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Road Transport Logistics Planning for Oil and Gas Operations in Rivers State, Nigeria: A Scenario-Based Decision-Support Framework

G. Dorbra Akamu [1], Ejem A. Ejem[2], Christopher C. Ikeogu[3], Mercy E. Ejem[4], Vivian N. Ikeogu[5], and Uchenna U. Fort-Edward[6]

[1,3,5]Department of Logistics and Transport Technology, Federal University of Technology, Owerri, Nigeria.
[2]Department of Logistics and Supply Chain Management, Federal University of Technology, Owerri, Nigeria.
[4]Department of Entrepreneurship and Innovation, Federal University of Technology, Owerri, Nigeria.
[6]Department of Finance and Innovation Technology, Federal University of Technology, Owerri, Nigeria.

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Abstract: *Road transport planning for oil and gas operations requires coordinated decisions about routing, vehicle allocation, delivery time and operational risk. This study develops a scenario-based decision-support framework for examining these decisions in the context of Rivers State, Nigeria. The analysis uses 15 logistics-operation cases and a separate illustrative network comprising five service nodes and five heterogeneous vehicles. Descriptive statistics and ordinary least squares regression were recalculated from the operational cases, while the network parameters were examined for capacity adequacy and routing feasibility. The cases recorded a mean transport cost of ₦818,667, mean delivery time of 21.8 hours, mean fleet utilisation of 68.5% and mean risk index of 6.7. Distance was positively associated with both transport cost and delivery time within the dataset. The network scenario contained 150 tonnes of demand against 100 tonnes of aggregate vehicle capacity, making complete service infeasible under a single-trip, single-loading-cycle assumption. A separate illustrative performance comparison specified reductions of 20.0% in cost, 20.3% in delivery time and 15.9% in the risk index, alongside a 13.7-percentage-point increase in fleet utilisation. These differences are scenario assumptions or reported comparisons, not verified optimisation benefits. The study contributes a structured framework for integrating demand, fleet capacity, cost, time and risk while identifying the data and implementation requirements for operational validation.*

Keywords: road freight transport; oil and gas logistics; fleet allocation; vehicle routing; scenario analysis; decision support; Rivers State.

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INTRODUCTION

Road transport logistics planning involves coordinating vehicle movements, delivery requirements and operational resources across interconnected service locations. Its effectiveness depends not only on the distance travelled but also on how vehicle capacities, customer requirements, operating costs and service constraints are represented in planning decisions. Vehicle-routing research demonstrates that apparently similar distribution problems can require substantially different solutions when their assumptions about fleet composition, demand, service times and route structure differ (Braekers et al., 2016). Consequently, an appropriate logistics model must reflect the characteristics of the decision problem rather than apply a shortest-distance rule without regard to operational feasibility. For oil and gas operations, the planning problem may also involve safety-sensitive cargo and operational exposure that cannot be represented adequately by monetary cost alone. Research on hazardous-materials transportation treats routing as a problem involving both operational efficiency and the potential consequences of incidents. Accordingly, the least-cost route need not be the preferred route when safety and risk restrictions are considered (Erkut et al., 2007). This distinction is relevant to petroleum-product movements, although hazardous-material requirements should not be assumed to apply identically to every category of equipment, material or personnel movement within the industry.

Within Rivers State, previous research has examined organisational challenges affecting logistics coordination in selected oil and gas companies. Esima et al. (2019) identified equipment provision and maintenance, communication between service providers and client organisations, quality assurance and project monitoring as important considerations in logistics outsourcing. Their findings suggest that transport performance depends partly on the relationships and information exchanges through which logistics activities are organised. However, an examination of outsourcing challenges does not, by itself, establish which routes should be selected or how vehicles should be scheduled to meet a specified distribution requirement. The broader supply chain integration literature reinforces the need to examine coordination carefully. Fabbe-Costes and Jahre (2008) found considerable diversity in how integration and performance were defined and measured, cautioning against a simple assumption that greater integration necessarily produces better performance. For transport planning, the implication is that coordination must be translated into identifiable mechanisms, such as consistent demand information, compatible dispatch schedules and visibility of vehicle availability. Integration becomes analytically useful when its operational meaning and performance consequences are explicitly specified.

Developments in dynamic vehicle routing further demonstrate the importance of information availability. Pillac et al. (2013) distinguish routing problems according to the quality and evolution of information, showing why plans developed from fixed inputs differ from decisions that must respond to information arriving during operations. A static routing model can provide a useful planning baseline, but it should not be described as dynamically responsive unless its information inputs and re-planning procedures support that capability. A further methodological issue concerns

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the distinction between statistical analysis and operational decision-making. Statistical models can describe relationships or support prediction, whereas optimisation selects actions subject to an objective and a set of constraints. Shmueli (2010) shows that explanation and prediction are distinct modelling goals, while Bertsimas and Kallus (2020) develop a framework connecting data-based prediction with prescriptive decisions. Together, these contributions indicate that a well-fitting regression equation is not equivalent to a feasible or effective transport plan.

Against this background, the present study develops a scenario-based decision-support framework for road transport logistics planning in the oil and gas context of Rivers State, Nigeria. Its analytical purpose is to connect the description of logistics performance with explicit route-and-fleet planning requirements. The study examines operational cases, explores associations among selected performance variables and evaluates whether the network and fleet assumptions are sufficient to support the proposed service requirement. The study addresses three objectives: first, to describe the performance characteristics represented by the logistics cases; second, to examine exploratory associations between transport cost, delivery time and selected operational variables; and third, to develop a planning framework that makes demand fulfilment, capacity adequacy, vehicle movements, time and risk considerations explicit. Its contribution is therefore methodological and decision-support oriented. It does not treat observations as representative company records or scenario differences as measured intervention effects.

LITERATURE REVIEW

Supply chain coordination and logistics performance

The relationship between coordination and logistics performance provides an organisational foundation for transport planning. Fabbe-Costes and Jahre (2008) reviewed evidence linking supply chain integration with performance and found that differences in definitions, scope and measurement prevented a universal conclusion that more integration necessarily produces better outcomes. Their review shifts attention from integration as a general managerial aspiration to the particular interfaces, practices and performance measures involved. This perspective is relevant to oil and gas logistics because transport arrangements may involve client organisations, logistics contractors and other operational units. In selected companies in Rivers State, Esima et al. (2019) examined logistics outsourcing challenges and highlighted the importance of equipment maintenance, communication, quality assurance and monitoring. Their contribution is contextually valuable because it identifies coordination concerns within the setting motivating this study. Nevertheless, the outsourcing focus differs from the present route-and-fleet problem: organisational recommendations do not establish the feasibility or comparative performance of specific vehicle assignments. These studies support a framework in which coordination improves the quality and consistency of planning inputs but is not substituted for mathematical feasibility. Demand communication and vehicle-status information can support planning, while the resulting assignments must still be checked against capacity and scheduling restrictions.

Ucheobi et al. (2024) identify the wider distribution constraints within which petroleum transport decisions operate, while Ucheobi et al. (2025) emphasise information visibility and ICT-enabled coordination as enablers of logistics responsiveness. Obianife et al. (2025) extend this perspective by identifying operational cost drivers and fleet-management concerns in Nigerian road haulage. Ejem et al. (2021) demonstrate a structured approach to evaluating competing logistics criteria, whereas Ejem et al. (2025) connect logistics planning with risk management, business continuity and resilience. Collectively, these contributions support evaluating transport performance through the interaction of operating conditions, information quality, resource allocation and service requirements rather than through distance or monetary cost alone. The present study organises logistics planning into four connected stages: assessment of the operating context and available information; generation of feasible route-and-fleet alternatives; multi-criteria evaluation of those alternatives; and execution, monitoring and review. This sequence represents an analytical synthesis developed for the present study rather than a model reproduced from any single publication. It places contextual constraints and information requirements before route selection, establishes operational feasibility as a prerequisite for alternative ranking, and incorporates monitoring as the basis for subsequent planning adjustments. The distinction between feasibility and preference is particularly important.

