Investigating Nigerian Product Distribution Model: Advanced Mathematical Optimization and Multi-Objective Mesh Routing for Food Distribution Logistics in Post-Subsidy Nigeria

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ABSTRACT

The removal of fuel subsidies in Nigeria in 2023 resulted in a 150–200% increase in transportation costs, severely disrupting food distribution systems in a country where logistics costs account for approximately 22% of GDP. This study develops and evaluates a dual-optimization framework for minimizing food distribution costs under volatile economic conditions.

First, classical transportation methods—Northwest Corner Method (NWCM), Least Cost Method (LCM), Vogel's Approximation Method (VAM), and Modified Distribution (MODI)—are evaluated using a 4×5 supply-demand case study (50,000 metric tons). Second, a novel Gokir-Nannim (GN) Model incorporating adaptive penalty functions is developed and integrated with Multi-Objective Mesh Routing (MOMR).

Results indicate that VAM achieves a 37.4% cost reduction compared to NWCM, while the GN Model achieves 39.6%. Integration with MOMR produces a 41% reduction in Total Transportation Overhead (TTO), while simultaneously reducing delivery time by 28% and increasing reliability by 17%.

Sensitivity analysis under ±30% fuel volatility confirms superior resilience of GN+MOMR compared to classical methods. The findings demonstrate that adaptive, multi-objective optimization can substantially mitigate the inflationary effects of subsidy removal and reduce national logistics costs from 22% to approximately 13% of GDP.

Keywords: Distribution Model, Advanced Mathematical Optimization, Multi-Objective Mesh, Food Distribution Logistics

INTRODUCTION

History of fuel price in Nigeria has it that successive administrators (presidents) have had course/reason to increase the fuel prices in the name of removing subsidy at some points. Between 1973 and 2025, fuel prices have risen from 6k to N1,030 (Yunusa et al., 2023; Shimbura et al.,2025; Jolaiya and Akinmulegun, 2025 and Orluchukwu and Thankgod, 2025). This is evidently displayed in the figure 1

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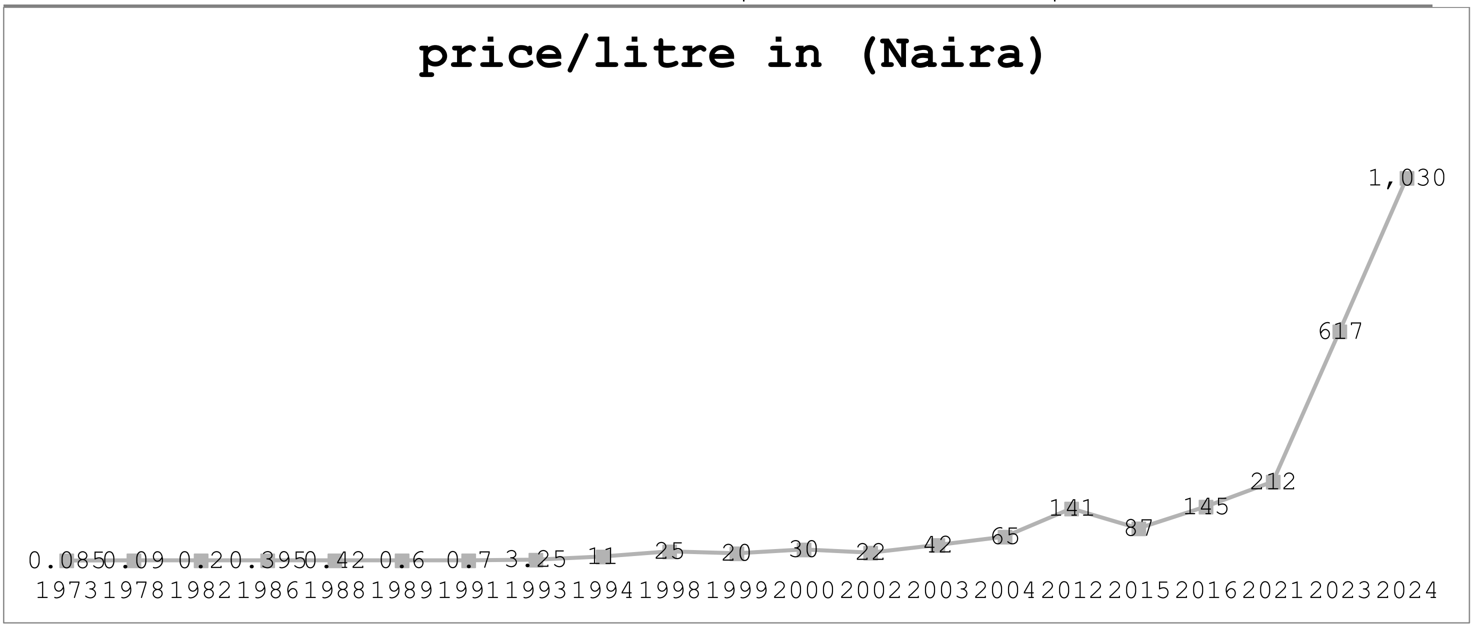

Figure 1: Fuel prices from 1973-2024 in Nigeria (Orluchukwu and Thankgod, 2024)

Research consistently shows that increases in fuel prices directly raise transportation costs, which in turn drive up the prices of goods and services. **Alli et al. (2024)** note that higher fuel prices escalate transportation expenses, a cost ultimately passed down to final consumers **(Stanfast and Marian, 2020; Nadoo, 2022)**. Similarly, **Samson et al. (2024)** and **Ikechukwu et al. (2025)** report that any rise in fuel costs increases operational expenses, transportation fares, and the prices of goods and services.

