**Pertashop**	**Vertex**	**Pertashop**
$\boldsymbol{v_{20}}$	Sitiarjo	v_{41}	Jambangan		

To determine the optimal distribution routes, the following sequential steps are carried out using the Clarke-Wright Savings and Nearest Neighbour algorithms:

1. Create the Distance Matrix
   The first step involves determining the distance matrix, which provides the distances between each pair of vertices. The distance matrix from the depot (v_0) to each Pertashop (v_1 to v_{60}) is presented in Table 2.

Table 2. Distance Matrix

	$\boldsymbol{v_0}$	$\boldsymbol{v_1}$	$\boldsymbol{v_2}$	$\cdots$	$\boldsymbol{v_{58}}$	$\boldsymbol{v_{59}}$	$\boldsymbol{v_{60}}$
$\boldsymbol{v_0}$	0			$\cdots$			
$\boldsymbol{v_1}$	34	0		$\cdots$			
$\boldsymbol{v_2}$	8,5	39,5	0	$\cdots$			
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$			
$\boldsymbol{v_{58}}$	33,1	20,4	35,2	$\cdots$	0		
$\boldsymbol{v_{59}}$	28	37,2	35,5	$\cdots$	18,1	0	
$\boldsymbol{v_{60}}$	14	23,9	18,2	$\cdots$	23,2	27,1	0

2. Create the Savings Matrix
   The savings matrix is generated by calculating the savings value for each pair of Pertashops using the following formula:

$$S_{ij} = C_{i0} + C_{0j} - C_{ij} \tag{1}$$

   for $i, j = 1,2, \dots, n$ and $i \neq j$. Here, C_{i0} represents the distance from Pertashop i to the depot, C_{0j} is the distance from the depot to Pertashop j, and C_{ij} is the direct distance between Pertashop i and Pertashop j. The resulting savings matrix, computed using equation (1), is presented in Table 3.

Table 3. Saving Matrix

	$\boldsymbol{v_1}$	$\boldsymbol{v_2}$	$\cdots$	$\boldsymbol{v_{58}}$	$\boldsymbol{v_{59}}$	$\boldsymbol{v_{60}}$
$\boldsymbol{v_1}$	0		$\cdots$			
$\boldsymbol{v_2}$	3	0	$\cdots$			
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$
$\boldsymbol{v_{58}}$	46,7	6,4	$\cdots$	0		
$\boldsymbol{v_{59}}$	25	1,2	$\cdots$	43	0	
$\boldsymbol{v_{60}}$	24,5	4,7	$\cdots$	24,3	15,5	0

3. Sorting the Savings Values
   The savings values from the matrix in Table 3 are sorted in descending order to prioritize route combinations that provide the greatest savings. The sorted savings values are presented in Table 4.

Table 4. Descending Order of Saving Values

No	**Pair**	**Saving Values**
1	(v_5, v_{20})	88,2
2	(v_7, v_{36})	84,7
3	(v_{10}, v_{36})	81,5
$\vdots$	$\vdots$	$\vdots$
3720	(v_{44}, v_{47})	-8,9
3721	(v_{44}, v_{49})	-10,5

4. Route grouping Using Clarke-Wright Savings algorithm:
   a. The first Pertashop pair is selected based on the highest saving value, 88.2,

between v_5 and v_{20}. These vertices are included in the first route, forming the temporary route (v_0, v_5, v_{20}, v_0) with a total demand of 2.000+2.000=4.000 L.

b. The next Pertashop is selected based on the next highest saving value is 72.7, between v_{20} and v_7, leading to an updated route $(v_0, v_5, v_{20}, v_7, v_0)$ with a total demand of 2.000+2.000+1.000=5.000 L.

The iteration process of the CWS algorithm is repeated until all Pertashop vertices are included in the routes, which meet the vehicle capacity constraint of 8,000 liters. The route grouping continues following the same pattern until all vertices have been visited once. All route groupings is presented in Table 5 below.