The multi-criteria approach demonstrated by Ejem et al. (2021) provides a basis for comparing alternatives with different performance characteristics, but ranking does not replace the capacity, demand-fulfilment and scheduling restrictions required in a transport model. Similarly, the digital capabilities examined by Ucheobi et al. (2025) can support the availability and exchange of planning information, but they do not independently establish the feasibility or effectiveness of a particular route assignment. Accordingly, the present framework first requires alternatives to satisfy operational constraints before evaluating their relative cost, delivery time and risk exposure. The contribution of the present study therefore lies in translating these complementary considerations into an explicit, scenario-based decision-support structure, rather than claiming that their integration is theoretically unprecedented. The framework makes demand fulfilment, vehicle capacity, route feasibility, cost, time and risk explicit while distinguishing exploratory statistical associations from operationally validated improvements.

Vehicle routing and heterogeneous fleet planning

Braekers et al. (2016) provide a taxonomic review of vehicle-routing research, demonstrating the wide variation in assumptions underlying routing models. Their classification highlights why the vehicle-routing problem is not a single uniform task. Differences in customer requirements, fleet characteristics and operational conditions change both the formulation and the meaning of a satisfactory solution. For a heterogeneous fleet, vehicle selection and route construction are connected. Vehicles differ in carrying capacity and potentially in their operating characteristics, so assigning a vehicle to a route affects both cost and the quantity that can be served. The relevant analytical task is therefore to identify compatible combinations of routes, loads and vehicles rather than minimise network distance independently of fleet allocation (Braekers et al., 2016).

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Multiple-trip operations add another layer of complexity. Cattaruzza et al. (2016) review routing problems in which vehicles can perform successive trips and organise the associated formulations and solution approaches. Their work is particularly relevant where total demand exceeds the fleet's capacity in one loading cycle. Under those conditions, a service plan must show when vehicles return, reload and become available for subsequent assignments. Aggregate payload capacity alone does not establish whether the complete requirement can be served within the available operating period. The implication for the present study is that a route sequence should be evaluated as part of a complete service schedule. Where the available inputs do not establish depot locations, trip durations or loading cycles, the analysis can identify candidate corridors and capacity requirements but cannot claim a fully validated multi-trip solution.

Dynamic information and adaptive routing

Pillac et al. (2013) review dynamic vehicle-routing problems through the quality and evolution of information. Their classification distinguishes planning situations in which the relevant information is available in advance from those in which information changes or becomes available during execution. The review therefore connects routing methods with the information environment in which decisions are made. This distinction limits what can reasonably be claimed for a static scenario. A model using fixed demand, distance and travel-time inputs may support baseline planning or comparison of assumed operating conditions. It does not automatically support real-time response to disruptions. Dynamic capability requires a mechanism for receiving updated information, identifying its decision relevance and revising assignments while accounting for movements already completed or under way (Pillac et al., 2013). For the present framework, digital visibility is consequently treated as an enabling condition rather than a demonstrated performance benefit. Vehicle tracking and updated operational information become valuable when they improve the parameters or constraints used in a defined decision process.

Risk-sensitive transport planning

Erkut et al. (2007) review hazardous-materials transportation as a planning domain in which risk considerations accompany conventional transport objectives. Their treatment establishes that monetary cost and transport risk are not necessarily aligned and that route evaluation must reflect the relevant exposure and consequence measures. This literature is applicable to hazardous petroleum-product movements but requires care when extended to the full range of oil and gas logistics activities. Equipment transport, routine supplies and hazardous cargo do not necessarily share the same risk structure. A context-specific framework should therefore identify what its risk variable measures and how it affects decisions. In this study, a risk index is interpreted as a scenario indicator unless supported by a documented measurement procedure. It should not be treated automatically as an accident probability or an estimate of expected loss. The distinction matters because a reduction in an ordinal or composite score cannot, without additional calibration, be interpreted as an equivalent percentage reduction in incident probability. Risk-sensitive planning requires clarity about both the measure and its decision role, consistent with the modelling concerns reviewed by Erkut et al. (2007).

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From statistical analysis to prescriptive decision support

Shmueli (2010) distinguishes explanation from prediction and shows that the intended modelling goal influences choices throughout the analytical process. This distinction is useful for logistics research because a model that describes the supplied observations well may still lack predictive validity or a defensible causal interpretation. Bertsimas and Kallus (2020) extend the discussion toward action by developing a prescriptive-analytics framework that combines data-driven information with optimisation. Their contribution shows that learning from data and selecting decisions can be connected, but the relevant objective is decision quality within the specified optimisation problem rather than statistical fit alone. These studies support a staged evaluation of logistics models. The operational data must first be suitable for the claimed analysis; estimated relationships must then be assessed for their intended purpose; and proposed actions must satisfy the service constraints. Finally, performance comparisons must use a transparent baseline. The present study adopts this separation to avoid presenting exploratory regression results as proof of operational savings.

Gap in Literature

The reviewed literature contributes complementary perspectives. Supply chain integration research explains why coordination practices and performance measures require precise definition (Fabbe-Costes & Jahre, 2008). Rivers State outsourcing research identifies relevant organisational concerns in selected oil and gas companies (Esima et al., 2019). Vehicle-routing research establishes the importance of matching formulations to fleet and service characteristics, while multiple-trip research makes vehicle reuse and scheduling explicit (Braekers et al., 2016; Cattaruzza et al., 2016). Dynamic-routing and hazardous-materials research add information evolution and risk-sensitive decision-making (Pillac et al., 2013; Erkut et al., 2007). The present study does not claim that integrating these considerations is theoretically unprecedented. Its narrower contribution is to organise them into a transparent scenario-based framework for the study setting, while distinguishing descriptive associations, feasible planning decisions and validated performance outcomes. This positioning avoids an unsupported claim that no relevant integrated models exist and places the emphasis on reproducibility, capacity consistency and appropriate interpretation.

Conceptual Framework

Logistics performance as a connected planning problem

This study conceptualises logistics performance as the outcome of connected decisions concerning demand allocation, vehicle deployment, route selection, scheduling and information coordination. These decisions cannot be evaluated adequately in isolation because they draw on shared resources and influence the same service outcomes. The diversity of vehicle-routing formulations reviewed by Braekers et al. (2016) illustrates how fleet characteristics, customer requirements and operational restrictions jointly determine the structure of a distribution problem. The connected-planning perspective has several implications. A route may be short but unsuitable for a vehicle or cargo assignment. A high-capacity vehicle may reduce the number of loaded movements while

remaining unavailable for another time-sensitive task. Similarly, combining deliveries may improve loading efficiency but create a longer service sequence. These are not reasons to favour one planning rule universally; they are reasons to represent the relevant trade-offs within a common decision structure rather than assess each indicator independently (Braekers et al., 2016). Organisational coordination provides an additional connection between planning and performance. In their review, Fabbe-Costes and Jahre (2008) demonstrate that integration is a multidimensional construct whose relationship with performance depends on how both concepts are defined. Consistent with that caution, the present framework does not assume that coordination automatically improves outcomes. Instead, it locates coordination in specific planning functions: communicating demand, confirming vehicle availability, synchronising loading and dispatch, and documenting delivery completion.

The framework is organised around five interrelated dimensions: transport cost, delivery time, fleet utilisation, operational risk and service feasibility. Transport cost represents the monetary expenditure associated with executing a specified service plan, while delivery time refers to the elapsed time required to complete the relevant transport and service activities. Fleet utilisation captures the extent to which available transport resources are deployed, measured using an explicitly defined capacity- or time-based indicator. Operational risk reflects the level of exposure represented by a documented risk measure or an explicitly identified scenario score. Service feasibility, in turn, establishes whether the proposed assignments and movements can satisfy demand within the prevailing capacity, accessibility and scheduling restrictions. Although these dimensions collectively inform transport planning and operational performance, they serve distinct analytical purposes. Cost and delivery time may constitute performance outcomes; vehicle availability and capacity function as resource constraints; operational risk may be incorporated as an optimisation objective, a threshold or a route-exclusion condition; and service feasibility determines whether a proposed plan can practically meet the specified demand. This distinction is consistent with the emphasis in the vehicle-routing literature on clearly specifying the objectives and constraints of each problem rather than treating different performance measures as interchangeable (Braekers et al., 2016; Erkut et al., 2007).