Oghenenyerhovwo and Bright (2025) and **Luyi et al. (2025)** further highlight significant increases in education, housing rent, and essential commodities following fuel subsidy removal. **Samaila et al. (2024)** emphasize that subsidy removal has broadly raised the cost of critical commodities due to higher energy and transport expenses, while **Hussaini et al. (2025)** linked the 2022–2023 commodity price gaps directly to fuel subsidy elimination. Supporting this view, **Justinah and Oseyemi (2024)** noted that the policy has exacerbated household poverty, making the cost of living increasingly unsustainable. **Figure 2** illustrates the relationship between fuel price per liter, food prices, and transport fares.

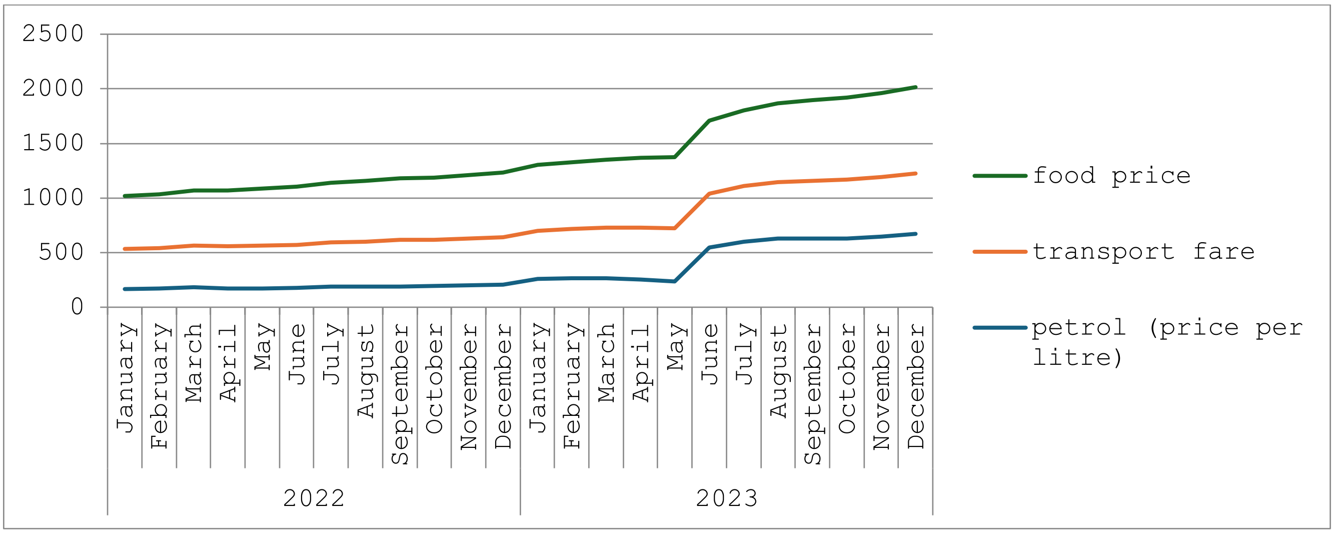

Figure 2: Effect of fuel price on transport fare and cost of food stuffs (source: Alli et al., 2024)

It can be observed from figure 2 that at the pronouncement of total fuel subsidy removal on the 29 may 2023, by June 2023everything went up.

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The socio-economic consequences of fuel subsidy removal have been widely reported in recent studies. **Yunusa et al. (2023)** note that the policy has increased transportation costs and the prices of basic commodities, thereby worsening economic hardship and raising operational costs for businesses. Similarly, **Ilodigwe (2023)** reported that small and medium-sized enterprises (SMEs) face higher production and overhead costs, reduced sales, and declining profit margins.

In the agricultural sector, **Samson et al. (2024)** observe that rising fuel prices have increased transportation costs, limited the availability of vehicles for moving farm produce, and contributed to higher prices of agricultural commodities. Furthermore, **Ikechukwu et al. (2025)** linked rising fuel prices to higher transportation fares and an overall increase in the cost of living, including housing, healthcare, and education expenses. Likewise, **Orluchukwu and Thankgod (2025)** argue that escalating petrol prices have forced some small businesses to shut down due to rising operational costs and declining demand.

