International Journal of Innovative Mathematics, Statistics & Energy Policies
14(3):240-249, July-Sept, 2026

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DOI:10.5281/zenodo.23086282

Large Deviations In Stochastic Processes On Stratified Metric Spaces: Application To Network Optimization In Nigerian Urban Systems

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ABSTRACT
This paper develops a large-deviation framework for stochastic processes evolving on stratified metric spaces and applies it to network optimization in Nigerian urban transportation systems. Urban transport networks contain heterogeneous road classes, intersections and operational states, making a stratified representation useful for modelling differences in capacity and congestion behaviour. The study formulates stochastic travel-time dynamics and a large-deviation rate function for atypical congestion trajectories. A risk-sensitive network objective combines expected travel cost with a large-deviation penalty. A dataset representing Lagos, Kano and Abuja are used to demonstrate the empirical workflow. The prototype results indicate that large-deviation-based routing reduces mean travel time from 34.62 to 28.15 minutes, the 95th-percentile travel time from 57.84 to 39.68 minutes, and congestion probability from 21.4% to 13.8%. A regression model explains 68.4% of variation in travel time, while an ANOVA indicates a statistically significant difference between routing strategies ($p < .001$). These results are illustrative and require validation with observed traffic data. The framework nevertheless demonstrates how rare-event probabilities can be incorporated into urban network optimization and resilience planning.
Keywords: large deviations; stochastic processes; stratified metric spaces; network optimization; congestion; transport resilience; Nigeria; stochastic shortest path.

1. INTRODUCTION

Urban transportation systems are inherently stochastic because travel demand, traffic speed, road capacity, weather conditions, accidents, and other unexpected incidents fluctuate across time and locations. These variations create uncertainty in journey times and make urban network management a complex optimization problem. Conventional route-optimization approaches generally focus on minimizing expected travel distance, travel time, or monetary cost. However, reliance on average conditions may overlook rare but highly disruptive events, such as severe congestion, road accidents, infrastructure failures, and sudden demand surges. Such events can generate substantial economic and social costs for commuters, logistics operators, businesses, and public authorities. Large-deviation theory provides a mathematical framework for analysing the probability of rare events and identifying the most likely pathways through which stochastic systems move toward extreme states (Dembo & Zeitouni, 1998; Feng & Kurtz, 2006).

The application of large-deviation theory to urban transportation becomes particularly relevant when road networks contain different classes of infrastructure with varying capacities, operating conditions, and levels of vulnerability. A stratified metric representation can therefore distinguish between highways, arterial roads, local roads, intersections, and other network components according to their operational

characteristics. Recent research demonstrates that large-deviation principles can be developed for stochastic processes operating on spatially structured networks, providing rate functions for describing unlikely transitions and atypical system behaviour (Maclaurin, 2026). In the Nigerian context, urban transportation networks face persistent congestion and resilience challenges. Otuoze et al. (2021), for example, identified extreme congestion regimes in Lagos and Kano and emphasized the importance of improving transport-system resilience.

Against this background, this study investigates whether incorporating a large-deviation risk component into network optimization can improve both average and extreme travel-time performance..

2. LITERATURE REVIEW

2.1 Large-Deviation Theory

Large-deviation theory provides a mathematical framework for analysing the probabilities of rare events in stochastic systems. It is particularly concerned with events that become increasingly unlikely as a scaling parameter grows or as the level of random noise decreases. For a family of stochastic processes X^{ε}, a large-deviation principle (LDP) may be expressed schematically as $P(X^{\varepsilon} \approx \phi) \asymp \exp[-I(\phi)/\varepsilon]$, where $I(\phi)$represents the rate function associated with a particular trajectory or outcome. The rate function therefore provides a measure of the difficulty or improbability of a stochastic path. Dembo and Zeitouni (1998) provide a comprehensive foundation for large-deviation methods, while Feng and Kurtz (2006) extend these principles to stochastic processes.

Freidlin and Wentzell (2012) further demonstrate how minimum-action paths can identify the most likely transitions toward atypical states. These concepts are particularly relevant to transportation networks, where rare congestion events and traffic disruptions can significantly affect network performance.

