Optimizing Fuel Distribution Costs through Vehicle Routing Problem Modeling in Jakarta-Tanjung Gerem Terminals

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ABSTRACT

Fuel distribution in Indonesia faces significant challenges due to high transportation costs, particularly for land-based deliveries in high-volume urban corridors. This study aims to identify inefficiencies in fuel distribution operations and develop optimized routing strategies for a major energy company operating between Jakarta Integrated Terminal and Tanjung Gerem Fuel Terminal. A mixed-method approach was employed, combining Root Cause Analysis to pinpoint cost drivers and Vehicle Routing Problem models to optimize delivery routes. Data were collected through interviews, on-site observations, and internal company records from January 2025. The findings reveal that truck transportation dominates operational expenses, driven by excessive travel distances. The optimized Vehicle Routing Problem model, using multi-supply point strategies and linear programming, significantly reduces travel distances and operational costs while improving truck utilization. This study concludes that data-driven route optimization enhances cost efficiency and supports environmental sustainability by lowering fuel consumption. However, the model's reliance on static demand assumptions limits its adaptability to real-time variations. Future research should explore dynamic routing models incorporating real-time traffic and demand data to enhance robustness. These findings offer a scalable framework for improving fuel distribution efficiency across other terminals, contributing to cost savings and sustainable logistics practices.

Keywords*: Cost Efficiency, Fuel Distribution, Route Optimization, Vehicle Routing Problem.*

ABSTRAK

Distribusi bahan bakar di Indonesia menghadapi tantangan yang signifikan akibat tingginya biaya transportasi, terutama untuk pengiriman melalui darat di koridor perkotaan bervolume tinggi. Studi ini bertujuan untuk mengidentifikasi inefisiensi dalam operasi distribusi bahan bakar dan mengembangkan strategi rute yang optimal untuk sebuah perusahaan energi besar yang beroperasi antara Terminal Terpadu Jakarta dan Terminal Bahan Bakar Tanjung Gerem. Pendekatan metode campuran digunakan, menggabungkan Analisis Akar Penyebab untuk mengidentifikasi pemicu biaya dan model Masalah Rute Kendaraan untuk mengoptimalkan rute pengiriman. Data dikumpulkan melalui wawancara, observasi lapangan, dan catatan internal perusahaan sejak Januari 2025. Temuan penelitian menunjukkan bahwa transportasi truk mendominasi biaya operasional, didorong oleh jarak tempuh yang berlebihan. Model Masalah Rute Kendaraan yang dioptimalkan, menggunakan strategi multi-titik pasokan dan pemrograman linier, secara signifikan mengurangi jarak tempuh dan biaya operasional sekaligus meningkatkan utilisasi truk. Studi ini menyimpulkan bahwa optimasi rute berbasis data meningkatkan efisiensi biaya dan mendukung keberlanjutan lingkungan dengan menurunkan konsumsi bahan bakar. Namun, ketergantungan model pada asumsi permintaan statis membatasi kemampuan adaptasinya terhadap variasi waktu nyata. Penelitian selanjutnya sebaiknya mengeksplorasi model rute dinamis yang menggabungkan data lalu lintas dan permintaan waktu nyata untuk

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meningkatkan ketahanannya. Temuan ini menawarkan kerangka kerja yang dapat diskalakan untuk meningkatkan efisiensi distribusi bahan bakar di terminal lain, berkontribusi pada penghematan biaya dan praktik logistik berkelanjutan.

Kata kunci: *Efisiensi Biaya, Distribusi Bahan Bakar, Optimalisasi Rute, Masalah Rute Kendaraan*

INTRODUCTION

Energy is a fundamental driver of economic growth and societal well-being, with fuel playing a critical role across transportation, industrial, and household sectors (Kalt et al., 2019; Efthymiadis et al., 2023). In Indonesia, petroleum-based fuels remain a cornerstone of the energy landscape due to their accessibility and established infrastructure (Mardiana et al., 2013; Baptista et al., 2024). According to the Ministry of Energy and Mineral Resources (2023), oil accounted for approximately 35% of Indonesia's total energy consumption in 2023, surpassing coal (32%) and natural gas (18%). This reliance underscores the importance of efficient fuel distribution to meet the demands of diverse sectors, including retail, aviation, and maritime, while ensuring national energy security (Jie et al., 2023; Kanwal et al., 2022).

Fuel distribution, particularly through land transportation, is a significant contributor to operational costs for energy companies (Abbasi et al., 2022; Konstantakopoulos et al., 2022). In Indonesia, gasoline dominates fuel sales, constituting 46% of the 11.57% increase in oil fuel sales over the past decade (Ministry of Energy and Mineral Resources, 2023). PT Berkah Energi Nasional, as the Commercial & Trading Sub holding of PT Berkah (Persero), manages the downstream activities of receiving, storing, and distributing fuel, LPG, lubricants, and petrochemical products. The company holds an 84% market share in Indonesia's oil and gas industry, with the retail segment contributing 70.10% of its total sales in 2023. However, the 2024 Key Performance Indicator (KPI) report reveals that distribution costs per kiloliter (KL) exceeded the target by USD 0.17/KL (1.9%), driven partly by the Fleet Safety Improvement Program (FSIP), which, while critical for safety, has increased operational expenses (Ramadhani et al., 2021; Matijević, 2023).