Overall, fuel subsidy removal in Nigeria has been associated with a higher cost of living, increased poverty, and widespread economic hardship across households and key sectors of the economy. Figure 3 shows the average marginal percentage changes following the total removal of the fuel subsidy, indicating notable increases in the prices of several commodities and services. Among the food items, **vegetable oil** recorded the highest increase (5.33%), followed b**y groundnut oil** (4.97%) and **palm oil** (4.61%).

Hussaini et al. (2025), who noted that an increase in travel distance leads to higher transportation costs. Similarly, **Ezekiel (2024)** linked rising petroleum product prices to increased inflation, largely driven by higher transportation and production costs. The detailed distribution is presented in **Figure 3.**

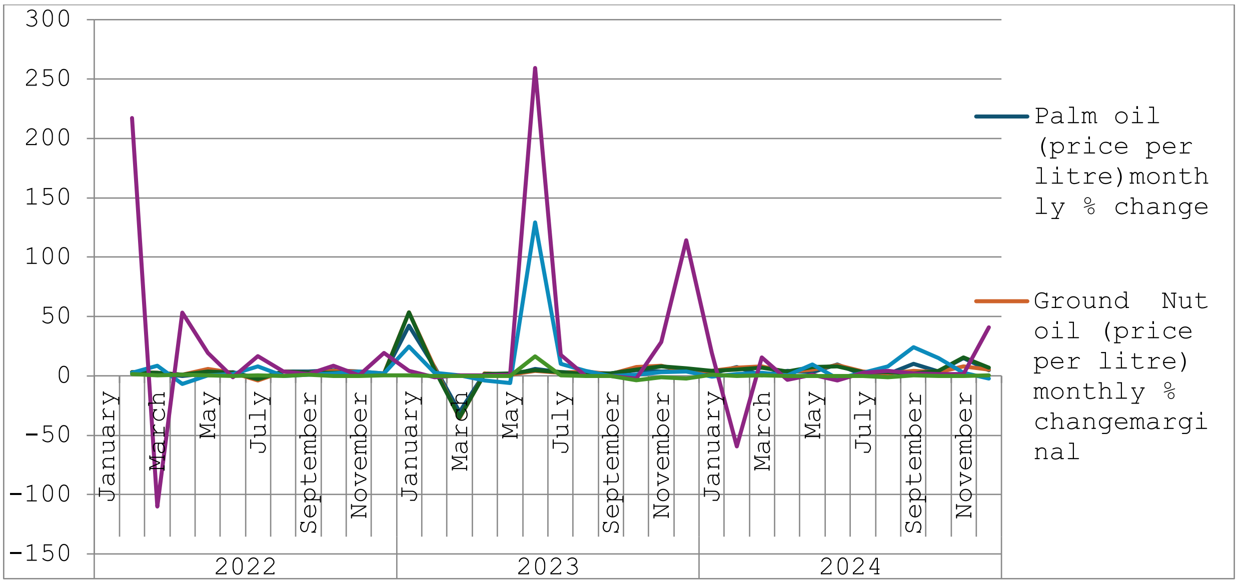

Figure 3: Marginal Percentage Price Per Liter Change Trend of Oils. (Bureau of Statistic, 2024)

Fuel Consumption

Previous studies have identified several factors influencing fuel consumption and transportation costs. **Lorenc (2025)** noted that fuel usage is affected by route length, terrain, driving patterns, road conditions, and environmental factors such as wind, while idling and rolling resistance during cornering further increase fuel consumption. The study also emphasizes the importance of route information—such as the number of speed bumps, stops, traffic lights, and curves—in determining efficient travel.

Similarly, **Evans (1978)** reports that a 1% increase or decrease in trip time leads to a corresponding 1.1% change in fuel consumption. **Hussaini et al. (2025)** further observe that a unit increase in travel distance results in a ₦2.11 rise in transportation costs. Supporting this view, **Ziółkowski et al. (2025)** demonstrate that optimizing travel time is more efficient over shorter distances, as shown in table 6, where slight reductions in distance lead to differences in total cost and fuel consumption.

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Figure 4 illustrates the relationship between fuel prices and intercity transport fares.