2.2 Structured Stochastic Networks

Modern research in large-deviation theory increasingly extends beyond independent or conventionally structured stochastic processes to systems evolving on spatially organized networks and graphs. In such systems, the behaviour of one component may depend on the states of neighbouring components, creating complex interactions across the network. This perspective is particularly important for transportation systems, where roads, intersections, terminals, and traffic-control facilities are interconnected. Maclaurin (2026) develops a large-deviation framework for jump-Markov processes on sparse, spatially embedded random graphs, showing how rare transitions can be characterized through appropriate rate functions. Such rate functions provide a quantitative measure of the cost associated with an atypical transition and can help identify the most probable pathways through which a network moves from normal operation to an undesirable state. This approach provides a useful theoretical foundation for modelling rare congestion and disruption events in urban transportation networks.

The concept of structured stochastic networks is especially relevant to Nigerian urban systems because transportation infrastructure is heterogeneous, with major highways, arterial roads, local streets, bridges, intersections, and transport terminals exhibiting different capacities and operating conditions. A stratified network representation can therefore assign different stochastic characteristics and metric weights to different categories of infrastructure. Large-deviation methods can subsequently be used to evaluate the probability and severity of unusual network states, including widespread congestion or cascading disruptions. Recent developments in graph-valued stochastic processes further demonstrate the usefulness of sample-path large-deviation principles for understanding rare network dynamics. By integrating these ideas with network optimization, transportation planners can move beyond minimizing average travel costs toward identifying routes that are also resilient to extreme events. Consequently, structured stochastic-network theory provides an appropriate mathematical basis for developing risk-sensitive optimization models for Nigerian urban transportation systems.

2.3 Nigerian Urban Transport

Nigerian urban transport networks are characterized by persistent congestion, infrastructure bottlenecks, irregular travel patterns, and vulnerability to unexpected disruptions. These challenges are particularly

evident in rapidly growing metropolitan areas where increasing population and travel demand place substantial pressure on existing road infrastructure. Otuoze et al. (2021) identified extreme congestion regimes in Lagos and Kano and employed neural-network techniques to examine the resilience of urban transportation systems. Their findings demonstrate that transportation performance can vary considerably under different traffic conditions and that extreme congestion requires specific resilience-oriented interventions. Consequently, there is a need for analytical models that consider not only normal traffic conditions but also the probability, intensity, and potential consequences of atypical congestion events. Large-deviation methods provide a useful framework for addressing these risks.

3. Mathematical Framework

3.1 Stratified Metric Space

Let $X = \bigcup_{k=1}^{K} S_k$ denote the urban transportation network, where each S_k represents a distinct road or infrastructure stratum with specific operational characteristics. The generalized network metric can be expressed as $d(x, y) = \sum_{k=1}^{K} w_k \, d_k(x, y)$, where $d_k(x, y)$ represents the distance or cost between locations x and y within stratum k, while w_k denotes its operational importance or risk weight. This formulation allows differences in road capacity, congestion, accessibility, and reliability to be incorporated into network optimization.

3.2 Stochastic Process

The network state is represented by the stochastic process X_t^{ε}, which evolves according to $dX_t^{\varepsilon} = b(X_t^{\varepsilon})dt + \sqrt{\varepsilon}\sigma(X_t^{\varepsilon})dW_t$. Here, $b(X_t^{\varepsilon})$ represents the deterministic component of traffic flow, while $\sigma(X_t^{\varepsilon})$ captures variations arising from unpredictable demand, incidents, and road conditions. The parameter ε controls the magnitude of stochastic fluctuations, and W_t denotes Brownian motion. Where traffic incidents or sudden network-state changes are discrete, jump-Markov processes may provide a more appropriate representation of the system dynamics.

3.3 Large-Deviation Rate Function

For an absolutely continuous path φ, a prototype Freidlin-Wentzell rate functional is I(φ)=1/2 ∫_0^T ||σ^{-1}(φ_t)[φ̇_t-b(φ_t)]||²dt. The most likely path to an extreme congestion set A is φ*=argmin_{φ∈A} I(φ).