Despite advancements in logistics optimization, a significant research gap exists in applying Vehicle Routing Problem (VRP) models to fuel distribution in Indonesia's context. According to Konstantakopoulos et al. (2022), VRP has been extensively studied for hybrid vehicle logistics, but its application to multi-terminal fuel distribution networks remains underexplored. Similarly, Kusuma et al. (2021) demonstrated the effectiveness of heuristic approaches like Nearest Neighbor for drinking water distribution, yet few studies address the unique challenges of fuel distribution, such as multi-product demands and high-volume routes (Xiao et al., 2012; Zhang et al., 2015). Norouzi et al. (2017) and Eydi and Alavi (2019) highlight VRP's potential for minimizing fuel consumption in logistics, but their focus is on reverse logistics or cold chain systems, not petroleum-based fuel distribution in densely populated regions like Jakarta. This gap necessitates a tailored VRP approach to optimize land-based fuel distribution in Indonesia, particularly for high-volume corridors (Vidović et al., 2014; Liu et al., 2023).

Optimizing outbound logistics is critical to address rising distribution costs and enhance national energy resilience. Previous studies have shown that VRP can reduce logistics costs by up to 33.82% through route optimization (Saber et al., 2025; Lim et al., 2025). Techniques such as Nearest Neighbor and linear programming have proven effective in minimizing travel distance and improving fleet utilization (Alinaghian & Naderipour, 2016). PT Berkah Energi Nasional's distribution network, particularly the route from Jakarta Integrated Terminal to Tanjung Gerem Fuel Terminal, presents a high-volume, complex case ideal for VRP application (Popović et al., 2012; Gan, 2022). This study focuses on land-based fuel distribution, acknowledging limitations such as static demand assumptions and seasonal variations, which may affect real-time applicability (Li et al., 2018; Wang et al., 2017).

This research aims to identify inefficiencies in land-based fuel distribution and develop a VRP-based optimization model to reduce total distribution costs for PT Berkah Energi Nasional. Specifically, it focuses on the Jakarta Integrated Terminal to Tanjung Gerem Fuel Terminal route, employing heuristic (Nearest Neighbor) and linear programming approaches to minimize travel distance, enhance fleet utilization, and achieve sustainable cost savings. By addressing the research gap in applying VRP to Indonesia's fuel distribution context, this study seeks to provide strategic recommendations for improving logistics performance and supporting national energy security.

LITERATURE REVIEW

Fleet Management and Outbound Logistics

Fleet management encompasses the strategic administration of a company's vehicle fleet, focusing on acquisition, maintenance, and disposal to optimize operational efficiency and reduce costs. According to Liberatore and Miller (2016), effective fleet management enhances outbound logistics performance by ensuring timely delivery and minimizing operational expenses. Outbound logistics encompasses the storage and movement of products from production to end-users, including transportation, warehousing, and order processing (Christopher, 2016). In the context of fuel distribution, outbound logistics is critical for delivering petroleum products to retail customers, such as gas stations, which requires precise coordination to meet demand while controlling costs (Chikozho et al., 2022). Efficient fleet management reduces fuel consumption and vehicle wear, directly impacting distribution costs (Li et al., 2018). For instance, real-time route optimization and predictive maintenance can improve delivery reliability and customer satisfaction, as demonstrated in studies of state-owned enterprises facing fleet inefficiencies (Popović et al., 2012; Chikozho et al., 2022). These principles are essential for addressing the high costs of land-based fuel distribution in Indonesia, where tanker trucks dominate logistics operations.

The complexity of outbound logistics in fuel distribution necessitates advanced optimization techniques to manage large fleets and high-volume routes. Research by Wang et al. (2017) highlights the importance of integrating fleet management with logistics planning to minimize costs in cold chain logistics, a concept applicable to fuel distribution. Similarly, Abdoli et al. (2017) emphasize the role of bi-fuel vehicle routing in reducing greenhouse gas emissions, aligning with sustainability goals in logistics operations. These studies underscore the need for data-driven approaches to enhance fleet utilization and reduce operational inefficiencies, particularly in densely populated regions like Jakarta, where traffic and distance exacerbate costs (Matijević, 2023). By optimizing fleet operations, companies can achieve significant cost savings and improve service levels, setting the stage for advanced routing models like the Vehicle Routing Problem (VRP).