Table 5. Result of CWS Algorithm

Route	Pertashop	Demand	Total Demand	Route	Pertashop	Demand	Total Demand
1	v_{20}	2000	8000	**2**	v_{36}	1000	8000
	v_5	2000			v_{10}	2000	
	v_7	1000			v_{22}	3000	
	v_{49}	1000			v_{41}	1000	
	v_{42}	1000			v_{58}	1000	
	v_{26}	1000					
3	v_1	2000	8000	**4**	v_{56}	3000	8000
	v_{48}	2000			v_{44}	2000	
	v_{15}	1000			v_{55}	1000	
	v_{33}	1000			v_{54}	1000	
	v_{53}	1000			v_{14}	1000	
	v_{28}	1000					
5	v_{59}	3000	7000	**6**	v_{19}	2000	8000
	v_{25}	2000			v_{39}	1000	
	v_{23}	1000			v_4	1000	
	v_{46}	1000			v_{29}	1000	
	v_{34}	1000			v_{60}	3000	
7	v_9	2000	8000	**8**	v_{16}	2000	8000
	v_{17}	1000			v_{30}	2000	
	v_{37}	1000			v_{45}	3000	
	v_{51}	1000			v_{38}	1000	
	v_{11}	3000					
9	v_3	2000	8000	**10**	v_{12}	2000	7000
	v_{47}	2000			v_{40}	1000	
	v_8	3000			v_{35}	2000	
	v_{31}	1000			v_{50}	2000	
11	v_2	2000	7000	**12**	v_{24}	2000	8000
	v_{32}	1000			v_{18}	2000	
	v_{57}	2000			v_{43}	2000	
	v_6	2000			v_{27}	2000	
13	v_{13}	1000	6000				
	v_{21}	3000					
	v_{52}	2000					

5. Route sequencing using Nearest Neighbour algorithm

Once the route groupings are established, the Nearest Neighbour (NN) algorithm is applied to optimize the delivery sequence within each route. Route 1 consists of $v_5, v_{20}, v_7, v_{42}, v_{26}$and v_{49}. Next, a distance matrix is created for the selected Pertashop.

Table 6. Distance Matrix of Route 1

	$\boldsymbol{v_0}$	$\boldsymbol{v_5}$	$\boldsymbol{v_{20}}$	$\boldsymbol{v_7}$	$\boldsymbol{v_{42}}$	$\boldsymbol{v_{26}}$	$\boldsymbol{v_{49}}$
$\boldsymbol{v_0}$	0						

v_5	46,8	0					
v_{20}	58,2	16,8	0				
v_7	60,7	45,4	46,2	0			
v_{42}	37,9	10,5	26,7	47,7	0		
v_{26}	33,3	14,2	25,5	36,8	11,3	0	
v_{49}	40,1	19,3	27,6	25,4	26,5	15,5	0

The route formed based on the distance matrix for Route 1, as shown in Table 6 above, begins at the depot (v_0). From v_0, the closest vertex is v_{26}, followed by v_{42}, which is the nearest to v_{26}. Then, from v_{42}, the closest vertex is v_5. The next nearest vertex from v_5 is v_{20}, and after that, the closest vertex to v_{20} is v_{49}. Finally, the remaining point is v_7, completing the route as (v_0, v_{26}, v_{42}, v_5, v_{20}, v_{49}, v_7, v_0). The total distance for this route is 33.3 + 11.3 + 10.5 + 16.8 + 27.6 + 25.4 + 60.7 km = 185.6 km. The iteration process of sorting the vertices on the route using NN algorithm continues repeatedly in a similar pattern until route 13 is formed. The resulting routes from the Clarke-Wright Savings algorithm, with the sequence determined using the Nearest Neighbour algorithm, are presented in Table 7.

Table 7. Optimal Route Using CWS and NN Algorithm

No.	Route	Demand	Distances (Km)
1	$(v_0, v_{26}, v_{42}, v_5, v_{20}, v_{49}, v_7, v_0)$	8.000	185,6
2	$(v_0, v_{41}, v_{22}, v_{10}, v_{36}, v_{58}, v_0)$	8.000	102,3
3	$(v_0, v_{28}, v_{53}, v_{33}, v_{15}, v_1, v_{48}, v_0)$	7.000	119,4
4	$(v_0, v_{14}, v_{54}, v_{55}, v_{56}, v_{44}, v_0)$	8.000	100,1
5	$(v_0, v_{34}, v_{59}, v_{25}, v_{23}, v_{46}, v_0)$	7.000	76,2
6	$(v_0, v_{60}, v_{29}, v_4, v_{19}, v_{39}, v_0)$	8.000	71,4
7	$(v_0, v_{51}, v_{37}, v_9, v_{17}, v_{11}, v_0)$	8.000	71
8	$(v_0, v_{45}, v_{38}, v_{30}, v_{16}, v_0)$	8.000	44,1
9	$(v_0, v_8, v_{31}, v_3, v_{47}, v_0)$	8.000	46,9
10	$(v_0, v_{50}, v_{40}, v_{53}, v_{12}, v_0)$	7.000	38,2
11	$(v_0, v_{57}, v_2, v_{32}, v_6, v_0)$	7.000	30,6
12	$(v_0, v_{43}, v_{24}, v_{18}, v_{27}, v_0)$	8.000	33,4
13	$(v_0, v_{21}, v_{52}, v_{13}, v_0)$	6.000	62,6
	TOTAL	98000	981,8