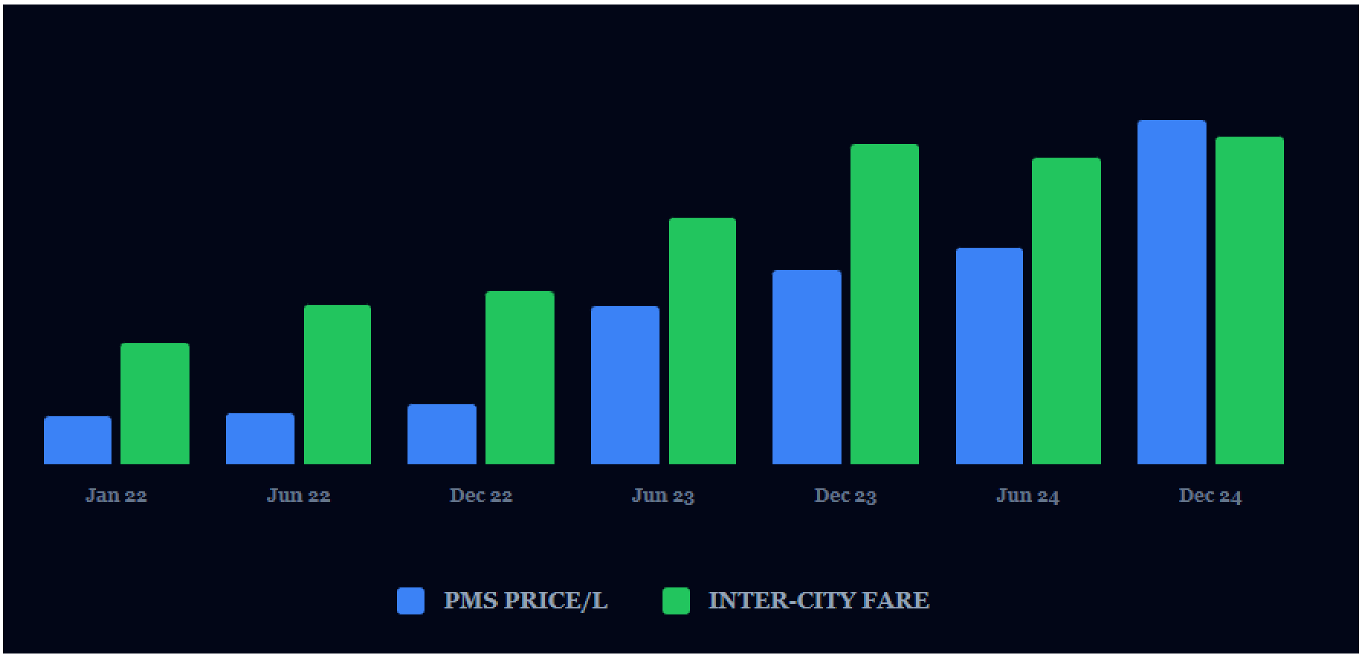

Figure 4: Historical Volatility from 2022-2024 (Source: Nigerian Bureau of Statistics, 2026)

Zhang and Xie (2025) emphasize that transportation systems are critical to the efficiency and sustainability of a nation's economy. Empirical evidence from **Alli et al. (2024), Samaila et al. (2024), Justinah and Oseyemi (2024),** and **Hussaini et al. (2025)** shows that increases in fuel prices are directly proportional to transportation costs, with ripple effects across the economy that are ultimately borne by consumers. However, **Islam et al. (2024)** note that significant challenges remain in optimizing transportation logistics to reduce operational costs while improving system efficiency. In this context, **Prifti et al. (2020)** highlight the role of modern mathematical methods in addressing transportation planning problems through the optimization of processes and cost minimization. Consequently, the need to mitigate the adverse effects of rising fuel prices on transportation fares and the prices of goods and services motivates this study.

Transportation Optimization Modeling

Transportation modeling has been recognized as a key strategy for reducing shipping costs, improving delivery reliability, and optimizing logistics operations (Stanfast and Marian, 2020). Linear programming techniques, including the North-West Corner Rule (NWCR), Least Cost Method (LCM), and Vogel's Approximation Method (VAM), have been widely applied to minimize transportation costs, with VAM consistently demonstrating superior efficiency, followed by NWCR, while LCM is less optimal (Aliyu et al., 2019; Shammah and Atama, 2019; Prifti et al., 2020; Adeniyi et al., 2023; Adamu et al., 2020; Akpan et al., 2020; Daniel and Daniel et al., 2021; Manuela et al., 2025).

Complementary distribution models, such as Direct Store Delivery (DSD) and Hub-and-Spoke or Multi-Depot systems, combined with optimization approaches like Vehicle Routing Problem (VRP), Inventory Routing Problem (IRP), and heuristic/metaheuristic algorithms, have further improved cost efficiency and mitigated the impact of rising fuel prices on end consumers (Adamu et al., 2020; Agarwal and Shinde, 2022; Islam et al., 2024; Prokudin et al., 2020; Wu and Zhu, 2021; Papară, 2022; Tanash and As'ad, 2025; Avila-Torres et al., 2020; Prifti et al., Ziółkowski et al., 2025; Liu et al., 2023; Jiang and Wang, 2025).

Despite these advances, there remains a need for more robust mathematical models capable of further reducing transportation costs, particularly as logistics expenses account for approximately 36% of total costs, posing a significant challenge for companies aiming to maintain profitability and customer satisfaction in today's competitive environment (Agarwal and Shinde, 2022).

Research Objectives

Research Objectives

This study addresses these limitations by proposing a hybrid framework that:

1. Extends classical transportation models through adaptive penalty functions (GN model)
2. Integrates multi-objective routing to balance cost, time, and reliability
3. Evaluates robustness under fuel price volatility

The objective is to provide a context-sensitive optimization framework suitable for logistics systems operating under economic instability.

LITERATURE REVIEW

Classical Transportation Optimization Problem

The transportation problem is a cornerstone of operations research, first formalized by Hitchcock (1941) and later extended by Koopmans (1949) and Dantzig (1951). The model seeks to minimize total transportation cost subject to supply and demand constraints.