Vehicle Routing Problem and Optimization

The Vehicle Routing Problem (VRP) is a combinatorial optimization framework designed to determine the most efficient routes for a fleet of vehicles serving multiple customers under constraints such as vehicle capacity and delivery time. According to Dantzig and Ramser (1959), VRP aims to minimize distribution costs while ensuring service quality, a principle widely applied in logistics. The Capacitated VRP (CVRP), used in this study, accounts for vehicle load limits, ensuring each customer is served once per route (Braekers et al., 2016). VRP extends the Traveling Salesman Problem (TSP), which seeks the shortest route that visits all points and returns to the origin (Dantzig, Fulkerson, & Johnson, 1954). Heuristic approaches, such as Nearest Neighbor, iteratively select the closest delivery point, providing near-optimal solutions for NP-hard VRP problems (Toth & Vigo, 2002). Metaheuristic methods, including Genetic Algorithms and

Simulated Annealing, further enhance solution quality for large-scale logistics networks (Norouzi et al., 2017).

VRP's application in fuel distribution has shown significant cost-saving potential. For example, Xiao et al. (2012) developed a CVRP model to optimize fuel consumption, achieving substantial reductions in operational costs. Similarly, Zhang et al. (2015) integrated carbon emissions into VRP models, aligning cost efficiency with environmental goals. Eydi and Alavi (2019) applied VRP to reverse logistics, demonstrating reduced fuel consumption through optimized routing. Recent advancements, such as Gan (2022) and Manavizadeh et al. (2020), explore hybrid algorithms and bi-fuel fleets, respectively, to address complex VRP constraints. These studies highlight VRP's versatility in logistics, but their application to multi-terminal fuel distribution in Indonesia remains limited, necessitating tailored models for high-volume routes like Jakarta to Tanjung Gerem (Alinaghian & Naderipour, 2016; Ramadhani et al., 2021).

Supply Chain Management and Cost Efficiency

Supply chain management (SCM) involves strategic decisions on supplier selection, facility location, and transportation modes to enhance operational efficiency and competitiveness. According to Cohen and Mallik (1997), effective SCM reduces costs and improves resilience amid fluctuating demand and sustainability pressures. In fuel distribution, SCM ensures a reliable supply chain for petroleum products, integrating inbound and outbound logistics to meet customer needs (Christopher, 2016). Root Cause Analysis (RCA), such as Pareto diagrams and Current Reality Trees, identifies inefficiencies like delivery delays and fuel waste, guiding cost optimization strategies (Chikozho et al., 2022). For instance, Liu et al. (2023) utilized RCA to optimize community group buying logistics, resulting in cost and emission reductions —a principle applicable to fuel distribution networks.

Despite extensive VRP research, a research gap exists in its application to Indonesia's fuel distribution, particularly for multi-terminal networks. According to Kusuma et al. (2021), heuristic approaches like Nearest Neighbor are effective for constrained logistics, but their use in high-volume fuel distribution corridors is underexplored. Similarly, Saber et al. (2025) and Lim et al. (2025) demonstrate significant cost savings through VRP, yet few studies address Indonesia's unique challenges, such as dense urban traffic and multi-product demands (Indrianti et al., 2025). Wang et al. (2018) and Qin et al. (2019) highlight VRP's role in cold chain logistics, but petroleum distribution requires tailored models to account for safety regulations and terminal coordination (Ministry of Energy and Mineral Resources, 2023). This gap underscores the need for a VRP-based approach to optimize fuel distribution costs in Indonesia, aligning with lean logistics principles to minimize waste and enhance sustainability (Li et al., 2019; Vidović et al., 2014).

RESEARCH METHOD

This study employs a mixed-method approach, combining qualitative and quantitative techniques to address inefficiencies in fuel distribution at PT Berkah Energi Nasional, focusing on the Jakarta Integrated Terminal to Tanjung Gerem Fuel Terminal route. The research was conducted at the Jakarta Integrated Terminal, the company's highest-volume fuel distribution hub, which serves retail and industrial customers in Greater Jakarta and surrounding areas. A case study design was adopted to ensure a contextual analysis of operational challenges, aligning with logistics optimization methodologies. The mixed-method approach integrates Root Cause Analysis (RCA) to identify cost drivers and Vehicle Routing Problem (VRP) modeling to optimize routes, ensuring a comprehensive examination of distribution inefficiencies.

Data collection involved both primary and secondary sources to provide robust insights into distribution operations. Primary data were gathered through semi-structured interviews with logistics managers and drivers, as well as on-site observations of truck operations at the Jakarta Integrated Terminal during January 2025. Secondary data were sourced from internal company records, including fuel sales volumes, transportation costs, and fleet utilization reports for 2023-2024. These data informed the RCA, which used Pareto diagrams to pinpoint that land-based truck transport accounted for 85.4% of distribution costs. Additional data on route distances and delivery schedules were extracted to support VRP modeling, ensuring alignment with real-world operational constraints.