Comparison with Existing Routes

The next step is to compare the generated route with the existing route currently in use.

Table 8. Route Existing Company

No.	Route	Demand	Distances (Km)
1	$(v_0, v_{21}, v_{27}, v_{50}, v_{40}, v_0)$	8.000	24,5
2	$(v_0, v_{57}, v_2, v_{32}, v_{35}, v_{14}, v_0)$	8.000	49,6
3	$(v_0, v_{43}, v_{24}, v_{18}, v_{11}, v_{51}, v_0)$	8.000	51,4
4	$(v_0, v_6, v_{60}, v_{13}, v_{53}, v_{28}, v_0)$	8.000	53,9
5	$(v_0, v_8, v_{31}, v_3, v_{47}, v_0)$	8.000	46,9
6	$(v_0, v_{12}, v_{45}, v_{38}, v_{52}, v_0)$	8.000	46,6
7	$(v_0, v_{37}, v_9, v_{34}, v_{23}, v_{25}, v_0)$	8.000	65,6
8	$(v_0, v_{16}, v_{30}, v_{17}, v_{59}, v_0)$	8.000	95,2
9	$(v_0, v_{29}, v_4, v_{19}, v_{39}, v_{33}, v_1, v_0)$	8.000	101
10	$(v_0, v_{54}, v_{55}, v_{56}, v_{44}, v_{41}, v_0)$	8.000	153,7
11	$(v_0, v_{46}, v_{58}, v_{26}, v_{42}, v_{15}, v_5, v_{49}, v_0)$	8.000	132,7
12	$(v_0, v_{22}, v_{10}, v_{36}, v_7, v_{48}, v_0)$	8.000	184,3
13	(v_0, v_{20}, v_0)	2.000	116,4
	Total	98000	1.121,8

The calculation results using the Clarke-Wright Savings and Nearest Neighbour algorithms, as shown in Table 7, indicate a total distance of 981.8 km, while the existing route in Table 8 results in a total distance of 1,121.8 km. The 140 km reduction, or approximately 12.5%, demonstrates that the combination of these two algorithms is effective in designing a more optimal distribution route compared to the previously used existing route, which employed tree logic with a greedy approach.

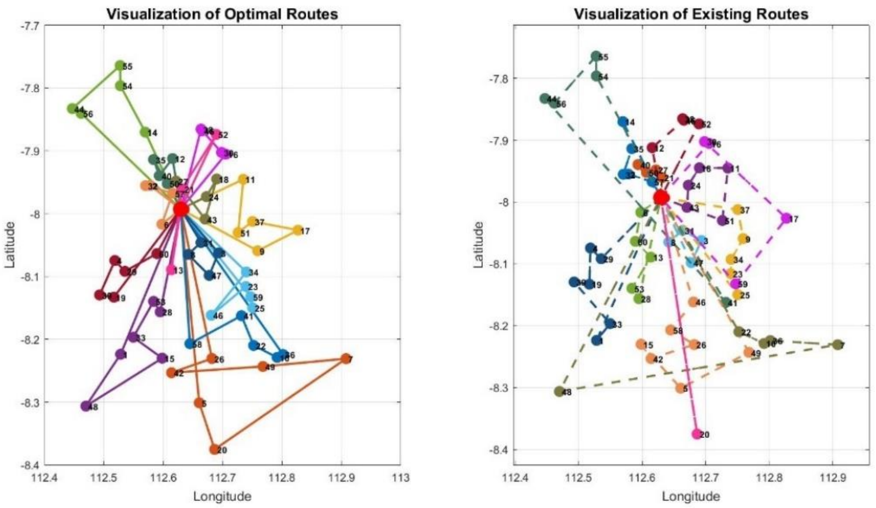

Figure 2. Visualization of Routes

Visualization of the routes is shown in Figure 2, where the optimized route appears more structured with direct connections and well-distributed clusters, reducing unnecessary detours and overlapping paths. In contrast, the existing route exhibits more scattered and intersecting connections, leading to inefficient travel distances and increased operational costs. The improved spatial distribution in the optimized route highlights the effectiveness of optimization methods in achieving a more balanced and cost-effective fuel distribution network.