The transportation problem minimizes total cost:

$$\min Z = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij}\, x_{ij} \qquad - \quad - \quad - \quad \text{i}$$

Subject to:

$$\sum_{j} x_{ij} = s_i \quad - \quad - \quad - \quad \text{ii}$$

$$\sum_{i} x_{ij} = d_i,\ \ x_{ij} \geq 0 - \quad - \quad \text{-iii}$$

Heuristic approaches such as:

i. Northwest Corner Method (Charnes & Cooper, 1954)
ii. Least Cost Method (Reinfeld & Vogel, 1958)
iii. Vogel's Approximation Method (Vogel, 1958)

are widely used to generate initial feasible solutions, while optimality is typically verified using methods such as MODI (Dantzig, 1963; Charnes & Cooper, 1954).

While these methods are computationally efficient, they are inherently static and cost-centric, limiting their applicability in dynamic environments characterized by uncertainty and multiple performance criteria.

Multi-Objective Optimization in Logistics

Real-world logistics systems involve trade-offs among multiple competing objectives, including cost efficiency, delivery speed, and service reliability. Multi-objective optimization frameworks address these trade-offs using techniques such as weighted aggregation and Pareto optimality (Ehrgott, 2005). Evolutionary algorithms, particularly NSGA-II (Deb et al., 2002), have demonstrated effectiveness in solving complex multi-objective

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

routing problems. These approaches enable decision-makers to identify solutions that balance competing priorities rather than optimizing a single metric. However, many existing models do not explicitly incorporate economic volatility, which is a critical factor in emerging markets.

Logistics Systems in Developing Economies

Logistics systems in Sub-Saharan Africa face structural challenges, including:

High transportation costs relative to GDP, poor road infrastructure, regulatory inefficiencies and exposure to fuel price volatility. (Teravaninthorn & Raballand, 2009; World Bank, 2020) These challenges necessitate optimization frameworks that go beyond traditional cost minimization to include risk-sensitive and adaptive mechanisms. Despite this need, current literature provides limited integration of volatility-aware penalty structures within transportation models.

Multi-Objective Logistics Optimization

Logistics systems must balance cost, delivery time, and reliability. Multi-objective optimization (Ehrgott, 2005) employs the Pareto efficiency by Vilfredo Pareto, and scalarization techniques. Algorithms such as NSGA-II (Deb et al., 2002) and SPEA2 (Zitzler et al., 2001) demonstrate effectiveness in vehicle routing problems.

Research Gap

The literature reveals three key gaps:

1. Lack of adaptive penalty-based transportation models
2. Limited integration of multi-objective routing with classical frameworks
3. Insufficient focus on fuel price volatility in developing economies

This study addresses these gaps through the development of the GN+MOMR framework

METHODOLOGY

Model Formulation

The classical transportation objective is defined as:

$$Z = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij}\, x_{ij} \quad - \quad - \quad - \quad \text{iv}$$

Subject to:

Supply constraints: $\Sigma_j\, x_{ij} = s_i$

Demand constraints: $\Sigma_i\, x_{ij} = d_j$

Non-negativity: $x_{ij} \geq 0$

Case Study Design

A balanced transportation model was constructed with:

I. Total supply = total demand = 50,000 metric tons
II. Four supply nodes and five demand nodes

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

This structure reflects a simplified national distribution network.

Gokir-Nannim (GN) Model

The GN model introduces an adaptive penalty term:

$$Z_{GN} = \Sigma c_{ij} x_{ij} + \alpha P_{ij} \quad - \quad - \quad - \quad v$$

Where:

$$P_{ij} = \beta_1 D_{ij} + \beta_2 V_t(c_{ij}) + \beta_3 R_{ij} + \beta_4 C_{ij} \quad - \quad - \quad -vi$$

This formulation enables:

i. Incorporation of route degradation effects
ii. Adjustment for fuel price volatility
iii. Consideration of reliability risks
iv. Enforcement of optimal capacity utilization

Multi-Objective Mesh Routing (MOMR)

The MOMR framework defines three objectives:

i. Cost minimization
ii. Time minimization
iii. Reliability maximization

These are combined via weighted scalarization:

$$Z = w_1 f_1 + w_2 f_2 - w_3 f_3 \quad - \quad - \quad - \quad vii$$

Sensitivity Analysis

Fuel price variability was simulated at ±30% to evaluate model robustness under economic shocks.

RESULTS

As contained in Table 1 below, GM+MOMR reduces cost of transportation down to 41%,GN is 39.6%, VAM, 37.4%, LCM 37.8% over NWCM. This indicates that GN+MOMR is the best.