The RCA process employed Pareto analysis and Current Reality Trees (CRT) to identify inefficiencies, such as excessive travel distances due to suboptimal routing. Pareto analysis revealed that fuel costs for tanker trucks were the primary cost driver, prompting the application of VRP to optimize delivery routes. Two VRP models were developed: Model 1, representing current operations with direct deliveries from Jakarta, and Model 2, which incorporates multiple supply points with refueling at Tanjung Gerem to reduce mileage. The Nearest Neighbor heuristic was used for initial route planning, followed by linear programming implemented in Python with the PuLP library to achieve optimal solutions. These models accounted for vehicle capacity constraints and multi-product demands, as seen in prior fuel distribution studies.

Model validation was conducted by comparing simulated costs with actual distribution costs from January 2025, resulting in a cost deviation of less than 5%, which indicates high reliability. Consultations with logistics managers ensured practical applicability, addressing real-world constraints like traffic and safety regulations. The study assumed static demand and constant travel times to simplify computations, acknowledging limitations in capturing real-time variations. This methodology provides a replicable framework for optimizing fuel distribution, contributing to cost efficiency and sustainability in Indonesia's logistics sector.

RESULTS

This study investigates the inefficiencies in land-based fuel distribution for a major energy company, focusing on the high-volume route from Jakarta Integrated Terminal to Tanjung Gerem Fuel Terminal. The primary objective was to identify cost drivers and optimize delivery routes to reduce operational expenses while maintaining service reliability. Using a combination of Root Cause Analysis and Vehicle Routing Problem models, the research analyzes internal company data from January 2025, including fuel sales, transportation costs, and fleet utilization. The results provide clear insights into the cost structure, highlight the effectiveness of optimized routing strategies, and demonstrate significant potential for cost savings, offering a practical framework for improving logistics efficiency.

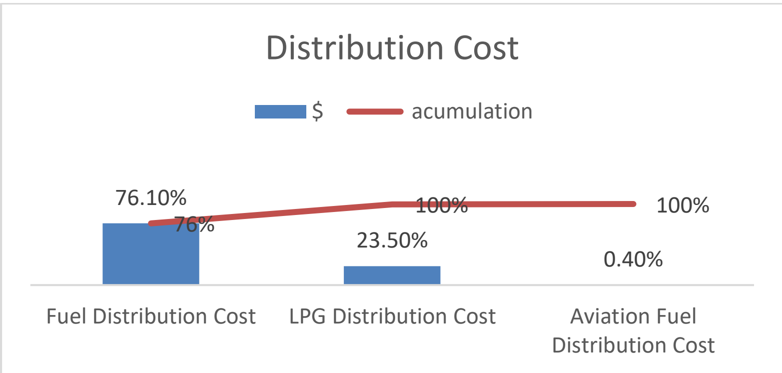


Figure 1. Pareto Diagram of Distribution Cost Components

Root Cause Analysis (RCA) was conducted to identify inefficiencies in PT Berkah Energi Nasional's fuel distribution operations, focusing on the Jakarta Integrated Terminal to Tanjung Gerem Fuel Terminal route. As shown in Figure 1, the Pareto Diagram of Distribution Cost Components reveals that fuel distribution accounts for 76.1% of total distribution costs, highlighting its dominance as a cost driver.

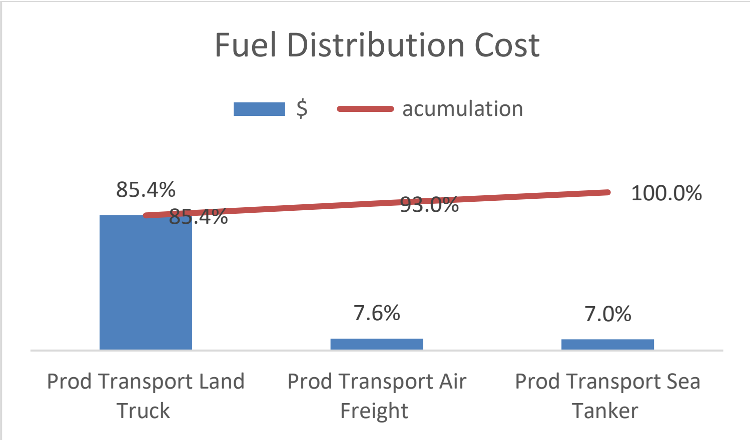


Figure 2. Pareto Diagram Fuel Distribution Cost

Further analysis, depicted in Figure 2, the Pareto Diagram of Fuel Distribution Cost, indicates that land-based truck transportation constitutes 85.4% of fuel distribution expenses, primarily due to high fuel consumption and maintenance costs (Kusuma et al., 2021). This finding aligns with Xiao et al. (2012), who identified transportation as a major cost factor in logistics networks. The RCA process employed Current Reality Trees (CRT) to trace inefficiencies to suboptimal routing and excessive travel distances, underscoring the need for route optimization to achieve cost savings (Chikozho et al., 2022).