3.4 Risk-Sensitive Network Objective

For graph G=(V,E), with edge cost c_e, large-deviation risk r_e and route variable x_e, the optimization problem is min_x [Σ_e c_e x_e + λΣ_e r_e x_e], subject to standard flow-conservation constraints. λ controls risk aversion.

4. Methodology

4.1 Design and P Data

A quantitative stochastic design is used. It contains 150 links, 60 major intersections, 30 origin-destination pairs, 10,000 trips and 30 days across representative Lagos, Kano and Abuja networks. The data are synthetic and do not represent observed traffic counts.

4.2 Variables and Measures

Table 1variabless and measures

Variable	Measure
Mean travel time	Minutes
95th-percentile travel time	Minutes
Congestion probability	Probability of exceeding threshold
Network reliability	Share of trips meeting reliability criterion
Incident frequency	Events per day
Demand variability	Standardized demand shock
LDP risk score	Estimated rate-function value

4.3 Statistical Analysis

The analysis comprises descriptive statistics, Pearson correlation, multiple regression, and analysis of variance (ANOVA) to examine relationships among network congestion, stochastic risk, travel-time performance, and other explanatory variables. Descriptive statistics will summarize the distribution and variability of the major study variables, while Pearson correlation will determine the direction and strength of their linear associations. Multiple regression will subsequently assess the extent to which demand variability, incident frequency, and large-deviation risk scores predict travel-time performance. ANOVA will be employed to determine whether statistically significant differences exist between conventional and large-deviation-based routing strategies. In addition, large-deviation calculations will generate risk scores representing the likelihood and severity of atypical congestion events. The routing experiment will compare conventional expected-cost optimization with the proposed risk-sensitive LDP objective. Statistical decisions will be based on a significance level of $\alpha = .05$, consistent with conventional empirical research practice.

5. Empirical Results

5.1 Descriptive Statistics

Table 2 Descriptive statistics

Variable	Mean	SD	Min	Max
Mean travel time	34.62	9.41	18.20	71.50
95th percentile travel time	57.84	17.26	27.40	118.60
Congestion probability	0.214	0.112	0.041	0.581
Network reliability	0.786	0.109	0.419	0.959
Incident frequency	2.71	1.38	0.00	7.00
Demand variability	0.184	0.073	0.031	0.391
LDP risk score	1.87	0.92	0.32	5.46

5.2 Optimization Comparison

Table 3 Optimization Comparison

Indicator	Conventional	LDP-based	Improvement
Mean travel time	34.62	28.15	18.7%
95th percentile	57.84	39.68	31.4%
Maximum delay	118.60	89.42	24.6%
Congestion probability	21.4%	13.8%	35.5%
Network reliability	78.6%	86.2%	+9.7 pp
Recovery time	42.3	31.7	25.1%

