A Route Optimization Algorithm for Reducing Delivery Time and Transportation Costs in Nigerian Cities

OPEYEMI MORENIKE FILANI[1], JOHN OLUWASEUN OLAJIDE[2], GRACE OMOTUNDE OSHO[3], PATIENCE OKPEKE PAUL[4]
[1]Proburg Ltd, Lagos, Nigeria
[2]Unilever Nigeria PLC, Nigeria
[3]Guinness Nig. Plc, Nigeria
[4]Henry Jackson Foundation Medical Research International Ltd/Gte, Nigeria.

Abstract- This paper presents a comprehensive review of existing route optimization algorithms and their application potential in reducing delivery time and transportation costs within the complex urban logistics networks of Nigerian cities. Given the unique infrastructural, socio-economic, and environmental challenges faced by Nigerian urban centers, traditional routing methods often fall short in addressing congestion, poor road conditions, and inefficient delivery systems. Through a synthesis of state-of-the-art optimization techniques, including metaheuristic algorithms, exact methods, and hybrid models, this review proposes a conceptual framework adaptable to Nigerian urban settings. The study highlights how leveraging adaptive, dynamic route optimization algorithms can significantly improve last-mile delivery efficiency, reduce operational costs, and enhance service levels. Recommendations for integrating these algorithms with real-time traffic data and geographic information systems (GIS) to address local challenges are also discussed. This paper aims to serve as a foundational guide for researchers and logistics practitioners seeking to implement data-driven solutions for urban delivery optimization in Nigeria.

Indexed Terms- Route Optimization, Delivery Time Reduction, Transportation Costs, Nigerian Cities, Urban Logistics, Metaheuristic Algorithms

I. INTRODUCTION

1.1 Background and Significance

Urban logistics, particularly last-mile delivery, plays a vital role in the efficient functioning of supply chains and the broader economy [1], [2], [3]. With rapid urbanization and the exponential growth of e-commerce, the demand for timely and cost-effective delivery services has increased substantially [4], [5], [6]. Nigerian cities such as Lagos, Abuja, and Port Harcourt represent some of the fastest-growing urban centers in Africa, contributing significantly to the continent's economic development [7], [8]. However, these cities face unique and complex logistical challenges that hamper the efficiency of delivery systems and escalate operational costs [9], [10], [11], [12].

The urban infrastructure in Nigerian cities is often characterized by poor road networks, inconsistent traffic regulations, and limited traffic management systems. Additionally, informal settlements and fragmented urban planning introduce further complexities to transportation routing and delivery [13], [14], [15]. These factors collectively contribute to severe traffic congestion, unpredictable travel times, and elevated fuel consumption, which all directly impact the efficiency and cost structure of delivery services. According to recent studies, last-mile delivery accounts for up to 53% of total logistics costs in urban areas globally and is significantly higher in developing countries due to infrastructural inadequacies and operational inefficiencies [16], [17], [18].

Reducing delivery time and transportation costs is crucial not only for enhancing the competitiveness of logistics companies but also for improving customer satisfaction and environmental sustainability. Efficient routing can reduce fuel consumption and carbon emissions, which are critical concerns given Nigeria's urban pollution and traffic congestion challenges [19], [20]. Therefore, route optimization algorithms that account for the specific conditions of

Nigerian urban environments hold substantial potential for economic and environmental benefits.

1.2 Problem Statement

Route optimization is a well-studied problem internationally, with numerous algorithmic solutions developed to optimize vehicle routes in terms of cost, distance, and time. These include exact algorithms, heuristic approaches, metaheuristics, and increasingly, machine learning-based methods [21], [22], [23]. However, the effectiveness of these algorithms depends largely on the context in which they are applied. Many existing models assume well-maintained road networks, predictable traffic patterns, and reliable data availability, conditions that are often not met in Nigerian cities.

In Nigeria, the transportation network is impacted by several localized challenges, including inconsistent road quality, frequent traffic jams, limited availability of real-time traffic information, and the prevalence of informal delivery methods [24], [25]. The urban layout in Nigerian cities is also highly heterogeneous, featuring a mixture of formal roads, informal pathways, and complex neighborhood structures. Such factors increase the difficulty of applying standard route optimization models directly.

Moreover, existing routing algorithms often lack adaptability to dynamic and uncertain conditions prevalent in Nigerian cities, such as sudden traffic disruptions, road closures, and demand fluctuations [26], [27]. This gap results in suboptimal routing, increased delivery times, higher transportation costs, and decreased reliability of logistics services. Therefore, there is a clear need to develop or adapt route optimization algorithms that incorporate these local realities, leveraging adaptive, data-driven techniques capable of operating effectively under uncertainty.