Goal Programming

In this section, the optimal route results from the Clarke-Wright Savings and Nearest Neighbor algorithms are used as constraint functions to determine the value of the decision variables in the Goal Programming model. The decision variables used in this model are related to the number of vehicles (X) used for each route obtained from the CWS-NN algorithms, so that the decision variable X_i can be written as the number of vehicles for route -i. Next, the constraint function for the Goal Programming model will be determined.

a. Cost Analysis
In this category, the distribution costs for each route are calculated based on fuel consumption and the cost per liter of fuel (Dexlite). The shipping cost for each route is determined using the following equation:

$$Cost\ of\ Distribution = \frac{Fuel\ Consumption\ (L)}{5\ km} \times Cost\ per\ Liter\ (Rp13.600) \quad (2)$$

Fuel consumption for each route is divided by 5 because the data provided represents every liter of Dexlite fuel used to cover a distance of approximately 5 km. The cost calculation for each route, obtained using Equation (2), serves as the coefficient for decision variables (C_i) in the constraint model for minimizing distribution costs. These coefficients represent the cost contribution of each route in the total cost function. Since cost efficiency is a key objective in the distribution process, the Goal Programming model incorporates a constraint function to ensure that total distribution costs remain within the company's budget. This constraint function is formulated as follows:

$$\left(\sum_{i=1}^{13} C_i\, X_i\right) + d_i^- - d_i^+ \leq 6.623.156 \tag{3}$$

To achieve the constraint function in Equation (3), the deviation that must be minimized is d_i^+.

b. Time Analysis

In this category, the distribution time for each route is calculated based on travel time and the time spent loading/unloading the fuel. The travel time for each route is determined using the following equation:

$$Total\ Time\ of\ Distribution = \frac{Distance\ (km)}{Speed\ (\frac{km}{h})} + \left(\frac{Demand}{1.000} \times 0.0833\right) \tag{4}$$

The total time for each route is obtained by summing the travel time and the loading/unloading time. The travel time is calculated by dividing the distance of each route by the vehicle's speed, which is assumed to be 30 km/h. Meanwhile, the loading/unloading time is determined based on the demand at each Pertashop, where 0.0833 hours represents the time required to load or unload 1,000 liters of fuel, assuming a processing rate of 1,000 liters per 5 minutes. Since time efficiency is a critical factor in distribution operations, the Goal Programming model incorporates a constraint function to ensure that the total distribution time remains within the company's operational hours. The total time calculated for each route using Equation (4) serves as the coefficient for decision variables (T_i) in this constraint model, representing the time contribution of each route in the overall time function. The constraint function is formulated as follows:

$$\left(\sum_{i=1}^{13} T_i\, X_i\right) + d_i^- - d_i^+ \leq 84 \tag{5}$$

To achieve the constraint function in Equation (5), the deviation that must be minimized is d_i^+.

c. Fleet Analysis

After analyzing cost and time efficiency, another crucial aspect of the distribution process is optimizing fleet utilization. This ensures that each route is fully utilized with an optimal number of vehicles. Based on the results of the CWS-NN algorithms, each route is assigned one vehicle to maximize operational efficiency. The constraint function for this optimization can be formulated as follows:

$$X_i + d_i^- - d_i^+ = 1 \tag{6}$$

To achieve the constraint function in Equation (6), the deviation that must be minimized is d_i^- and d_i^+.

d. Demand Fulfillment Analysis

In addition to optimizing costs, time, and fleet utilization, ensuring that fuel distribution meets consumer demand is a crucial objective. This constraint function is designed to guarantee that the total fuel delivered to all Pertashops meets the required demand levels. The constraint function for this objective is formulated as follows:

$$\left(\sum_{i=1}^{13} D_i\, X_i\right) + d_i^- - d_i^+ \leq 98.000 \tag{7}$$

To achieve the constraint function in Equation (7), the deviation that must be minimized is d_i^+.