The framework also distinguishes single-trip capacity from service capacity over a planning horizon. When vehicles can reload and undertake additional journeys, the quantity they can deliver depends on more than their physical payload. Loading times, travel durations, return movements and available operating hours become relevant. Cattaruzza et al. (2016) show that multiple-trip vehicle routing requires formulations that explicitly account for the possibility of successive trips by the same vehicle. Consequently, repeated vehicle assignments should be represented through a timetable or trip-indexed formulation rather than assumed feasible from aggregate capacity figures alone. Conceptually, the study adopts a sequential framework in which demand and operating conditions inform the generation of feasible route-and-fleet alternatives, which are subsequently subjected to performance evaluation before a suitable plan is selected and validated. This sequence ensures that feasibility is established before alternative service plans are compared in terms of their operational performance. It also provides a mechanism for reviewing and adjusting an existing

plan when new information becomes available or operating conditions change. Such flexibility is particularly important in dynamic routing environments, where updated information may necessitate the reassessment of routing and scheduling decisions, as highlighted by Pillac et al. (2013).

From Statistical Inference to Operational Optimisation

The analytical framework separates the functions of statistical modelling and optimisation. Statistical analysis examines patterns in a dataset; optimisation determines which actions should be selected from a feasible set. Although statistical estimates may inform optimisation parameters, the two tasks require different forms of evidence and different validation procedures (Bertsimas & Kallus, 2020). For the present study, exploratory regression relates transport cost and delivery time to distance, fleet utilisation, risk and road-condition ratings:

$$C_i = \beta_0 + \beta_1 D_i + \beta_2 U_i + \beta_3 R_i + \beta_4 S_i + \varepsilon_i \quad (1)$$

$$T_i = \alpha_0 + \alpha_1 D_i + \alpha_2 U_i + \alpha_3 R_i + \alpha_4 S_i + \nu_i \quad (2)$$

where C_i denotes transport cost; T_i, delivery time; D_i, distance; U_i, fleet utilisation; R_i, risk; and S_i, road-condition rating.

These equations describe conditional associations within the dataset used for estimation. They do not independently demonstrate that changing a predictor will produce the corresponding change in an operating system. Shmueli's (2010) distinction between explanatory and predictive modelling is important here: model interpretation must follow the study objective and research design rather than rely solely on goodness of fit. In the present scenario-based study, the nature of the cases further limits the equations to exploratory analysis. Optimisation begins with a different question: which vehicle assignments and movements can satisfy the service requirement while achieving a specified objective? A general formulation is:

$$\min f(x), \text{ subject to } x \in \mathscr{F} \quad (3)$$

where x represents planning decisions, $\mathscr{F}$ is the feasible set and f(x) is the performance criterion.

For transport planning, the feasible set must reflect the applicable demand, capacity, vehicle-availability, route-continuity and scheduling restrictions. Where vehicles undertake multiple trips, their assignments must also be compatible over time (Braekers et al., 2016; Cattaruzza et al., 2016). A low-cost assignment that violates these restrictions is not an implementable solution.The distinction is particularly important when cost, time and risk are considered together. An estimated association between risk and transport cost does not determine an acceptable risk threshold. Likewise, a regression coefficient for fleet utilisation does not establish the dispatch sequence required to achieve a particular utilisation target. Risk preferences, service requirements and operational limits must be specified separately before they can guide route selection (Erkut et al., 2007).

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The present framework therefore uses statistical analysis to describe the cases and identify relationships requiring further investigation. It uses optimisation concepts to structure the selection of feasible actions. Claims about predictive accuracy require appropriate predictive assessment; claims about operational improvement require a reproducible planning implementation and comparison with a defined baseline. Connecting these stages is consistent with prescriptive analytics, but their connection should be demonstrated rather than presumed (Shmueli, 2010; Bertsimas & Kallus, 2020).

METHODOLOGY

Study design

The paper adopts a quantitative scenario-analysis design based on the numerical information contained in the source paper. Three numerical components are retained: a table comprising 15 logistics-operation cases, a five-node network specifying vehicle capacities, operating rates and node demands, and a separate illustrative comparison of baseline and improved operational performance. However, the 15 logistics-operation cases are not treated as observed company trips because the source paper does not provide dated trip records, vehicle identification details, invoices, GPS traces or independently documented procedures for assigning scores to the operational risk and road-condition variables. Consequently, company names mentioned in the source paper are not used to attribute the observations to identifiable organisations. Although the paper also reports a questionnaire target of 109 personnel drawn from a stated population of 150, the proposed sample size does not establish that the questionnaire was administered or that the intended number of responses was obtained. In the absence of verifiable information on the achieved sample, response rate, respondent characteristics and underlying response database, the questionnaire summaries are excluded from the empirical results of the paper.

Operational Variables and Their Analytical Roles

Table 1 presents the variables extracted from the operational-case table and specifies their respective measurement units or scales and analytical roles in the study. Seven variables are identified: distance, transportation cost, delivery time, fleet utilisation, operational risk index, road condition and freight demand. Distance is measured in kilometres and represents an explanatory variable, while transportation cost, expressed in thousands of naira (₦'000), and delivery time, measured in hours, serve as the principal outcome variables for the exploratory regression analyses. Fleet utilisation, expressed as a percentage, is included as an explanatory variable to represent the extent to which available transport capacity is deployed. Similarly, the operational risk index, measured on a scale of 1–10, and road condition, measured on a scale of 1–5, are included as explanatory variables to represent operational exposure and the condition of the transport environment, respectively. Freight demand, measured in tonnes, serves as a descriptive planning variable because it provides the basis for assessing the relationship between delivery requirements and available vehicle capacity. The classification of these variables establishes their respective roles in the descriptive and regression analyses.

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Table 1. Variables included in the operational-case analysis

Variable	Unit or scale	Analytical role
Distance	Kilometres	Explanatory variable
Transport cost	₦'000	Outcome variable
Delivery time	Hours	Outcome variable
Fleet utilisation	Percentage	Explanatory variable
Risk index	1–10	Explanatory variable
Road condition	1–5	Explanatory variable
Demand	Tonnes	Descriptive planning variable

Descriptive and regression model

Means, sample standard deviations, minima and maxima were recalculated directly from the 15 cases. Two ordinary least squares models were then estimated:

$$C_i = \beta_0 + \beta_1 D_i + \beta_2 U_i + \beta_3 R_i + \beta_4 S_i + \varepsilon_i \quad (4)$$

$$T_i = \alpha_0 + \alpha_1 D_i + \alpha_2 U_i + \alpha_3 R_i + \alpha_4 S_i + \nu_i \quad (5)$$

where C_i denotes transport cost in thousands of naira; T_i, delivery time in hours; D_i, distance; U_i, fleet utilisation; R_i, risk index; and S_i, road-condition rating.

Each model contains four predictors and an intercept, leaving ten residual degrees of freedom. Regression results are interpreted as relationships generated by the cases, not estimates of causal effects or population parameters. The thesis's reported multicollinearity and influence diagnostics are considered when assessing interpretability. Each model contains four predictors and an intercept, leaving ten residual degrees of freedom. Regression results are interpreted as relationships generated by the cases, not estimates of causal effects or population parameters.