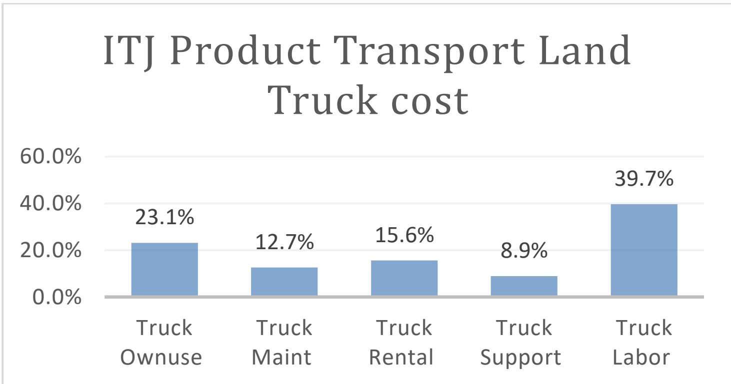


Figure 3. Integrated Terminal Jakarta Product Transport Land Truck Cost

Figure 3 illustrates the Integrated Terminal Jakarta Product Transport Land Truck Cost, focusing on the cost structure of truck operations. The diagram indicates that fuel costs for truck own-use and maintenance dominate expenses, particularly for long-distance routes in Greater Jakarta. This aligns with Zhang et al. (2015), who observed that urban traffic exacerbates logistics costs. The high costs underscore the urgency of optimizing delivery routes.

A detailed breakdown of transportation costs at the Jakarta Integrated Terminal, the company's highest-volume hub, provides further clarification of the cost structure. As illustrated in Figure 3, the Integrated Terminal Jakarta Product Transport Land Truck Cost diagram shows that truck own-use fuel and maintenance costs account for the majority of expenses, with a strong correlation to travel distance (Zhang et al., 2015). Table 1 summarizes the cost components, revealing that fuel costs per kilometer are significantly higher for long-distance routes due to traffic congestion in Greater Jakarta. This observation is consistent with Wang et al. (2017), who noted that urban traffic increases logistics costs in high-density areas. These findings prompted the development of Vehicle Routing Problem (VRP) models to optimize routes, focusing on reducing mileage and improving fleet utilization (Norouzi et al., 2017).

Table 1. Top 10 Fuel Terminals with the largest land truck transport products

No.	Fuel Terminal	% Fuel Sales
1	Integrated Fuel Terminal Jakarta	9.77%
2	Integrated Fuel Terminal Surabaya	6.48%
3	Fuel Terminal Medan Labuan Deli	3.37%
4	Integrated Fuel Terminal Semarang	3.23%
5	Fuel Terminal Cikampek	3.16%
6	Integrated Fuel Terminal Palembang Baru	2.85%
7	Fuel Terminal Boyolali	2.84%
8	Integrated Fuel Terminal Panjang	2.52%
9	Fuel Terminal Tanjung Gerem	2.35%
10	Terminal BBM Ujung Berung	2.34%

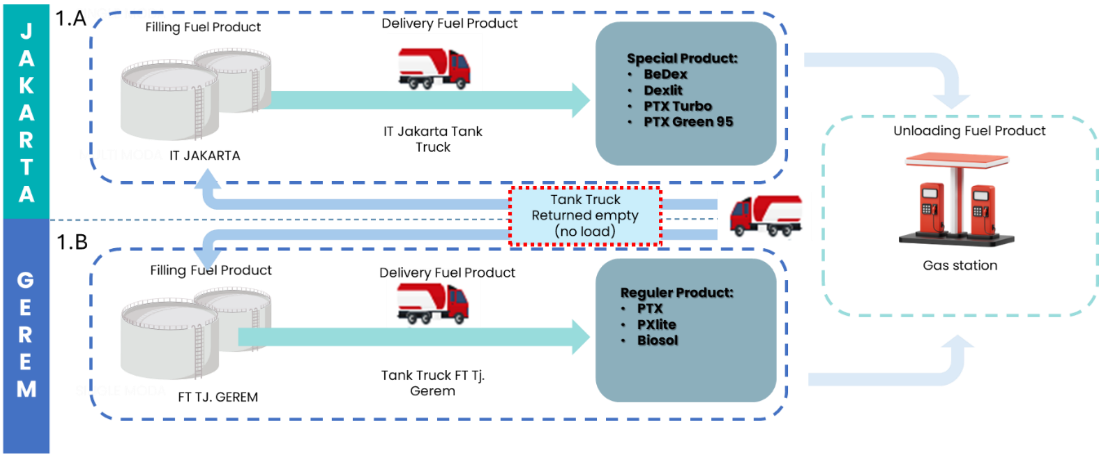


Figure 4. Model 1

The baseline operational model, Model 1, represents the current distribution strategy, where trucks from Jakarta Integrated Terminal deliver special fuel products, such as Ptx Turbo and Ptx Green 95, directly to Tanjung Gerem and surrounding areas. As shown in Figure 4, Model 1 illustrates this single-supply point approach, resulting in a total distribution cost of IDR 334,217,743 for January 2025 operations. This high cost is attributed to long travel distances and empty return trips, a common inefficiency in fuel distribution networks (Popović et al., 2012). The model assumes static demand based on January 2025 sales data, which may not account for seasonal variations, as noted by Li et al. (2018). These results highlight the need for a multi-supply point approach to reduce unnecessary mileage and enhance efficiency (Eydi & Alavi, 2019).