Based on the previously defined constraint functions, the objective function of the Goal Programming model is formulated to minimize the deviation from each constraint. The objective function is formulated as follows:

$$\begin{aligned} Min\ Z = \ & d_1^- + d_1^+ + d_2^- + d_2^+ + d_3^- + d_3^+ + d_4^- + d_4^+ + d_5^- + d_5^+ + d_6^- + d_6^+ + d_7^- + d_7^+ \\ & + d_8^- + d_8^+ + d_9^- + d_9^+ + d_{10}^- + d_{10}^+ + d_{11}^- + d_{11}^+ + d_{12}^- + d_{12}^+ + d_{13}^- + d_{13}^+ \\ & + d_{14}^+ + d_{15}^+ + d_{16}^+ \end{aligned}$$

To solve this optimization model, MATLAB software is utilized. The decision variables, goal constraints, and objective function are implemented within MATLAB to obtain the optimal solution. The following section presents the results of the Goal Programming approach.

Table 9. Optimal Result Of Goal Programming

Constraint	***Route***	***Goal***	***Result***			***Conclusion***
			Value	d_1^-	d_1^+	
Maximizing the utilization of routes	1	1	1	0	0	Achieved
	2	1	1	0	0	Achieved
	3	1	1	0	0	Achieved
	4	1	1	0	0	Achieved
	5	1	1	0	0	Achieved
	6	1	1	0	0	Achieved
	7	1	1	0	0	Achieved
	8	1	1	0	0	Achieved
	9	1	1	0	0	Achieved
	10	1	1	0	0	Achieved
	11	1	1	0	0	Achieved
	12	1	1	0	0	Achieved
	13	1	1	0	0	Achieved
Minimizing the distribution costs		6.623.156	2.670.496	3.952.660	0	Achieved
Minimizing the distribution time		84	40,8901	43,1099	0	Achieved
Maximizing Pertashop demand		98.000	98.000	0	0	Achieved

Based on the results presented in Table 9, all the desired goals in this model have been successfully achieved. This confirms that the Goal Programming approach effectively refines the initial solution obtained from the CWS-NN algorithm, providing a more optimal distribution strategy.

1. Maximizing the Utilization of Routes
   Each route is optimally utilized, as indicated by the fact that all routes (1 to 13) meet the target value of 1 without any deviation (d_1^- and d_1^+ both equal to 0). This means that each route is assigned exactly one vehicle, ensuring efficient fleet deployment.

2. Minimizing the Distribution Costs
   The total distribution cost is successfully minimized, achieving a cost of Rp6,623,156. The negative deviation d_1^- is Rp3,952,660, while the positive deviation d_1^+ is 0, indicating that the total cost remains within the allocated budget and does not exceed the constraint limit. Additionally, total distribution costs were successfully reduced beyond the set target, with cost savings of 59.68%.

3. Minimizing the Distribution Time
   The total distribution time is also minimized to 84 hours, with a negative deviation d_1^- of 43.1099 hours and a positive deviation d_1^+ of 0. This means the actual distribution time is well within the operational limits, contributing to improved scheduling efficiency. Furthermore, the distribution time was successfully reduced approximately 48.68% beyond the initial target, allowing for faster deliveries and improved service reliability.
4. Maximizing the Pertashop Demand
   The total fuel demand for all Pertashop locations, amounting to 98,000 liters, is fully met with no deviation (d_1^- and d_1^+ both equal to 0). This ensures that the supply is sufficient to meet consumer demand without excess or shortage.

Discussion

This study demonstrates the effectiveness of integrating Clarke-Wright Savings (CWS) and Nearest Neighbour (NN) algorithms in optimizing fuel distribution routes. The results confirm that route optimization significantly reduces travel distance, leading to lower fuel consumption and operational costs while improving delivery efficiency. Compared to conventional routing, the optimized routes exhibit better cluster distribution, minimal overlaps, and fewer detours, ensuring a more structured and cost-effective delivery process.

Beyond route efficiency, the goal programming model successfully enhances vehicle allocation and scheduling, optimizing both cost and time. The substantial reduction in distribution expenses and delivery time highlights the model's practicality in improving Pertashop service reliability. If scaled, this approach could contribute to more efficient fuel distribution at a national level, supporting cost savings and resource reallocation for potential network expansion.