Network and fleet inputs

The network contains nodes A–E. Its demand totals 150 tonnes, distributed as 20, 30, 25, 35 and 40 tonnes respectively. Five vehicles provide individual capacities of 15, 20, 25, 18 and 22 tonnes, giving 100 tonnes of aggregate capacity. The listed vehicle operating rates range from ₦2,500 to ₦3,000 per kilometre. The analysis checks whether these inputs are consistent with complete demand fulfilment under a single-trip assumption. It also examines the completeness of the proposed routing structure, including repeated vehicle assignments and the absence of a defined depot and delivery timetable.

Decision-support formulation

The paper proposes a capacitated network framework in which vehicle movements and delivery quantities are decision variables. A cost-minimisation baseline can be expressed as:

$$\min C = \sum_{k \in K} \sum_{(i,j) \in A} c_{ijk}\, x_{ijk} \quad (6)$$

where K is the fleet, A is the set of permissible links, c_{ijk} is the traversal cost for vehicle k, and x_{ijk} indicates whether that vehicle uses the link. Demand-fulfilment and capacity restrictions require:

$$\sum_{k \in K} y_k d = qd \quad \text{for every demand node } d \quad (7)$$

$$\sum_{d} y_k d \leq Q_k \quad \text{for every vehicle } k \quad (8)$$

where $y_k d$ is the quantity assigned to vehicle k for demand node d, qd is demand and Q_k is vehicle capacity. These are core allocation restrictions, not a complete routing implementation: vehicle continuity, depot movements and the connection between delivered quantities and visited nodes must also be specified.

The paper further identifies time and risk as planning objectives. However, it does not document defensible weights or a normalisation procedure for combining naira, hours and risk scores in a single weighted objective. They are therefore retained as explicit decision dimensions requiring additional parameterisation, rather than presented as components of a validated multi-objective solution.

RESULTS

Characteristics of the operational cases

The descriptive statistics provide an overview of the operational characteristics represented in the 15 logistics cases. The results indicate a mean transportation distance of 112.67 km, with a standard deviation of 26.11 km and a range of 75–160 km. This variation suggests that the scenarios incorporate different journey lengths, allowing the illustrative analysis to consider how distance may be associated with transportation expenditure and delivery time. The mean transport cost of ₦818,670, ranging from ₦600,000 to ₦1,020,000, similarly reflects variation in the financial requirements assigned to the cases. Delivery time averages 21.80 hours, with a standard deviation of 5.60 hours and a range of 14–32 hours. These figures establish that the cases represent different combinations of distance, cost and delivery-time requirements. However, because the observations are scenario-based rather than verified records of completed trips, they should be interpreted as characteristics of the analytical dataset, not as estimates of prevailing logistics performance in Rivers State.

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Table 2. Descriptive statistics for the 15 logistics cases

Variable	Mean	Standard deviation	Minimum	Maximum
Distance, km	112.67	26.11	75	160
Transport cost, ₦'000	818.67	128.83	600	1,020
Delivery time, hours	21.80	5.60	14	32
Fleet utilisation, %	68.47	5.98	58	78
Risk index	6.67	1.54	4	9
Road-condition rating	2.80	0.94	1	4
Demand, tonnes	28.60	7.09	18	42

The mean fleet utilisation of 68.47%, with a standard deviation of 5.98 percentage points, indicates that the cases assume varying levels of vehicle deployment, ranging from 58% to 78%. This variable is relevant to logistics performance because vehicle utilisation is associated with the productive use of available transport capacity and the incidence of underutilised or empty vehicle movements. Abate and Kveiborg (2013) explain that freight vehicle utilisation should be examined in relation to vehicle movements, trip chains and the commercial activities generating transport demand. Their discussion reinforces the importance of considering not only the proportion of capacity used but also the operational circumstances under which vehicles are deployed. In the present analysis, however, the utilisation figures are descriptive scenario inputs; they do not provide sufficient evidence to establish the actual efficiency of fleet deployment or the extent of empty running in the study area.

The operational risk index has a mean of 6.67 and a standard deviation of 1.54, with values ranging from 4 to 9. This variation introduces a risk-related dimension into the logistics cases and reflects the relevance of operational uncertainty to transport planning. Previous research demonstrates that risk considerations can influence route selection and the evaluation of alternative transportation plans. For instance, Erkut and Verter (1998) show that alternative approaches to measuring transportation risk can produce different route choices, indicating that the definition and measurement of risk are consequential to routing decisions. Similarly, Braekers et al. (2016) identify the diversity of problem characteristics and modelling assumptions across vehicle-routing studies, supporting the need to specify clearly how operational factors are represented in a routing framework. Nevertheless, because the source material does not establish the scale construction, component indicators or scoring procedure for the risk index, its mean value should not be interpreted as an independently validated measure of actual operational risk.

The road-condition rating has a mean of 2.80, a standard deviation of 0.94 and a range of 1–4. Its inclusion recognises that road conditions may be relevant to transport planning, particularly where route accessibility and journey-time performance are important. Research on freight routing has established the importance of travel-time reliability and changing traffic conditions in route-selection decisions. For example, Kong et al. (2018) demonstrate that congestion information and

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travel-time reliability can influence truck drivers' routing decisions, while Pillac et al. (2013) explain how the availability and evolution of operational information affect dynamic vehicle-routing decisions. These studies provide a conceptual basis for considering road and traffic conditions when evaluating transport alternatives. However, the present rating cannot establish the actual quality of roads in Rivers State because the direction of the rating scale, its measurement criteria and the procedure used to assign scores are not documented. It should therefore be treated as an illustrative scenario variable rather than an objective road-infrastructure assessment.

Demand ranges from 18 to 42 tonnes, with a mean of 28.60 tonnes and a standard deviation of 7.09 tonnes. This variation is important because the quantity of freight to be transported determines, in part, the capacity required to serve a given logistics assignment. In vehicle-routing research, demand is a fundamental problem characteristic that must be considered alongside vehicle capacity, route structure and other operational restrictions (Braekers et al., 2016). The relationship between demand and available capacity is also important in determining whether a proposed distribution plan is feasible. Consequently, the demand values provide a basis for illustrating how alternative logistics assignments might be assessed against vehicle-capacity limitations. Nevertheless, the demand figures should not be interpreted as measured freight volumes or as evidence of actual demand patterns among logistics operators in Rivers State.

The descriptive results demonstrate that the 15 logistics cases incorporate variation across distance, transportation cost, delivery time, fleet utilisation, operational risk, road condition and freight demand. This provides a numerical basis for illustrating the multiple considerations involved in logistics planning and for examining how alternative operating conditions may be represented in a quantitative framework. The pattern of variables is consistent with the broader vehicle-routing literature, which recognises that routing decisions involve the interaction of cost, time, demand, vehicle characteristics and operational constraints rather than the optimisation of distance alone (Braekers et al., 2016; Pillac et al., 2013). However, the descriptive statistics do not establish relationships among these variables, explain the causes of differences in operational performance or demonstrate the representativeness of the cases. In particular, the relatively small number of logistics observations and the absence of independently verified operational records limit the extent to which the findings can be generalised to logistics operations in Rivers State. The results are therefore best understood as a scenario-based description supporting the subsequent analytical illustration, rather than as empirical estimates of the performance of identifiable logistics organisations.

A further methodological consideration concerns the consistency of the descriptive statistics. The recalculated mean transportation cost of ₦818,670 differs from the ₦836,000 reported in the thesis summary table. Similarly, the recalculated mean delivery time of 21.80 hours differs from the previously reported 22.3 hours, while mean fleet utilisation is 68.47% rather than 68.9%. These differences indicate that the summary statistics in the original thesis were not fully consistent with the underlying operational-case table. The present article consequently adopts the recalculated values derived directly from the 15 cases and applies them consistently in the subsequent analysis.

This approach improves numerical traceability and internal consistency, although it does not resolve the broader limitation arising from the logistics nature of the observations.