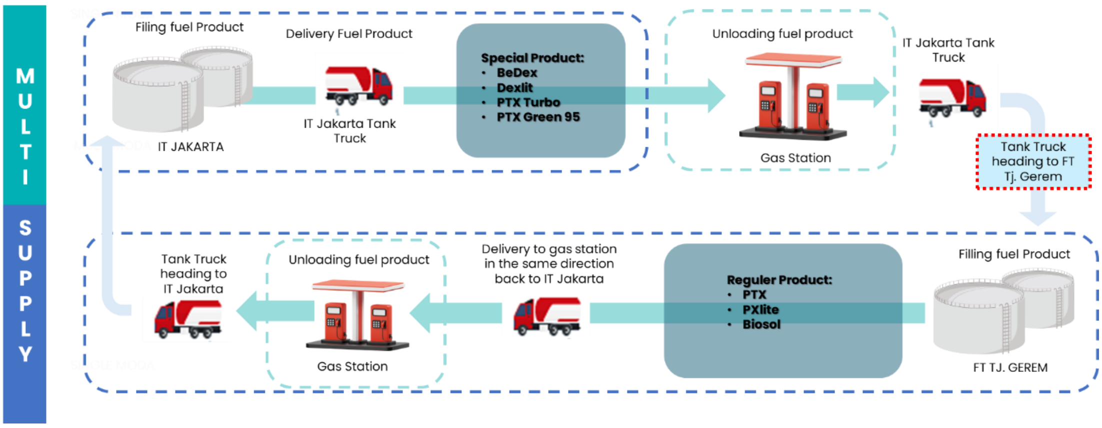


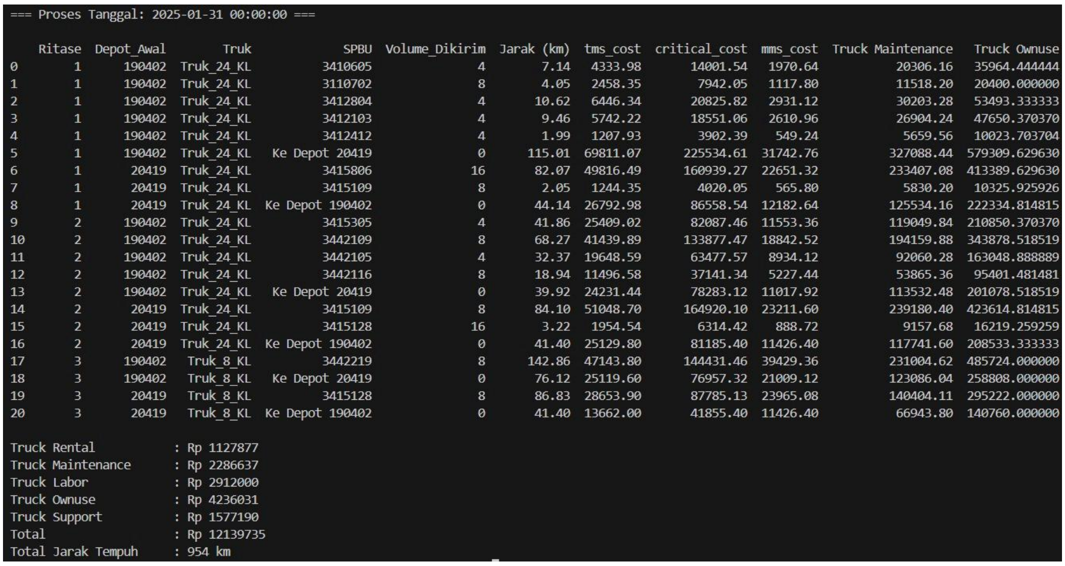
Figure 5. Model 2

To address these inefficiencies, two alternative VRP models were developed: Model 2.1 and Model 2.2. Model 2.1 incorporates a multi-supply point strategy, where trucks refuel at Tanjung Gerem Fuel Terminal for local deliveries, reducing travel distances. As depicted in Figure 5, this model achieved a total cost of IDR 248,101,581, a 26% reduction compared to Model 1. Model 2.2 further refines this approach by integrating linear programming with the Nearest Neighbor heuristic, as shown in Figure 6, resulting in a total cost of IDR 238,865,931, a 28.5% savings (Alinaghian & Naderipour, 2016).