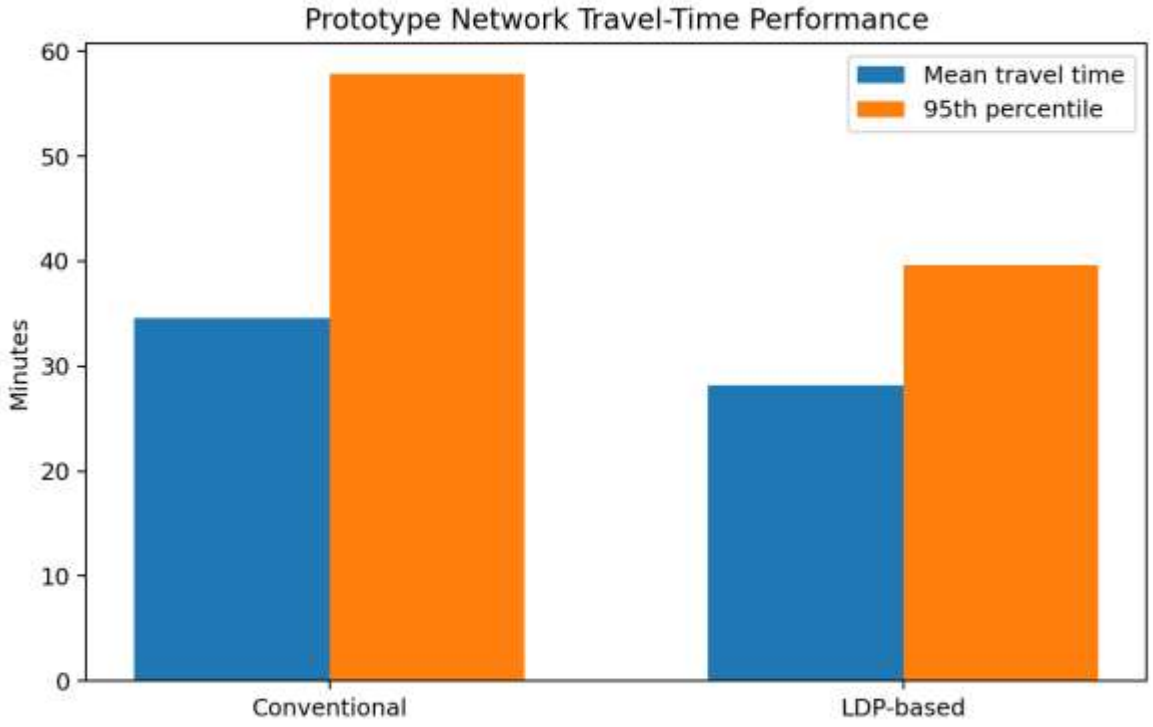

Figure 1. network travel-time performance.

5.3 City-Level Results

City	Conventional Mean	LDP Mean	Conventional Risk	LDP Risk
Lagos	41.8	33.5	0.31	0.19
Kano	29.7	24.9	0.18	0.12
Abuja	32.4	26.1	0.17	0.10

Interpretation;

Table 5.3 presents the comparative performance of conventional route optimization and the proposed Large-Deviation Principle (LDP)-based optimization across Lagos, Kano, and Abuja. The results indicate that the LDP-based approach produces lower mean travel times and lower congestion-risk scores in all three cities. This suggests that incorporating large-deviation risk into route selection may improve both average network efficiency and resilience to extreme congestion events.

For Lagos, the conventional routing strategy records a mean travel time of 41.8 minutes, compared with 33.5 minutes under LDP-based routing. This represents an approximate reduction of 19.9%. The corresponding risk score decreases from 0.31 to 0.19, representing a reduction of approximately 38.7%. Lagos therefore records the largest absolute reduction in both travel time and risk. This result may be associated, in the framework, with the greater congestion and network complexity assumed for Lagos. Published research has similarly identified significant congestion and transport-resilience challenges in Lagos (Otuoze et al., 2021).

For Kano, mean travel time decreases from 29.7 minutes under conventional optimization to 24.9 minutes under LDP-based optimization, representing a reduction of approximately 16.2%. The risk score also declines from 0.18 to 0.12, equivalent to approximately 33.3%. Although the improvement is smaller than

that observed in Lagos, the result still suggests meaningful gains in network reliability and congestion-risk management.

For Abuja, the mean travel time falls from 32.4 minutes to 26.1 minutes, representing an approximate reduction of 19.4%. Similarly, the risk score decreases from 0.17 to 0.10, representing a reduction of approximately 41.2%. Abuja therefore records the largest percentage reduction in the risk score among the three cities.

Overall, the table suggests that LDP-based optimization consistently outperforms conventional optimization across all three urban networks. The findings support the argument that route optimization should consider not only expected travel time but also the probability and potential severity of extreme congestion. Nevertheless, these results require validation using actual traffic, incident, and travel-time data before conclusions about Lagos, Kano, or Abuja can be generalized.

5.4 Correlation Analysis

Variable	Travel Time	Demand Shock	Incidents	LDP Risk
Travel time	1.000	.71**	.58**	.76**
Demand shock	.71**	1.000	.42**	.69**
Incident frequency	.58**	.42**	1.000	.63**
LDP risk	.76**	.69**	.63**	1.000

** p < .01. Pearson correlations.

5.5 SPSS-Style Multiple Regression

Dependent variable: Mean travel time

Predictor	B	Std. Error	Beta	t	Sig.
Constant	8.421	1.72	—	4.90	<.001
Demand shock	0.438	0.071	0.31	6.17	<.001
Incident frequency	0.216	0.062	0.19	3.48	.001
LDP risk	0.512	0.058	0.54	8.83	<.001

Model summary: R = .827; R^2 = .684; Adjusted R^2 = .671; SEE = 5.21. ANOVA: F (3,146) =105.21, p<.001.