These findings align with optimization studies in logistics and supply chain management, where hybrid approaches combining heuristic algorithms and mathematical programming have proven effective. However, this study extends previous work by demonstrating how integrating CWS and NN within a goal programming framework provides additional benefits, particularly in structured route clustering and proportional vehicle allocation.

Despite its effectiveness, certain limitations remain. The model assumes constant travel speeds and static demand, which may not fully capture real-world traffic conditions and fluctuations in fuel consumption. Future research should incorporate dynamic traffic data, demand forecasting, and real-time fleet tracking to improve adaptability. Additionally, exploring a mixed-fleet approach with varying vehicle capacities could further optimize cost efficiency and resource utilization. A hybrid model integrating real-time scheduling and dynamic demand adjustments would enhance the resilience and scalability of fuel distribution networks.

By addressing these challenges, this research contributes to the development of more adaptive and scalable logistics optimization models applicable beyond fuel distribution, extending to broader supply chain and transportation sectors.

CONCLUSIONS

Based on the results obtained, this study demonstrates that integrating Clarke-Wright Savings (CWS) and Nearest Neighbour (NN) algorithms effectively optimizes fuel distribution routes, reducing total travel distance by 140 km (12.5%) to 981.8 km. This reduction confirms that the combined approach enhances route efficiency by minimizing detours and improving delivery structuring. Additionally, Goal Programming successfully optimizes vehicle allocation, ensuring that each of the 13 routes can be completed with a single vehicle. The optimization framework also significantly reduces distribution costs by Rp3,952,660 (59.68%) and delivery time by 40.89 hours (48.68%), surpassing initial targets.

These findings advance logistics optimization by demonstrating the effectiveness of integrating heuristic methods with mathematical programming for fuel distribution. The proposed approach not only improves cost and time efficiency but also ensures accurate demand fulfillment for each Pertashop. The methodology can be adapted to other industries with similar distribution challenges, such as retail logistics and pharmaceutical supply chains.

Future research should focus on integrating real-time traffic data, dynamic demand forecasting, and mixed-fleet vehicle allocation to enhance adaptability and further optimize cost efficiency. Expanding this model to larger-scale distribution networks could provide broader insights into sustainable and resilient logistics planning.

REFERENCES

[1] M. Ridwan and M. Rizal Gaffar, “Efisiensi Persediaan Dan Distribusi Melalui Integrasi Supply Chain Management,” *Applied Business and Administration Journal*, vol. 1, no. 2, pp. 36–44, 2022, [Online]. Available: https://journal.ebizmark.id/index.php/abaj/article/view/14.

[2] F. Wahyuni, “Kualitas Pelayanan PT Pertamina Meulaboh Dalam Penyaluran Bahan Bakar Minyak (BBM) Di Meulaboh,” *Jurnal Akuntansi Manajemen dan Ilmu Ekonomi,* pp. 268–273, 2022.

[3] B. P. Statistik, “Jumlah Kendaraan Bermotor Menurut Provinsi dan Jenis Kendaraan (unit),” 2023. https://www.bps.go.id/id/statistics-table/3/VjJ3NGRGa3dkRk5MTlU1bVNFOTVVbmQyVURSTVFUMDkjMw==/jumlah-kendaraan-bermotor-menurut-provinsi-dan-jenis-kendaraan--unit---2023.html (accessed Jan. 10, 2025).

[4] A. M. Siregar, C. A. Siregar, and M. Yani, “Rekayasa Saluran Gas Buang Sepeda Motor Guna Mengurangi Pencemaran Udara,” *Jurnal Rekayasa Material Manufaktur dan Energi*, vol. 2, no. 2, pp. 171–179, 2019, doi: 10.30596/rmme.v2i2.3672.

[5] N. Larasati, “Prediksi Emisi Karbon Kendaraan Pribadi Dan Rekomendasi Kendaraan Alternatif Menggunakan Machine Learning Dengan Model Neural Network,” *Proceedings of Life and Applied Sciences*, vol. 8, p. 2023, 2023, [Online]. Available: https://www.kaggle.com/datasets/debajyotipodder/co2-emission-by-vehicles.