Exploratory transport-cost model

The exploratory transport-cost model indicates that distance is positively and statistically significantly associated with transportation cost in the logistics cases. The estimated coefficient of 5.080 suggests that, holding fleet utilisation, operational risk and road-condition rating constant, an additional kilometre is associated with an increase of approximately ₦5,080 in transport cost. This finding is consistent with the general economic logic of freight transportation, in which longer journeys are likely to require greater fuel consumption, vehicle operating time, maintenance expenditure and other trip-related resources. It also accords with the vehicle-routing literature, where distance and travel cost are commonly incorporated as central components of routing objectives (Braekers et al., 2016). However, the coefficient should be interpreted as a conditional association within the logistics data, rather than as a verified marginal cost applicable to logistics operators in Rivers State.

The positive coefficients for fleet utilisation, operational risk and road-condition rating require more cautious interpretation. Although their estimated coefficients are positive, none is statistically significant at the conventional 5% level. The fleet-utilisation coefficient of 4.828 ($p = .488$) does not provide sufficient evidence that higher utilisation independently increases transportation cost. In practical terms, the relationship between fleet utilisation and cost may depend on factors such as vehicle capacity, load consolidation, empty running, trip frequency and the extent to which vehicles are productively deployed. Research on freight transport has emphasised that vehicle utilisation cannot be assessed independently of vehicle movements and the structure of transport demand (Abate & Kveiborg, 2013). Similarly, the operational risk coefficient is positive but does not attain statistical significance at the 5% level ($\beta = 37.272$, $p = .056$). Although this result is relatively close to the conventional threshold, it should not be described as statistically significant. The coefficient may indicate a possible cost association within the logistics study cases, but the available evidence does not establish that higher operational risk independently increases transport expenditure.

The positive road-condition coefficient ($\beta = 38.014$, $p = .175$) also requires careful treatment. Its interpretation depends on how the road-condition rating was coded, particularly whether higher scores represent better or poorer road conditions. Without a documented coding direction and measurement procedure, it would be inappropriate to conclude that improved road conditions increase transportation cost or that deteriorating roads necessarily produce the estimated effect. More broadly, transport-cost research recognises that road and traffic conditions may influence vehicle operating costs through travel speed, fuel consumption, vehicle wear and journey reliability. Nevertheless, the present model does not isolate these mechanisms. The estimated equation therefore provides an exploratory indication of the association between distance and transport cost, while the independent contributions of fleet utilisation, risk and road condition remain uncertain.

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$$Transport_cost = -439.222 + 5.080Distance + 4.828Fleet_utilisation + 37.272Risk_index + 38.014Road_condition \quad (9)$$

Table 3. Estimated transport-cost regression

Predictor	Coefficient	Standard error	p-value
Intercept	−439.222	586.411	0.471
Distance	5.080	1.522	0.008
Fleet utilisation	4.828	6.705	0.488
Risk index	37.272	17.232	0.056
Road-condition rating	38.014	26.047	0.175

The model reports an R^2 of 0.972 and an adjusted R^2 of 0.960, indicating that the four predictors jointly account for a substantial proportion of the variation in transportation cost within the 15 logistics cases. This high explanatory value should not, however, be interpreted as evidence of strong predictive reliability. The very small sample, substantial multicollinearity among the predictors and the presence of potentially influential observations limit the stability of the estimated coefficients. As Braekers et al. (2016) explain, vehicle-routing problems involve interdependent operational characteristics, and the specification of objectives and constraints is important to the validity of the resulting model. Accordingly, the present cost equation is best regarded as an exploratory description of the logistics scenarios, not a calibrated cost-estimation model for operational or policy decisions.

Exploratory delivery-time model

The delivery-time regression similarly identifies distance as the only predictor with a statistically significant coefficient at the 5% level. The estimated coefficient of 0.278 indicates that, within the logistics cases, an additional kilometre is associated with an increase of approximately 0.278 hours, equivalent to about 16.7 minutes, in delivery time, holding the other included variables constant. This positive association is consistent with the basic relationship between journey distance and travel duration in freight distribution. It also reflects the importance of distance and travel time in vehicle-routing models, where route construction and scheduling decisions are commonly evaluated against the time required to serve demand (Braekers et al., 2016). Nevertheless, the estimated coefficient should not be treated as a universal travel-time rate. Actual journey duration may also depend on road geometry, traffic congestion, vehicle characteristics, loading and unloading activities, waiting time and other operational conditions that are not separately represented in the model.

The estimated delivery-time equation is:

$$Delivery_time = -29.083 + 0.278Distance + 0.151Fleet_utilisation + 0.573Risk_index$$

$$+ 1.924 Road_condition \quad (10)$$

The road-condition rating has a positive coefficient of 1.924 (p = .063), indicating a possible association with delivery time within the logistics cases, although the coefficient does not meet the conventional 5% significance criterion. Its 95% confidence interval includes zero, further indicating that the direction and magnitude of the independent association remain uncertain. In particular, the positive sign cannot be interpreted as evidence that better road conditions increase delivery time. Such an interpretation would require confirmation of the rating scale's coding direction and a reliable measure of road quality. Pillac et al. (2013) explain that dynamic vehicle-routing decisions are affected by the quality and evolution of operational information, while Braekers et al. (2016) show that routing models vary substantially in their treatment of travel-time and other operational characteristics. These contributions reinforce the need to represent road and traffic conditions through clearly defined and operationally meaningful variables.

Table 4. Estimated delivery-time regression

Predictor	**Coefficient**	**Standard error**	**p-value**
Intercept	−29.083	20.670	0.190
Distance	0.278	0.054	<0.001
Fleet utilisation	0.151	0.236	0.537
Risk index	0.573	0.607	0.368
Road-condition rating	1.924	0.918	0.063

Fleet utilisation has a positive coefficient of 0.151 (p = .537), while the operational risk index has a coefficient of 0.573 (p = .368). Neither relationship is statistically significant at the 5% level. These results do not establish that fleet utilisation or operational risk has no influence on delivery time; rather, the logistics dataset does not provide sufficiently reliable evidence of their independent associations after controlling for the other predictors. Fleet utilisation may affect delivery performance through the number of trips required, the allocation of vehicles to delivery assignments and the extent of capacity utilisation. Abate and Kveiborg (2013) emphasise that vehicle utilisation is connected to vehicle movements, trip chains and the commercial activities that generate freight demand. Similarly, Erkut and Verter (1998) demonstrate that the way transportation risk is defined and measured can affect route-selection outcomes. These studies suggest that utilisation and risk are relevant dimensions of transport planning, but their effects cannot be adequately established in the present model without more clearly defined measures and a larger, independently verified dataset.

The delivery-time model reports an R^2 of 0.981 and an adjusted R^2 of 0.974. Although these values indicate a high proportion of explained variation within the 15 cases. The model high explanatory power does not necessarily imply that its individual coefficients are stable or that it can accurately forecast delivery times under different operating conditions. The result is therefore consistent with

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the exploratory purpose of the analysis: it illustrates the potential relationship between transport distance and delivery time while identifying the need for more robust operational data and model validation before the equation can be used for forecasting or managerial decision-making.

Diagnostic limitations

The diagnostic results raise important concerns about the reliability and interpretation of the two regression models. The variance inflation factors (VIFs) in Table 5 range from 12.814 for road condition to 34.221 for fleet utilisation, while all corresponding tolerance values are below 0.10.

Table 5. Variance inflation factor and tolerance

Predictor	VIF	Tolerance
Distance	33.671	0.0297
Fleet utilisation	34.221	0.0292
Risk index	15.077	0.0663
Road condition	12.814	0.0780

These results indicate substantial multicollinearity among the explanatory variables. In practical terms, distance, fleet utilisation, operational risk and road-condition rating overlap considerably in the information they provide about the outcomes. This makes it difficult to isolate the independent contribution of each predictor and can inflate standard errors, reduce the precision of coefficient estimates and produce unstable coefficient signs or magnitudes. Consequently, the statistically significant distance coefficients should be interpreted cautiously, while the non-significant coefficients should not automatically be taken as evidence that the corresponding operational factors are unimportant.