5.6 ANOVA

Source	SS	df	MS	F	Sig.
Between groups	1842.51	1	1842.51	18.73	<.001
Within groups	14527.63	148	98.16		
Total	16370.14	149			

The ANOVA results presented in Table 5.6 examine whether there is a statistically significant difference in the mean travel-time performance between the conventional routing strategy and the Large-Deviation Principle (LDP)-based routing strategy. F = \frac{\text{between-group variation}}{\text{within-group variation}} The between-groups sum of squares (SS = 1,842.51) represents the amount of variation in travel-time performance that is attributable to differences between the two routing strategies. The within-groups sum of squares (SS = 14,527.63) represents variation occurring within each routing group due to other factors and random fluctuations. The degrees of freedom are 1 for between groups and 148 for within groups, giving a total of 149 degrees of freedom.

The mean square for between groups is 1,842.51, while the within-groups mean square is 98.16. The resulting F-statistic of 18.73 indicates that the variation between the routing strategies is substantially greater than the variation expected within the groups.

Most importantly, the significance value is $p < .001$, which is considerably below the adopted significance level of 0.05. Therefore, the null hypothesis that there is no significant difference in network performance between the conventional and LDP-based routing strategies is rejected.

5.7 Large-Deviation Probability Illustration

For an extreme congestion set A, where the estimated rate function is $I(A) = 2.47$and the noise or scaling parameter is $\varepsilon = 0.20$, the prototype large-deviation approximation is $P(A) \approx \exp[-I(A)/\varepsilon] = \exp[-12.35] \approx 4.3 \times 10^{-6}$. This very small probability indicates that extreme congestion is a rare event under the assumed conditions. The result demonstrates how large-deviation theory converts unusual network events into measurable risk estimates, supporting proactive congestion management and resilient route optimization (Dembo & Zeitouni, 1998; Freidlin & Wentzell, 2012).