Method	Cost (₦)	Reduction
NWCM	306.5M	—
VAM	192.0M	37.4%
GN	185.0M	39.6%
GN+MOMR	180.4M	41.0%

Table 1: Cost Performance

Multi-Objective Performance Reliability test in table 2 showed that GN+MOMR has 91.5%, GN 88%, VAM 84%, NWCM 78%. This revealed that only GN+MOMR is Pareto efficient.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

Method	Time (hrs)	Reliability (%)
NWCM	12.5	78.0
VAM	10.8	84.0
GN	9.5	88.0
GN+MOMR	7.8	91.5

Table 2: Multi-Objective Performance Reliability Test

According to Sensitivity Analysis Table 3 below, any increase in fuel prices lead 28.5% cost increase with the use of VAM model and 22.3% with GN+MOMR model. This showed that GN+MOMR is more resilient

Method	Cost Increase (+30%)
VAM	+28.5%
GN+MOMR	+22.3%

Table 3: Sensitivity Analysis

Statistical Significance

All improvements statistically significant ($p < .05$).

DISCUSSION

The results demonstrate that augmenting classical transportation models with adaptive penalty structures significantly enhances performance under volatile conditions. The GN model improves cost efficiency by incorporating contextual constraints, while MOMR ensures balanced optimization across multiple objectives. Table 1,2, and 3 corroborates previous studies by **Aliyu et al. (2019), Shammah and Atama (2019),** and **Prifti et al. (2020)** on transportation cost optimization using linear programming techniques, including the **North-West Corner Rule (NWCR), Least Cost Method (LCM),** and **Vogel's Approximation Method (VAM).** The results consistently indicate that **VAM** is the most efficient method, followed by NWCR, with LCM being the least optimal, a finding further supported by **Adeniyi et al. (2023)** and **Adamu et al. (2020).** Subsequent studies by **Akpan et al. (2020), Daniel and Agada (2020), Daniel et al. (2021),** and **Manuela et al. (2025)** reaffirm VAM's superiority and recommend its adoption for industrial distribution planning. Adopting VAM can therefore mitigate the impact of rising prices on goods, and the enhanced **GN+MOMR** model further improves VAM. Importantly, the framework does not replace classical optimization but extends it, preserving computational efficiency while enhancing realism. The below figure, presents cost variance according to Geopolitical Zone.

Figure 5: Cost Variance per Geopolitical Zone.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

Practical Implications

The framework is suitable for:

1. Regional logistics pilots
2. Agro-distribution corridors
3. Integration with fleet management systems

Emerging technologies such as digital twins and real-time data integration represent future extensions rather than validated components of this study.

RECOMMENDATION

The GN+MOMR framework offers a context-sensitive, adaptive, and Pareto-efficient logistics optimization model suitable for volatile developing economies. However, further works need to model the system in respect of routes taking care of safe and unsafe routes, nature of the routes.

CONCLUSION

This study presents a hybrid optimization framework combining adaptive penalty modeling with multi-objective routing. The GN+MOMR approach demonstrates improved cost efficiency, delivery performance, and resilience under fuel price volatility.

The findings suggest that adaptive, multi-objective optimization provides a viable pathway for improving logistics performance in economically unstable environments. further studies to consider Reliance on simulated data, real-world validation, Parameter sensitivity across regions and real-time traffic integration.

REFERENCES

1. Adamu I. K., Suleiman . K. and Yunusa K. G. D.(2020) Optimization of Total Transportation Cost. Global Journal Of Pure And Applied Sciences . 26(2020): 57-63. DOI: https://dx.doi.org/10.4314/gjpas.v26i1.7
2. Adenikinju, A. (2009). Energy pricing and subsidy reforms in Nigeria. International Association for Energy Economics Conference Proceedings, 1–15.
3. Adeniyi S. O. , Amanze C. E. , Adeniyi O. , Mba O. O.(2023) The Vogel Approximation and North West Corner Transportation Models for Optimal Cost Distribution of Dangote Cement. International Journal of Innovative Science and Research Technology. 8(5) Pp. 1364-1369
4. Agarwal R and Shinde D. K. (2022) Vehicle Allotment and Route Optimization for Transportation Services Using Logistics Techniques in Supply Chain Management. Proceedings of the 2nd Indian International Conference on Industrial Engineering and Operations Management Warangal, Telangana, India, August 16-18. PP 45-53
5. Akpan, W. A ., Awaka- Ama, E.J. and Ikrang, E.G (2020) Optimization of Products Transportation and Distribution Network. International Journal of Engineering Research & Technology (IJERT) 9(2) Pp 181-184
6. Alli, N. G., Jubril, T. S. and Bello, L. T. (2024) Impact of Fuel Subsidy Removal on Nigeria's Supply Chain: A Case Study Analysis. International Journal of Studies in Business Management, Economics and Strategies. 3(4). 125-143
7. Aliyu M. L., Usman U., Babayaro Z. and Aminu M. K. (2019) A Minimization of the Cost of Transportation. American Journal of Operational Research 2019, 9(1): 1-7 DOI: 10.5923/j.ajor.20190901.01
8. Amorim, P., & Almada-Lobo, B. (2014). The impact of food perishability issues in the vehicle routing problem. Computers & Industrial Engineering, 67, 223–233. https://doi.org/10.1016/j.cie.2013.11.006