This limitation is particularly relevant to vehicle-routing research because transport cost, travel time, vehicle utilisation, risk and road conditions are operationally interconnected. Braekers et al. (2016) demonstrate the diversity of vehicle-routing problem characteristics and modelling assumptions, highlighting the importance of specifying how operational variables interact within a particular problem. Erkut and Verter (1998) also show that alternative approaches to risk measurement can produce different route-selection outcomes. In the present analysis, the high VIF values suggest that the predictors may not provide sufficiently distinct information for reliable estimation of their separate effects. A larger dataset, improved variable definitions and a revised model specification would therefore be required to assess the independent relationships more convincingly.

The residual tests do not reject the assumptions of normality and homoscedasticity at the 5% significance level. However, these non-significant results should not be interpreted as definitive evidence that the assumptions are satisfied. With only 15 observations, the tests have limited power to detect departures from the assumed residual distributions. More importantly, the Cook's distance

result for the first observation in the delivery-time model (1.241) indicates that this case may exert substantial influence on the fitted regression. The identified influential observations in the cost model also warrant examination. Such cases should not be removed automatically; rather, their underlying values and data-generation procedures should be checked, and the sensitivity of the regression estimates to their inclusion should be assessed. The diagnostic findings qualify the interpretation of the high coefficients of determination reported for both models. The models may describe the logistics observations closely, but their coefficients are potentially sensitive to predictor overlap and individual cases. This distinction is important because a model that fits a small dataset closely is not necessarily a dependable forecasting or explanatory model for a wider population. Accordingly, the regression equations are retained as exploratory analytical illustrations. Their use for operational forecasting, cost estimation, route selection or policy calibration would require additional observations, validated measurement procedures, sensitivity analysis and independent model validation.

Fleet-capacity adequacy

The fleet-capacity assessment reveals a fundamental feasibility constraint in the proposed logistics scenario. The five vehicles have a combined carrying capacity of 100 tonnes, whereas the total demand across the five nodes is 150 tonnes. This produces a capacity shortfall of 50 tonnes if each vehicle is permitted to undertake only one loaded trip during the planning period. Consequently, the available fleet cannot satisfy the stated demand under a single-trip-per-vehicle assumption. This finding is important because it demonstrates that route optimisation cannot be meaningfully undertaken without first establishing whether the available transport resources can accommodate the demand to be served. The result is consistent with the capacitated vehicle-routing literature, which treats vehicle capacity as a fundamental constraint governing the allocation of customer demand to vehicle routes. Baldacci et al. (2010) explain that capacity restrictions are central to capacitated vehicle-routing formulations and must be respected when constructing feasible routes. Similarly, Braekers et al. (2016) identify vehicle capacity, customer demand and other operational restrictions as important characteristics in the classification and formulation of vehicle-routing problems. These studies reinforce the principle that a route may be geographically connected and operationally attractive but still be infeasible if the assigned freight exceeds the available vehicle capacity.

The capacity shortfall does not necessarily imply that the proposed fleet is permanently inadequate. Rather, it indicates that the scenario requires an explicit adjustment to its operating assumptions. Possible alternatives include allowing vehicles to undertake multiple loaded trips, increasing the number of vehicles, deploying vehicles with higher carrying capacities or extending the planning horizon to accommodate additional deliveries. The multi-trip vehicle-routing literature provides a methodological basis for considering repeated vehicle deployment within a defined planning period. Cattaruzza et al. (2016) demonstrate that allowing vehicles to perform multiple trips introduces additional scheduling and routing decisions that must be incorporated into the model. Therefore, if multiple trips are adopted in the present scenario, the analysis must specify vehicle return times, reloading arrangements, trip sequencing and the available operating period. Without

these details, the capacity deficit cannot be assumed to have been resolved. The implication is that capacity adequacy should be established before route optimisation and performance comparison. A complete logistics model must jointly consider demand allocation, vehicle capacities, route connectivity and scheduling feasibility. The present assessment therefore identifies a necessary condition for developing a valid delivery plan: the total quantity assigned to the fleet must be deliverable within the available capacity and planning period. Until this condition is satisfied, the proposed route structure cannot be regarded as a complete solution to the stated distribution problem.

Proposed route structure

The proposed corridors, A–B–C, C–D and D–E, with corresponding distances of 75 km, 30 km and 45 km, provide an illustrative representation of connected movements across the five-node network. Their arrangement suggests a sequential movement through the network, with node C linking the first corridor to the second and node D connecting the second to the third. However, the corridors alone do not constitute a fully specified vehicle-routing and delivery schedule. A feasible routing plan must identify the vehicles assigned to each movement, the quantity of freight carried, the sequence and timing of departures, delivery requirements at each node and any necessary return movements.

Route 1: A → B → C | Vehicle V3 (25 tons) + V1 (15 tons) | Distance = 75 km

Route 2: C → D | Vehicle V2 (20 tons) + V4 (18 tons) | Distance = 30 km

Route 3: D → E | Vehicle V5 (22 tons) + V2 (20 tons) | Distance = 45 km

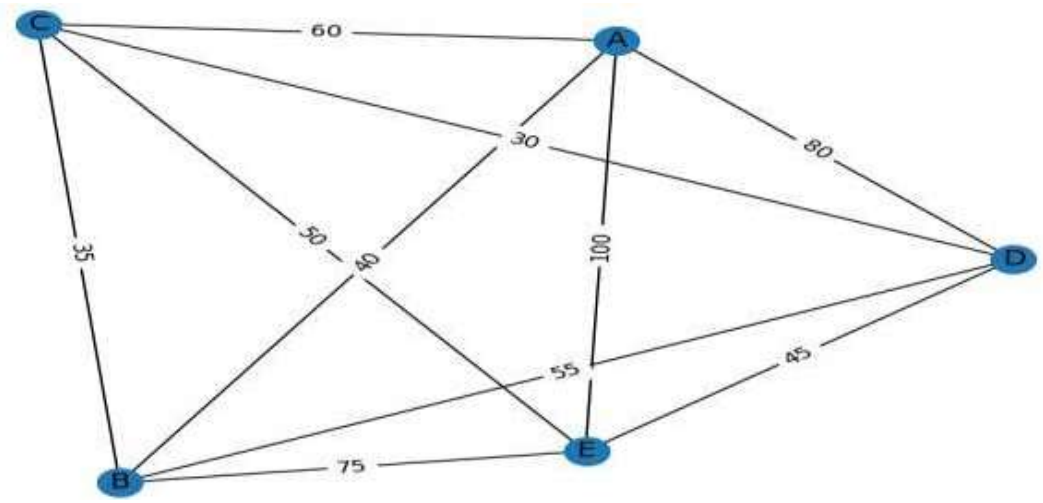


Figure 1: A Structured Route Optimization Network

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The repeated assignment of vehicle V2 to more than one corridor illustrates this distinction. Such an assignment is not inherently infeasible because a vehicle may undertake successive trips within the same planning period. However, its feasibility depends on whether sufficient time is available for the vehicle to complete the first assignment, return or reposition as required, reload where necessary and commence the subsequent assignment. This is consistent with the multi-trip vehicle-routing literature, which distinguishes between individual routes and the schedules through which vehicles undertake multiple trips (Cattaruzza et al., 2016). Without departure times, service durations, loading arrangements and vehicle availability information, it is not possible to establish whether the repeated use of V2 is operationally achievable.

The status of node A also requires clarification. Although it appears at the beginning of the first corridor, it is assigned a demand of 20 tonnes. This raises an important modelling question about whether A represents a depot with local demand, a customer location or a transfer facility. If A is a depot, the model must explain how its own demand is fulfilled and whether vehicles originate and return to it. If it is a customer node, its position in the network and relationship with the distribution origin must be specified. If it is a transfer point, the model must identify the relevant transshipment and loading arrangements. This distinction is important because depot location, customer demand and vehicle movements affect the structure and feasibility of routing decisions.