[6] L. N. Nainggolan, K. Akbar, T. Yuliaty, and S. Suhaimi, “Tinjauan Kebijakan Pemerintah Bagi Masyarakat Prasejahtera Dalam Menghadapi Fenomena Subsidi Listrik, Bahan Bakar Minyak Dan Gas Di Indonesia,” *Jurnal Ekonomi Pembangunan STIE Muhammadiyah Palopo*, vol. 10, no. 1, p. 114, 2024, doi: 10.35906/jep.v10i1.1923.

[7] M. Sajid *et al.*, “Article a novel algorithm for capacitated vehicle routing problem for smart cities,” *Symmetry*, vol. 13, no. 10, pp. 1–23, 2021, doi: 10.3390/sym13101923.

[8] S. Elatar, K. Abouelmehdi, and M. E. Riffi, “The Vehicle Routing Problem in The Last Decade: Variants, Taxonomy and Metaheuristics,” *Procedia Computer Science*, vol. 220, pp. 398–404, 2023, doi: 10.1016/j.procs.2023.03.051.

[9] M. S. Anggraeni, O. N. Tazkiya, E. Mawandi, and H. S. Amarilies, “Optimization of Fuel Distribution Routes for Green Logistics in Multi Compartment Vehicle Routing Problem (MCVRP) using Branch and Bound Algorithm (Case Study: Boyolali Fuel Terminal)”, *Proceedings of the International Conference on Industrial Engineering and Operations Management*, pp. 1132–1144, 2023, doi: 10.46254/an13.20230333.

[10] G. Clarke and J. W. Wright, “Scheduling of Vehicles from a Central Depot to a Number of Delivery Points,” *Operations Research*, vol. 12, no. 4, pp. 568–581, 1964, doi: 10.1287/opre.12.4.568.

[11] J. Fikejz, M. Brázdová, and Ľ. Jánošíková, “Modification of the Clarke and Wright Algorithm with a Dynamic Savings Matrix,” *Journal of Advanced Transportation*, vol. 2024, 2024, doi: 10.1155/2024/8753106.

[12] J. Šedivý and J. Čejka, “Optimisation of distribution routes for branch office of česká pošta, s.p. (Czech Post),” *Transportation Research Procedia*, vol. 53, no. 2019, pp. 252–257, 2021, doi: 10.1016/j.trpro.2021.02.032.

[13] S. Kunnapapdeelert and C. Thawnern, “Capacitated vehicle routing problem for thailand’s steel industry via saving algorithms,” *Journal of System and Management Sciences*, vol. 11, no. 2, pp. 171–181, 2021, doi: 10.33168/JSMS.2021.0211.

[14] F. Tunnisaki and Sutarman, “Clarke and Wright Savings Algorithm as Solutions Vehicle Routing Problem with Simultaneous Pickup Delivery (VRPSPD),” *Journal of Physics: Conference Series*, vol. 2421, no. 1, 2023, doi: 10.1088/1742-6596/2421/1/012045.

[15] R. F. Harahap and Sawaluddin, “Study Vehicle Routing Problem Using Nearest Neighbor Algorithm,” *Journal of Physics: Conference Series*, vol. 2421, no. 1, 2023, doi: 10.1088/1742-6596/2421/1/012027.

[16] A. H. Taha, *Operations Research An Introduction*, 10th ed. London.

[17] R. Jia, Y. Liu, and X. Bai, “Sustainable supplier selection and order allocation: Distributionally robust goal programming model and tractable approximation,” *Computers and Industrial Engineering*, vol. 140, no. January, p. 106267, 2020, doi: 10.1016/j.cie.2020.106267.

[18] E. E. Günay, G. E. Okudan Kremer, and A. Zarindast, “A multi-objective robust possibilistic programming approach to sustainable public transportation network design,” *Fuzzy Sets and Systems*, vol. 422, pp. 106–129, 2021, doi: 10.1016/j.fss.2020.09.007.

[19] S. Mulyono, *Riset Operasi*. Jakarta: Mitra Wacana Media, 2017.

[20] L. O. D. Munggaran and Z. F. Rosyada, “Pengoptimalan Pola Distribusi BBM Menggunakan Teori Transportasi Dan Metode Stepping Stone Pada PT. Pertamina Patra Niaga Regional Sumatera Bagian Selatan,” *Industrial Engineering Online Journal,* vol. 13, no. 4, 2024.