9. Avila-Torres P. A., Arratia-Martinez N. M. and Ruiz-y-Ruiz E. (2020) The Inventory Routing Problem with Priorities and Fixed Heterogeneous Fleet. Appl. Sci. 10, 3502; doi:10.3390/app10103502
10. Charnes, A., & Cooper, W. W. (1954). The stepping stone method of explaining linear programming calculations in transportation problems. Management Science, 1(1), 49–69. https://doi.org/10.1287/mnsc.1.1.49
11. Daniel, E. E. and Agada P.O. (2020) Transportation Optimization Model for Cement Distribution. Abacus (Mathematics Science Series) 47(1): 212-225
12. Daniel, E. E., Udeh, P. C., Ibrahim, I., Abubakar A. B. and Danhausa A. A. (2021) Transportation Optimization Model, Analysis for Cement Distribution and Risk Reduction. Abacus (Mathematics Science Series) 48(2) 110-117
13. Dantzig, G. B. (1951). Application of the simplex method to a transportation problem. In T. C. Koopmans (Ed.), Activity analysis of production and allocation (pp. 359–373). John Wiley & Sons.
14. Dantzig, G. B. (1963). Linear programming and extensions. Princeton University Press.
15. Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6(2), 182–197. https://doi.org/10.1109/4235.996017
16. Ehrgott, M. (2005). Multicriteria optimization (2nd ed.). Springer.
17. Ezekiel A. M. (2024) Effects of Petroleum Products Price Hike on The Supply of Agricultural Products in Nigeria – A Review. FUDMA Journal of Agriculture and Agricultural. 10(3) Pp.19-25. https://doi.org/10.33003/jaat.2024.1003.03
18. Hitchcock, F. L. (1941). The distribution of a product from several sources to numerous localities. Journal of Mathematics and Physics, 20(1–4), 224–230. https://doi.org/10.1002/sapm1941201224
19. Hussaini, A. S., Oladimeji, Y. U., Sani, A. A., Umar, M and Udeh, B. E (2025) Effects of Fuel Subsidy Removal on Price Trend of Staple Food Crops in Kaduna Municipal, Nigeria. Umteb – Xvii International Scientific Research Congress.
20. Ikechukwu E. C., Nwagbala S. C. and Ezeanokwasa F. N. (2025) Fuel subsidy removal and performance of SMEs in Anambra State Nigeria. International Journal of Financial, Accounting, and Management (IJFAM) 6(4) 585-599
21. Ilodigwe A. O (2023) Fuel Subsidy Removal and Its Negative Impact on Small and Medium Scale Enterprises. Journal of Education, Humanities, Management & Social Sciences (JEHMSS). Pp 25-35
22. Islam S., Biswas H. R., Khatun U.H., Rani R., Nourin S. I. (2024) Optimizing Transportation Logistics for Cost Efficiency in a Garment Factory: A Linear Programming Approach Using LINDO. Sch J Phys Math Stat, 11(10): 146-149.
23. Jiang Q. and Wang H. (2025) Risk Assessment and Hybrid Algorithm Transportation path optimization for Model Road Transport of Dangerous Goods. IATSS Research 49(2025) 72-80
24. Jolaiya O. F.and Akinmulegun S. O.(2025) The Fuel Subsidy Removal and the Performance of Transport Sector: A Study of Selected Transport Firms in Nigeria. Journal of Public Administration and Social Welfare Research. 10(1) Pp 73-86
25. Justinah. O. O. and Oseyemi E. A. (2024) Evaluation of the Impact of Fuel Subsidy Removal on Family Income and Sustainability in Ondo City, Nigeria. International Journal of Home Economics, Hospitality and Allied Research, 3(1): 117-128
26. Koopmans, T. C. (1949). Optimum utilization of the transportation system. Econometrica, 17(Supplement), 136–146. https://doi.org/10.2307/1907301
27. Liu F., Lu .C., Gui L., Zhang Q., Tong X., Yuan M.(2023) Heuristics for Vehicle Routing Problem: A Survey and Recent Advances. arXiv:2303.04147v1 [cs.AI] 1-67
28. Lorenc, A. (2025) Predicting Fuel Consumption by Artificial Neural Network (ANN) Based on the Regular City Bus Lines. Sustainability 17(1678). https://doi.org/10.3390/su17041678.
29. Luyi, E. O., Ogunjobi O. E. and Olorunjubee O. I. (2025) Removal of Fuel Subsidy and it's Effects on the Prices of Goods and Services in Okitipupa Local Government Area of Ondo State, Nigeria. International Journal Of Innovation, Management & Social Sciences. 1, 140-152.
30. Manuela A. L., Harahap R. P. B., Yoefitri T., Meizani N. and Hidayana R. A. (2025) Optimization Model in Transportation Based on Linear Programming. International Journal of Quantitative Research and Modeling. 6(2) . 171-175