The wider vehicle-routing literature emphasises that network structure, depot configuration, customer demand, vehicle capacity and scheduling restrictions must be represented consistently when developing a feasible distribution plan (Braekers et al., 2016; Cattaruzza et al., 2016). Pillac et al. (2013) further demonstrate that changing operational information may require route adjustments in dynamic routing environments. Applied to the present scenario, these insights suggest that the proposed corridors should be treated as preliminary network representations rather than validated delivery routes. A complete model would require a clearly defined origin and destination structure, demand allocation at each node, vehicle-to-route assignments, trip sequencing, capacity checks and scheduling constraints. Until these elements are specified, the feasibility and operational performance of the proposed route structure remain undetermined.

Illustrative performance comparison

The baseline-to-improved scenario comparison in Table 6 indicates potential improvements across the four reported performance indicators. Transport cost decreases from ₦875,000 to ₦700,000, representing an absolute reduction of ₦175,000 or 20.0%. Delivery time declines from 23.2 to 18.5 hours, equivalent to a reduction of 4.7 hours or approximately 20.3%. Fleet utilisation increases from 71.3% to 85.0%, representing an improvement of 13.7 percentage points or approximately 19.2% relative to the baseline value. The operational risk index decreases from 6.9 to 5.8, a difference of 1.1 index units or approximately 15.9%. These changes illustrate the possibility of improving several dimensions of logistics performance simultaneously through changes in transport planning and resource deployment.

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The simultaneous reduction in cost and delivery time, alongside increased fleet utilisation, is consistent with the broader objectives of vehicle-routing and logistics optimisation. Vehicle-routing models commonly seek to improve the allocation of vehicles and the sequencing of deliveries while reducing transportation expenditure and travel-related time (Braekers et al., 2016). The improvement in fleet utilisation is also relevant to freight transport efficiency. Abate and Kveiborg (2013) explain that vehicle utilisation is closely associated with vehicle movements, trip chains and the commercial activities that generate freight demand. From this perspective, the increase from 71.3% to 85.0% may be interpreted as an illustrative indication of more intensive use of available transport capacity. However, higher utilisation should not be treated as an objective in isolation, since excessive utilisation may reduce operational flexibility or create scheduling difficulties where demand and journey conditions are uncertain.

Table 6. Illustrative performance differences

Indicator	Baseline scenario	Improved scenario	Absolute difference	Relative difference
Transport cost	₦875,000	₦700,000	−₦175,000	−20.0%
Delivery time	23.2 hours	18.5 hours	−4.7 hours	−20.3%
Fleet utilisation	71.3%	85.0%	+13.7 percentage points	+19.2%
Risk index	6.9	5.8	−1.1 index units	−15.9%

The reduction in the operational risk index also suggests a possible improvement in the risk profile of the proposed scenario. This is consistent with the argument by Erkut and Verter (1998) that risk considerations can materially influence transport route selection and the evaluation of alternative transportation plans. However, the observed decline from 6.9 to 5.8 represents a change in the risk score, not a demonstrated reduction in accident probability, expected financial loss or exposure to a specific safety hazard. The interpretation of the difference therefore depends on the definition, scale and measurement procedure used to construct the risk index. Without a documented risk-assessment framework, the result should remain an illustrative score-based comparison.

An important methodological distinction is that the baseline values in Table 5 do not represent the means of the 15 operational cases. The comparison must therefore be understood as a separate illustrative scenario rather than a before-and-after evaluation of the regression dataset. Furthermore, the source material does not establish that the improved values were obtained from a fully specified optimisation algorithm, implemented operational intervention or independently validated simulation. It would consequently be inappropriate to attribute the reported differences to a proven optimisation effect or to claim that the improvements would necessarily occur in actual logistics operations. The comparison nevertheless provides a useful illustration of the multidimensional nature of logistics performance. A transport plan should not be assessed exclusively in terms of cost reduction or travel-time minimisation; it should also consider vehicle utilisation, operational risk and the feasibility of meeting demand. This is consistent with the broader vehicle-routing literature, which recognises the diversity of objectives and constraints involved in routing decisions (Braekers et al., 2016). Pillac et al. (2013) further highlight the

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importance of adapting routing decisions to changing operational information. Accordingly, the illustrative comparison provides a conceptual basis for evaluating alternative logistics plans across multiple performance dimensions, while the actual magnitude and reliability of the reported improvements would require a reproducible optimisation procedure, clearly specified baseline assumptions and independent validation.

Implications of the Findings

The exploratory analyses demonstrate the importance of distinguishing between statistical association, operational feasibility and illustrative performance improvement in logistics planning. The regression results identify distance as positively associated with both transportation cost and delivery time within the dataset. However, the high multicollinearity, small sample size and influential observations limit the reliability of the individual coefficient estimates. The network assessment further establishes that the available fleet capacity of 100 tonnes is insufficient to satisfy the stated demand of 150 tonnes under a single-trip-per-vehicle assumption. Similarly, the proposed corridors provide a preliminary representation of network connectivity but do not establish a complete and feasible delivery schedule. Although the separate performance comparison indicates potential improvements in cost, delivery time, fleet utilisation and the risk index, it does not constitute an independently validated before-and-after evaluation.

These findings reinforce an important principle in logistics and vehicle-routing research: an effective distribution plan must integrate performance objectives with the resource, network and scheduling constraints that determine whether the plan can be implemented. The vehicle-routing literature provides established approaches for representing these interdependencies, including capacitated routing, multi-trip scheduling and dynamic routing under changing operational information (Baldacci et al., 2010; Braekers et al., 2016; Cattaruzza et al., 2016; Pillac et al., 2013). For the present study, the principal contribution of the numerical analysis is therefore its illustration of the analytical requirements for developing an integrated logistics-planning framework. Further empirical application would require verified trip-level records, documented measurement procedures, a fully specified network and vehicle schedule, and a reproducible optimisation and validation process.

DISCUSSION

What the Analysis Establishes

The analysis establishes a reproducible descriptive and regression baseline for the 15 logistics-operation cases presented in the source paper. The recalculated results indicate that transportation distance is positively and statistically significantly associated with both transportation cost and delivery time within the dataset. Specifically, each additional kilometre is associated with an estimated increase of approximately ₦5,080 in transportation cost and 0.278 hours in delivery time, holding the other included variables constant. These findings are consistent with the general structure of vehicle-routing models, in which distance constitutes an important determinant of transportation expenditure and journey duration (Braekers et al., 2016). However, the results do

not establish that distance is the dominant independent determinant of cost and delivery time across actual oil and gas transport operations in Rivers State. The nature of the observations, small sample size and substantial multicollinearity among the explanatory variables limit the extent to which the estimated relationships can be generalised or interpreted causally. The observed associations may also partly reflect the assumptions and procedures through which the cases were assembled.

A more consequential finding emerges from the assessment of network capacity relative to aggregate demand. The five vehicles provide a combined carrying capacity of 100 tonnes, whereas the stated demand across the five nodes amounts to 150 tonnes. This produces a capacity deficit of 50 tonnes under the assumption that each vehicle undertakes only one loaded trip within the planning period. The implication is that the distribution problem cannot be adequately addressed by selecting geographically connected or shorter routes alone. Rather, the planning framework must determine how the available vehicles can undertake sufficient loaded movements to satisfy the total demand within the specified operating period. Vehicle reuse, loading and unloading arrangements, vehicle availability and trip sequencing consequently become essential components of the model. This finding reinforces the importance of capacity restrictions in vehicle-routing formulations, where route feasibility depends on the compatibility between vehicle capacity and assigned demand (Baldacci et al., 2010; Braekers et al., 2016).