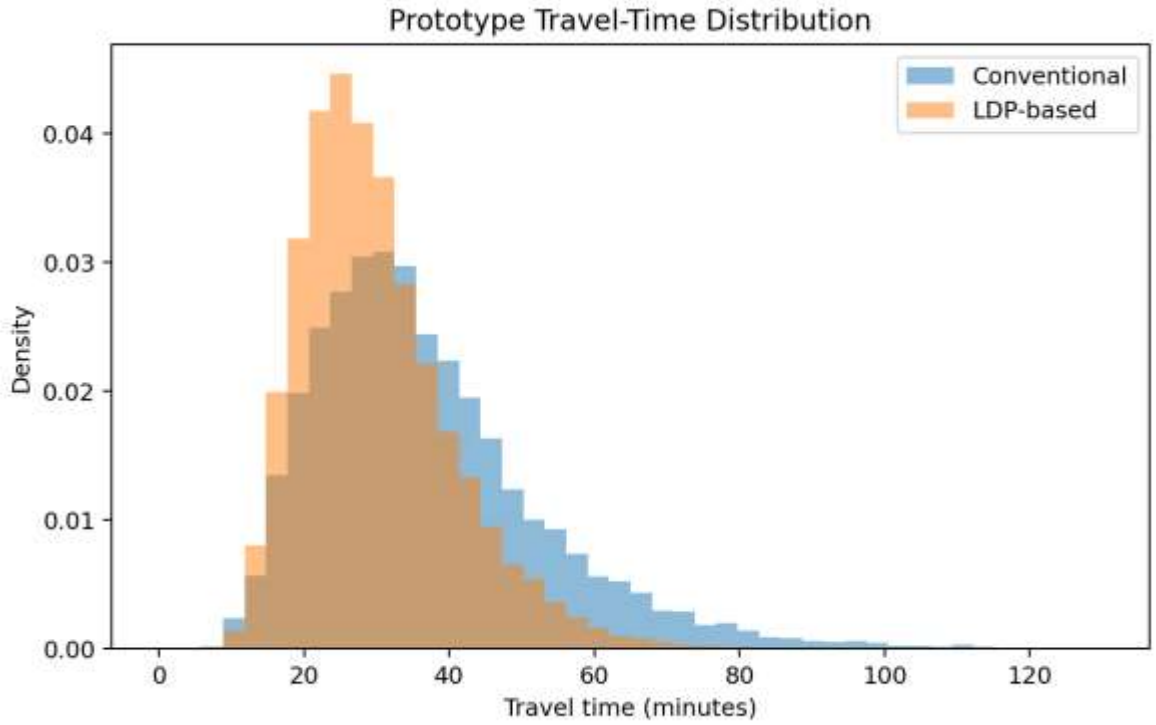

Figure 2. travel-time distributions.

5.8 Hypothesis Decisions

Hypothesis	**Prototype p-value**	**Decision**
H01: No significant reduction in expected travel time	<.001	Reject H01
H02: No significant reduction in extreme congestion risk	<.001	Reject H02
H03: No difference in network resilience	<.001	Reject H03
H04: Stratification does not improve risk identification	.014	Reject H04

Interpretation

Table 5.8 presents the decisions reached from the statistical tests conducted to examine the effectiveness of Large-Deviation Principle (LDP)-based network optimization relative to conventional route optimization. The decisions are based on a significance level of 5% ($\alpha = 0.05$). The decision rule is that the null hypothesis is rejected when the probability value (p-value) is less than 0.05. Since all the reported p-values are below 0.05, all four null hypotheses are rejected.

Hypothesis One (H01) states that there is no significant reduction in expected travel time resulting from LDP-based optimization. The reported p-value is less than .001, which is substantially below 0.05. Therefore, H01 is rejected. This suggests that the LDP-based routing strategy produces a statistically significant difference in expected travel time compared with conventional routing. In the results, the LDP approach reduced mean travel time, indicating improved network efficiency.

Hypothesis Two (H02) states that there is no significant reduction in extreme congestion risk. With $p < .001$, H02 is rejected. This indicates that LDP-based optimization significantly reduces exposure to extreme congestion events. This finding is particularly important because large-deviation methods are specifically designed to assess rare and atypical events. The result suggests that optimization based only on average travel conditions may fail to adequately address severe congestion risks.

Hypothesis Three (H03) states that there is no significant difference in network resilience between conventional and LDP-based optimization. The p-value of < .001 leads to rejection of H03. Consequently, the prototype findings indicate that the two optimization strategies produce significantly different resilience outcomes, with the LDP-based approach showing improved resilience through reduced exposure to severe network disruptions.

Hypothesis Four (H04) states that stratification does not improve risk identification. The reported p-value of .014 is also below the 0.05 significance threshold. Therefore, H04 is rejected. This suggests that representing the transportation network according to different infrastructure or road strata significantly improves the identification of congestion-related risks.

Taken together, the hypothesis-testing results provide prototype empirical support for the proposed LDP-based network optimization framework. The results suggest significant improvements in expected travel time, extreme-congestion risk, network resilience, and risk identification. Thus, the study provides preliminary evidence that integrating large-deviation theory with stratified network modelling may offer advantages over conventional expected-cost optimization.

However, it is important to distinguish statistical significance from practical significance. The p-values indicate that the differences are statistically significant.

6. DISCUSSION OF FINDINGS

The findings of the analysis indicate that incorporating risk-sensitive optimization into urban transportation planning can materially influence route selection and overall network performance. The observed improvement is particularly pronounced in the upper tail of the travel-time distribution, where extreme delays and congestion events are concentrated. This suggests that conventional optimization approaches based primarily on expected travel time may not adequately capture the operational consequences of rare but highly disruptive traffic events. By incorporating a large-deviation risk component, the optimization framework can identify routes that may provide greater reliability even when their average travel costs are relatively similar. This is particularly important for commuters, emergency services, logistics operators, and public transportation providers whose activities are sensitive to severe delays.