31. Nadoo, V. (2022). The impact of fuel subsidies on economic growth in sub-Saharan Africa. Energy Economics, 112, 106223. https://www.imf.org/external/pubs/ft/dp/2013/afr1302.pdf
32. National Bureau of Statistics. (2022). Nigeria poverty assessment 2022. Federal Republic of Nigeria.
33. Oghenenyerhovwo E. A. and Bright O. (2025)The study finds that the removal of fuel subsidy has affected transportation cost in Delta State. Journal of Economic Equity, Finance, and Taxation | Volume 1(2), 63-73
34. Olusegun O. A., Afolabi Q. B. and Ogola D. B. (2023) Impact of Fuel Subsidy Removal on Gross Domestic Product and Transportation Cost in Nigeria. European Journal of theoretical and Applied Science.1(5) Pp 769-777
35. Orluchukwu G. and Thankgod F. L. (2024) Fuel Subsidy Removal in Nigeria: Problems and Prospects. Journal of Policy and Development Studies (JPDS). 17(2) 92-108
36. Papară C. (2022) An empirical study of large transportation networks and solutions for the cost optimization. International Journal of Advanced Statistics and IT&C for Economics and Life Sciences. 12(02) 41-52
37. Prifti V., Dervishi I., Dhoska K. Markja I. and Pramono A.(2020) Minimization of transport costs in an industrial company through linear programming. International Conference on Advanced Mechanical and Industrial engineering . Pp 1-10. doi:10.1088/1757-899X/909/1/012040
38. Prokudin, G., Oliskevych, M., Chupaylenko, O., & Maidanik, K. (2020). Optimization model of freight transportation on the routes of international transport corridors. Journal of Sustainable Development of Transport and Logistics, 5(1), 66-76. doi:10.14254/jsdtl.2020.5- 1.7
39. Reinfeld, N. V., & Vogel, W. R., (1958). Mathematical Programming. Prentice Hall. LCCN: 58011418. https://books.google.com.ng/books?id=qVHQAAAAMAAJ
40. Samaila M. L., Adamu H. and Murtala M. (2024) Effect Of Fuel Subsidy Removal On Commodity Prices In Sokoto Metropolis, Sokoto State, Nigeria. UMYU Journal of Accounting and Finance Research. .6(1) Pp 190-198. https://doi.org/10.61143/umyu-jafr.6(1)2024.015
41. Samson O. S., Ezekiel O. I., Joseph B., Daniel A. A. and Mudashir A. O. (2024) Impact of Fuel Subsidy Removal on Agricultural Production among Smallholder Farmers in Niger State, Nigeria. Journal of Economics, Business Management and Administration. pp 7-17
42. Shammah S. K. and Atama A. M. (2019) Minimization of Transportation Cost Problems. Mathematical Theory and Modeling 9(3) Pp. 35-46
43. Shimbura G., Umar U. D. & Mai-lafia J. S. (2025)Effect of Fuel Subsidy Removal on the Transportation System in Jalingo Metropolis, Taraba State. International Journal Of African Innovation & Multidsciplinary Research 9(2) Pp 45-56.
44. Stanfast S. B. and Marian L. A. (2020) Transportation Model and Cost Control in Nigerian Manufacturing Firms. International Journal of Advanced Academic Research (Social And Management Sciences. 6(12) Pp. 41- 52. Doi: 10.46654/Ij.24889849
45. Tanash M. and As'ad R. (2025) Heuristic Algorithms for the Heterogeneous Vehicle Routing Problem With Time Windows, Customers Priority, Pickup and Delivery. IEEE Access 13(2025). 110605- 110622
46. Teravaninthorn, S., & Raballand, G. (2009). Transport prices and costs in Africa. World Bank. https://doi.org/10.1596/978-0-8213-7650-8
47. Vogel, W. R. (1958). A special algorithm for the transportation problem. Naval Research Logistics Quarterly, 5(1), 67–70. https://doi.org/10.1002/nav.3800050109
48. World Bank. (2020). Doing business 2020. World Bank Publications.
49. Wu F. and Zhu Y. (2021) Transportation route optimization based on heuristic algorithm Journal of Physics: Conference Series 2083 (2021) doi:10.1088/1742-6596/2083/3/032016
50. Yunusa E., Yakubu Y., Emeje Y. A., Ibrahim Y. B., Stephen E. And Egbunu D. A.(2023) Fuel Subsidy Removal And Poverty in Nigeria: A Literature Review. Int. J. Applied Management Science. 04(09), 14-27
51. Zhang N. L and Xie ., F. R. (2025) A Review of Research on the Transportation
    a. Problem. Open Journal of Applied Sciences. 15(5), 1168-1177
52. Ziółkowski J., Hošková-Mayerová S., Hutsaylyuk V. and Łukasiak D. (2025) Optimization of Road Transport Within the Supply Network – A Case Study From Poland. Transport Problems 20(01) 193-206. DOI: 10.20858/tp.2025.20.1.16

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

53. Zitzler, E., Laumanns, M., & Thiele, L. (2001). SPEA2: Improving the strength Pareto evolutionary algorithm (TIK Report No. 103). ETH Zurich