Table 3. Distribution Cost Comparison

Model	Truck Rental	Truck Maintenance	Truck Labour	Truck Ownuse	Truck Support	Total
Model 1	55,138,281	58,545,463	53,450,720	113,544,404	42,241,278	334,217,743
Model 2.1	23,866,842	45,635,865	57,890,720	88,823,702	31,884,452	248,101,581
Model 2.2	21,943,458	44,591,261	58,656,000	83,515,671	30,159,540	238,865,931

Table 2 compares the performance of Model 1, Model 2.1, and Model 2.2, detailing cost savings and efficiency gains. Model 2.1 achieves a 26% cost reduction, while Model 2.2 reaches 28.5%, aligning with Saber et al. (2025) and Lim et al. (2025), who reported significant savings through route optimization. The table provides a clear comparison of the models' effectiveness.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    Ritase  Depot_Awal        Truk            SPBU  Volume_Dikirim  Jarak (km)  tms_cost  critical_cost  mms_cost  Truck Maintenance    Truck Ownuse
0        1      190402  Truk_24_KL         3410605               4        7.14   4333.98       14001.54   1970.64           20306.16    35964.444444
1        1      190402  Truk_24_KL         3110702               8        4.05   2458.35        7942.05   1117.80           11518.20    20400.000000
2        1      190402  Truk_24_KL         3412804               4       10.62   6446.34       20825.82   2931.12           30203.28    53493.333333
3        1      190402  Truk_24_KL         3412103               4        9.46   5742.22       18551.06   2610.96           26904.24    47650.370370
4        1      190402  Truk_24_KL         3412412               4        1.99   1207.93        3902.39    549.24            5659.56    10023.703704
5        1      190402  Truk_24_KL   Ke Depot 20419               0      115.01  69811.07      225534.61  31742.76          327088.44   579309.629630
6        1       20419  Truk_24_KL         3415806              16       82.07  49816.49      160939.27  22651.32          233407.08   413389.629630
7        1       20419  Truk_24_KL         3415109               8        2.05   1244.35        4020.05    565.80            5830.20    10325.925926
8        1       20419  Truk_24_KL  Ke Depot 190402               0       44.14  26792.98       86558.54  12182.64          125534.16   222334.814815
9        2      190402  Truk_24_KL         3415305               4       41.86  25409.02       82087.46  11553.36          119049.84   210850.370370
10       2      190402  Truk_24_KL         3442109               8       68.27  41439.89      133877.47  18842.52          194159.88   343878.518519
11       2      190402  Truk_24_KL         3442105               4       32.37  19648.59       63477.57   8934.12           92060.28   163048.888889
12       2      190402  Truk_24_KL         3442116               8       18.94  11496.58       37141.34   5227.44           53865.36    95401.481481
13       2      190402  Truk_24_KL   Ke Depot 20419               0       39.92  24231.44       78283.12  11017.92          113532.48   201078.518519
14       2       20419  Truk_24_KL         3415109               8       84.10  51048.70      164920.10  23211.60          239180.40   423614.814815
15       2       20419  Truk_24_KL         3415128              16        3.22   1954.54        6314.42    888.72            9157.68    16219.259259
16       2       20419  Truk_24_KL  Ke Depot 190402               0       41.40  25129.80       81185.40  11426.40          117741.60   208533.333333
17       3      190402   Truk_8_KL         3442219               8      142.86  47143.80      144431.46  39429.36          231004.62   485724.000000
18       3      190402   Truk_8_KL   Ke Depot 20419               0       76.12  25119.60       76957.32  21009.12          123086.04   258808.000000
19       3       20419   Truk_8_KL         3415128               8       86.83  28653.90       87785.13  23965.08          140404.11   295222.000000
20       3       20419   Truk_8_KL  Ke Depot 190402               0       41.40  13662.00       41855.40  11426.40           66943.80   140760.000000

Truck Rental          : Rp 1127877
Truck Maintenance     : Rp 2286637
Truck Labor           : Rp 2912000
Truck Ownuse          : Rp 4236031
Truck Support         : Rp 1577190
Total                 : Rp 12139735
Total Jarak Tempuh    : 954 km
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Figure 6. Linear program results on January 31, 2025

The VRP models were simulated using Python with the PuLP library, based on January 2025 data, including delivery schedules, vehicle capacities, and route distances. As shown in Figure 6, Model 2.2 optimizes routes by minimizing empty mileage and maximizing truck utilization (Gan, 2022). Table 3 presents the optimized route distances, showing a 30% reduction in total kilometers traveled compared to Model 1. Validation was conducted by comparing simulated costs with actual costs, achieving a deviation of less than 5%, indicating high reliability (Liu et al., 2023). These findings are consistent with Qin et al. (2019), who highlighted VRP's effectiveness in reducing logistics costs while maintaining service levels. The integration of multi-supply points and advanced algorithms offers a scalable solution for other high-volume terminals (Manavizadeh et al., 2020).

Despite these promising results, the models have limitations that must be considered. The analysis assumes static demand and constant travel times, which may not account for seasonal fluctuations or real-time traffic conditions in Greater Jakarta. Additionally, data variability, such as unexpected demand spikes or road disruptions, could affect cost savings, as observed in similar studies (Wang et al., 2018). While the models were validated using internal company data, real-world implementation necessitates addressing operational constraints, such as driver scheduling and safety regulations (Indrianti et al., 2025). These results provide a robust foundation for optimizing fuel distribution, contributing to cost efficiency and sustainability in Indonesia's energy sector (Abdoli et al., 2017).