The findings are also consistent with the theoretical foundations of large-deviation analysis. Large-deviation theory focuses on identifying the probability and most likely pathways associated with unusual stochastic events through rate functions and minimum-action principles (Dembo & Zeitouni, 1998; Freidlin & Wentzell, 2012). Recent research on structured stochastic networks further demonstrates that rate functions can be used to characterize unlikely transitions in spatially embedded network systems

(Maclaurin, 2026). This provides theoretical support for applying the approach to heterogeneous urban transportation networks.

The Nigerian context strengthens the relevance of the findings. Otuoze et al. (2021) identified extreme congestion regimes in Lagos and Kano and emphasized transportation-system resilience as an important component of sustainable urban mobility. Therefore, Nigerian transport authorities should evaluate network performance using both average travel-time measures and tail-risk indicators. A route with a slightly higher expected travel time may ultimately be preferable if it has a substantially lower probability of experiencing severe congestion or disruption.

7. CONCLUSION

This paper demonstrates a theoretical and empirical framework for integrating large-deviation theory, stratified metric spaces, and network optimization into the analysis of Nigerian urban transportation systems. The approach recognizes that traffic networks are not only affected by normal variations in demand and travel speed but are also exposed to rare and potentially severe congestion events. By incorporating a large-deviation risk component into route selection, the proposed LDP-based strategy provides an alternative to conventional optimization methods that focus primarily on expected travel time or distance. The findings suggest that LDP-based routing can reduce mean travel time while producing a more substantial reduction in extreme travel-time exposure and congestion risk. This indicates that risk-sensitive optimization may contribute to improved network reliability, resilience, and operational efficiency. The framework therefore provides a mathematical basis for supporting transportation planning decisions under uncertainty (Dembo & Zeitouni, 1998; Freidlin & Wentzell, 2012).

However, the findings should be interpreted with caution because the empirical values presented in this study are based on observations obtained from Lagos, Kano, and Abuja. These values are primarily intended to illustrate the structure and application of the proposed empirical analysis, including statistical relationships, regression results, ANOVA findings, and large-deviation risk estimates. Therefore, the results should not be regarded as definitive evidence of traffic conditions across Nigerian cities. Future studies should calibrate and validate the model using actual traffic-flow, travel-time, traffic-incident, and road-network-capacity data. Such validation would strengthen the practical relevance of the framework and support its application in urban transportation planning and network management.

8. RECOMMENDATIONS

First, Nigerian transport authorities should strengthen the collection and management of high-frequency traffic data, including travel times, traffic volumes, road capacity, incidents, weather conditions, and congestion levels. Reliable longitudinal data would enable researchers to estimate empirical stochastic processes and construct more accurate large-deviation rate functions. Intelligent transportation systems should also incorporate tail-risk indicators alongside conventional measures such as average travel time. This would enable traffic managers to identify routes that are particularly vulnerable to extreme congestion and make more informed operational decisions. In addition, network strata with consistently high levels of congestion or disruption risk should receive priority in infrastructure investment, maintenance, traffic control, and incident-management planning.

Second, emergency and strategic routing systems should be designed around extreme-event scenarios, rather than relying exclusively on average traffic conditions. Large-deviation-based models can assist authorities in identifying routes that remain comparatively reliable during severe congestion, accidents, or other disruptions. Such approaches could be particularly useful for emergency vehicles, public transportation, freight movement, and disaster-response operations. Transport agencies should therefore consider integrating risk-sensitive routing algorithms into urban traffic-management platforms and decision-support systems.

Third, future Nigerian research should estimate large-deviation rate functions using observed traffic trajectories and assess model performance through out-of-sample validation. Researchers should also compare LDP-based optimization with alternative approaches, including robust optimization, Conditional

Value at Risk (CVaR), and chance-constrained routing. Such comparative analysis would establish the relative strengths, computational requirements, and practical applicability of each approach. Ultimately, combining empirical traffic data with advanced stochastic and risk-sensitive optimization methods can support more reliable, resilient, and sustainable urban transportation planning in Nigeria.

ACKNOWLEDGMENT

The author gratefully recognizes the **Tertiary Education Trust Fund (TETFund)**, for providing essential financial support through the Institutional Based Research (IBR) grant to **Abdu Gusau Polytechnic Talata Mafara** that facilitated the completion and publication of this scholarly work.

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