Implications for Integrated Logistics Planning

The practical value of the proposed framework lies in its ability to make the assumptions underlying logistics planning explicit and assessable. A complete service plan must identify vehicle origins, assigned cargo quantities, destination requirements, delivery sequences, vehicle availability and permissible movements within the planning horizon. These elements provide the operational foundation for connecting network configuration, demand allocation, fleet-capacity management and route selection within a common decision-support structure. The framework therefore extends the planning perspective beyond the identification of transport corridors to the development of complete and feasible vehicle schedules. This is consistent with the broader vehicle-routing literature, which emphasises the need to consider network structure, customer demand, vehicle characteristics and operational restrictions jointly when formulating distribution problems (Braekers et al., 2016).

An important implication concerns the treatment of cost, delivery time and operational risk as distinct performance dimensions. Although these indicators may be incorporated into a common multi-objective optimisation framework, their measurement and relative importance must first be established. Combining monetary cost, time and risk scores without appropriate normalisation and defensible weighting procedures may produce misleading comparisons and obscure the trade-offs that the model is intended to reveal. Erkut and Verter (1998) demonstrate that the measurement and representation of transportation risk can influence route-selection decisions. Similarly, the vehicle-routing literature recognises that different problem objectives and constraints require explicit formulation rather than being treated as interchangeable performance measures (Braekers et al., 2016). Consequently, any weighted multi-objective formulation developed from the present

framework should explain the basis for variable normalisation, the selection of weights and the sensitivity of the resulting solution to alternative weighting assumptions.

The illustrative baseline-to-improved comparison further identifies indicators that could be monitored in a future operational implementation. The reported differences suggest potential reductions in transport cost and delivery time, alongside improvements in fleet utilisation and the operational risk index. Nevertheless, the comparison does not establish the computational or operational procedures through which the improved values were generated. It should therefore be interpreted as an illustration of possible performance targets rather than evidence of realised savings or demonstrated intervention effects. Its prospective value lies in identifying the performance indicators that a future implementation should measure consistently. These should include total transportation expenditure, delivery duration, fleet utilisation, demand fulfilment and a clearly defined measure of operational risk. Such an approach would provide a more transparent basis for evaluating the effectiveness of alternative logistics plans and determining whether operational improvements are sustained over time.

Operational Validation Requirements

Moving the proposed framework from an illustrative analytical structure to an implementable logistics decision-support system requires systematic operational validation. The first requirement is the collection of dated and verifiable trip-level records covering origins, destinations, delivered quantities, vehicle identities, transportation costs and delivery durations. These records would provide the empirical basis for estimating operating relationships and assessing the extent to which the scenarios reflect actual logistics activities. Second, the variables representing fleet utilisation, operational risk and road condition must be defined through consistent and documented measurement procedures. This is particularly important because the present analysis cannot establish the independent effects of these variables without reliable operational definitions and measurement scales.

Third, the network and fleet configuration must be specified comprehensively. This requires identifying depot locations, vehicle–cargo compatibility, vehicle carrying capacities, loading and unloading arrangements, delivery requirements at each node and the planning horizon. The 50-tonne capacity shortfall identified in the present analysis must also be resolved through an explicitly defined arrangement involving additional vehicles, multiple loaded trips or an appropriate adjustment to the service plan. Fourth, the computational model must incorporate complete capacity, routing, scheduling and vehicle-continuity constraints to ensure that the resulting solution represents a feasible distribution plan. Where multiple trips are permitted, the model should explicitly account for vehicle return movements, reloading opportunities, trip sequencing and the time required to complete successive assignments. These requirements are consistent with the methodological considerations identified in capacitated and multi-trip vehicle-routing research (Baldacci et al., 2010; Cattaruzza et al., 2016).

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Fifth, the computational implementation must be sufficiently documented to permit independent reproduction and verification. This should include the optimisation software or solver employed, model formulation, input files, parameter settings, solution status, objective-function value and resulting vehicle schedules. Finally, the proposed solution should be compared with an explicitly defined operational baseline using consistent performance indicators and measurement periods. Where possible, sensitivity analysis should also examine the effects of changes in demand, vehicle capacity, travel time, operating cost and risk conditions on the feasibility and performance of the resulting plans. Collectively, these requirements provide an auditable validation pathway through which the proposed framework can be assessed beyond its present scenario-based application.

Limitations of the Study

The study has four principal limitations that should be considered when interpreting its findings. First, the 15 logistics-operation cases are independently observed records of completed transport activities. The descriptive statistics and regression coefficients therefore characterise the numerical scenarios supplied in the source paper and cannot be generalised to the wider population of oil and gas logistics operations in Rivers State. The absence of dated trip records, vehicle identification details, invoices, GPS traces and independently documented measurement procedures further limits the empirical interpretation of the operational variables. Accordingly, the regression findings are treated as exploratory associations rather than estimates of actual industry relationships.

Second, the small dataset and substantial multicollinearity among the explanatory variables limit the stability and precision of the regression coefficients. Although both models report high coefficients of determination, these values do not overcome the limitations associated with predictor overlap and potentially influential observations. The analysis therefore does not establish causal relationships or provide sufficiently reliable evidence for forecasting transportation cost and delivery time across different operating environments. The findings should instead be understood as an initial analytical examination of the relationships represented in the c cases.

Third, the five-node network does not provide a fully specified depot structure, multi-trip timetable or traceable optimisation implementation. In particular, the combined vehicle capacity is insufficient to meet the stated demand under a single-loaded-trip-per-vehicle assumption. The proposed route corridors also lack complete information on vehicle assignments, trip sequencing, departure times, return movements and loading arrangements. Consequently, the article assesses the conceptual framework and its operational feasibility requirements rather than claiming to have generated or validated a globally optimal routing solution.

Fourth, the questionnaire and interview summaries reported in the source paper cannot independently establish stakeholder experiences or operational findings without verifiable documentation of completed participation, response rates, respondent characteristics, underlying response data and analytical procedures. The intended questionnaire sample cannot be treated as an achieved sample in the absence of such evidence. The exclusion of these summaries narrows the empirical scope of the article but maintains a clear distinction between proposed data collection

and verified research evidence. These limitations do not negate the analytical usefulness of the framework; rather, they define the boundaries within which the present findings should be interpreted and identify the requirements for subsequent empirical validation.

CONCLUSION

This study develops a scenario-based framework for road transport logistics planning in the oil and gas context of Rivers State, Nigeria. Using the 15 operational cases contained in the source paper, the recalculated descriptive statistics yield a mean transportation cost of ₦818,667, mean delivery time of 21.80 hours and mean fleet utilisation of 68.47%. The exploratory regression results indicate positive associations between transportation distance and both transportation cost and delivery time. However, the nature of the observations, small sample size, substantial multicollinearity and presence of influential cases prevent population-level generalisation or causal interpretation of the estimated relationships. The network assessment identifies a more immediate operational constraint: the combined carrying capacity of the five vehicles is 100 tonnes, compared with total demand of 150 tonnes. Thus, the stated demand cannot be satisfied under a single-loaded-trip-per-vehicle assumption. Any complete distribution solution must explicitly accommodate additional loaded trips, increased vehicle capacity or an alternative service arrangement. Similarly, the proposed route corridors require further specification of depot configuration, vehicle assignments, loading arrangements, trip sequencing and delivery schedules before their operational feasibility can be established. The illustrative baseline-to-improved comparison also suggests possible improvements in cost, delivery time, fleet utilisation and the risk index, but these differences cannot be presented as verified savings or intervention effects without a reproducible optimisation procedure or documented operational implementation.

The principal contribution of the paper is therefore the development and clarification of a transparent decision-support structure rather than the demonstration of a field-validated performance improvement. By bringing demand fulfilment, fleet capacity, route configuration, transportation cost, delivery time and operational risk into a common planning process, the framework provides a basis for examining the interdependencies that shape road transport logistics decisions in the oil and gas sector. More importantly, it identifies the operational data, modelling specifications and validation procedures required to progress from an illustrative scenario-based framework to an implementable logistics planning system. Future research should therefore apply the framework to independently verified trip-level data and develop a fully specified capacitated and multi-trip optimisation model, supported by computational experiments, sensitivity analysis and operational validation.

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