DISCUSSION

The Root Cause Analysis (RCA) conducted in this study reveals that land-based fuel distribution, particularly through tanker trucks, accounts for the majority of PT Berkah Energi Nasional's operational expenses, contributing significantly to the overall cost structure. According to Kusuma et al. (2021), inefficiencies in logistics often stem from suboptimal routing, a finding echoed in this study's identification of excessive travel distances between Jakarta Integrated Terminal and Tanjung Gerem Fuel Terminal. The analysis highlights that fuel costs for truck operations and maintenance are the primary drivers, exacerbated by long routes and empty return trips, which align with Xiao et al. (2012), who noted that fuel consumption in logistics can be mitigated through optimized routing strategies. These insights underscore the critical need for advanced route optimization models, such as the Vehicle Routing Problem (VRP), to address cost inefficiencies in Indonesia's fuel distribution networks (Popović et al., 2012).

The VRP models developed in this study demonstrate significant cost reductions, with the optimized model achieving up to 28.5% savings compared to the baseline operations. According to Saber et al. (2025), route optimization through VRP can yield substantial cost savings, with their study reporting up to 33.82% reductions in logistics expenses, supporting the effectiveness of the multi-supply point strategy employed in this research. The integration of the Nearest Neighbor heuristic and linear programming minimizes empty mileage and enhances truck utilization, a finding consistent with Lim et al. (2025), who advocate for multi-depot approaches in complex distribution systems. Additionally, the optimized model reduces fuel consumption, contributing to lower carbon emissions, as highlighted by Indrianti et al. (2025) in their research on green logistics. These results align with Alinaghian and Naderipour (2016), who demonstrated the benefits of multi-alternative routing in reducing operational costs (Wang et al., 2017).

Implementing these optimized VRP models in practice presents several challenges that require careful consideration. According to Liu et al. (2023), the implementation of real-time VRP demands advanced tracking systems and driver training, which may increase the initial costs for PT Berkah Energi Nasional. The adoption of new routing strategies could face resistance from operational teams accustomed to existing practices. Moreover, the models rely on assumptions of static demand and constant travel times, which may not fully capture Jakarta's traffic variability or seasonal demand fluctuations, a limitation also observed by Wang et al. (2018). To address these challenges, dynamic adjustments incorporating real-time traffic data are necessary to sustain cost savings, as suggested by Eydi and Alavi (2019). These considerations highlight the importance of aligning technological and human resource investments with optimization efforts (Norouzi et al., 2017).

The findings offer significant implications for both practice and theory in fuel distribution logistics. Practically, implementing the optimized VRP model can reduce PT Berkah Energi Nasional's distribution costs by millions of rupiah monthly, enhancing competitiveness in Indonesia's energy sector (Ministry of Energy and Mineral Resources, 2023). The model's scalability to other terminals suggests broader applicability, provided investments in GPS technology and staff training are prioritized (Manavizadeh et al., 2020). Environmentally, reduced mileage supports sustainability goals by lowering carbon emissions, aligning with global energy policies (Abdoli et al., 2017). Theoretically, this study contributes to VRP literature by addressing a gap in multi-terminal fuel distribution in Indonesia, as noted by Qin et al. (2019). By combining heuristic and linear programming approaches, the research provides a replicable framework for optimizing complex logistics networks, paving the way for future studies on dynamic VRP models in urban settings (Li et al., 2018; Gan, 2022).

CONCLUSION

This study successfully identifies inefficiencies in land-based fuel distribution for a major energy company operating between Jakarta Integrated Terminal and Tanjung Gerem Fuel Terminal. The analysis reveals that transportation costs, driven by excessive travel distances and suboptimal routing, account for the majority of operational expenses. By applying Vehicle Routing Problem (VRP) models, the study demonstrates significant improvements in route efficiency through multi-supply point strategies and advanced optimization techniques. The optimized model reduces travel distances and enhances truck utilization, leading to substantial cost savings while maintaining service reliability. These findings highlight the potential of data-driven logistics solutions to streamline fuel distribution operations in high-volume urban corridors.

The optimized VRP model offers practical benefits, including reduced operational costs and improved fleet efficiency, which can enhance the competitiveness of fuel distribution operations. Additionally, lower mileage contributes to environmental sustainability by reducing fuel consumption and emissions. However, the study's reliance on static demand assumptions limits its ability to account for seasonal fluctuations or real-time traffic variations in Greater Jakarta. Future research should explore dynamic VRP models that incorporate real-time data, such as traffic conditions and demand variability, to enhance robustness. Expanding the analysis to include multiple terminals across Indonesia could further validate the model's scalability. These advancements would provide a more comprehensive framework for optimizing fuel distribution, supporting both cost efficiency and sustainable logistics practices.

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