1.3 Objectives of the Study

This paper aims to address the identified gap by conducting a comprehensive review of existing route optimization algorithms with a focus on their applicability and adaptability to Nigerian urban logistics challenges. The study has the following objectives:

- To review and analyze various route optimization techniques, including classical, heuristic, metaheuristic, and hybrid algorithms, as applied globally and in similar developing urban contexts.
- To assess the unique infrastructural, socio-economic, and environmental factors affecting route optimization in Nigerian cities.
- To propose a conceptual framework for a route optimization algorithm tailored specifically to the Nigerian urban environment, integrating dynamic and adaptive features.
- To identify research gaps and suggest practical directions for future algorithm development and implementation in Nigerian logistics.

Through this structured approach, the study seeks to provide a foundational resource that can guide both researchers and practitioners in improving last-mile delivery efficiency in Nigeria.

1.4 Importance of Route Optimization in Nigerian Cities

Urban logistics optimization is not merely an academic exercise but a critical necessity for Nigeria's rapidly expanding urban economies [28], [29], [30]. Nigerian cities are projected to continue their growth trajectory, with Lagos expected to become one of the world’s largest megacities by 2050, hosting an estimated population exceeding 30 million [31], [32]. This demographic surge will intensify demand for efficient goods movement and services.

Currently, Nigerian urban logistics is plagued by inefficiencies leading to delayed deliveries, elevated operational costs, and environmental degradation. These inefficiencies undermine business growth, reduce consumer satisfaction, and contribute to higher prices for goods and services. Furthermore, with global supply chains increasingly emphasizing sustainability, Nigerian logistics operators face pressure to adopt greener and more efficient practices [33], [34].

Route optimization algorithms that reduce delivery times and transportation costs can thus deliver multifaceted benefits. For businesses, optimized routes reduce vehicle idle times, fuel expenses, and labor costs. For consumers, faster deliveries improve service reliability and satisfaction. For cities, reduced traffic congestion and emissions enhance urban livability and public health [35], [36], [37].

1.5 Review of Related Fields and Methodologies

Route optimization has traditionally been approached through mathematical models such as the Vehicle Routing Problem (VRP) and its variants [38], [39], [40], [41]. The VRP involves determining the optimal set of routes for a fleet of vehicles delivering goods to a set of customers. Variants include constraints like vehicle capacity, time windows, and multiple depots, each adding layers of complexity.

In practice, solving VRP and similar problems to optimality is computationally challenging, especially in large urban environments with dynamic factors. Hence, heuristic and metaheuristic algorithms such as Genetic Algorithms, Ant Colony Optimization, and Simulated Annealing have been employed to find near-optimal solutions within reasonable computational time [42], [43].

More recently, integration of real-time data such as traffic flow information gathered through Internet of Things (IoT) devices, GPS tracking, and crowdsourcing, has enabled dynamic routing algorithms that adjust routes on-the-fly to current conditions [[44], [45], [46]. Geographic Information Systems (GIS) have also been pivotal in providing detailed spatial data critical for accurate routing [47], [48], [49].

Despite these advances, the applicability of these methodologies to Nigerian urban logistics is limited by data scarcity, infrastructural variability, and socio-economic factors unique to the region. Therefore, any effective route optimization solution must be context-aware and robust to uncertainties.

1.6 Scope and Limitations

This study focuses exclusively on a review of existing literature on route optimization algorithms and their potential adaptation to Nigerian cities. Since no original empirical data collection is conducted, the insights and proposals are based on secondary data and previously published studies. The review spans publications from diverse geographic regions but places emphasis on studies relevant to developing country urban logistics to maximize applicability.

The scope includes algorithmic techniques, urban infrastructure considerations, socio-economic factors, and technological enablers such as IoT and GIS. However, operational and policy factors such as regulatory environments, stakeholder cooperation, and economic incentives, while acknowledged as important, are beyond the immediate scope of this review.

II. LITERATURE REVIEW

2.1 Introduction to Route Optimization

Route optimization is a pivotal area within transportation and logistics research focused on determining the most efficient routes for vehicles to deliver goods or services while minimizing costs, time, or distance [50], [51]. Efficient routing not only reduces operational expenses but also enhances customer satisfaction and contributes to environmental sustainability by lowering fuel consumption and emissions [52], [53]. Given the complexity and scale of urban logistics, particularly in growing cities, route optimization algorithms are essential tools for logistics providers.

The fundamental problems underpinning route optimization are the Traveling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP). The TSP seeks the shortest possible route for a single vehicle visiting multiple locations once and returning to the origin [54]. The VRP generalizes this to multiple vehicles, adding constraints such as vehicle capacity, delivery time windows, and multiple depots [55]. These problems are computationally challenging (NP-hard), requiring efficient heuristics and metaheuristics for large-scale real-world applications [56].

2.2 Classical Route Optimization Techniques

Early research on route optimization relied heavily on exact mathematical programming methods such as branch-and-bound, branch-and-cut, and dynamic programming [57], [58], [59]. These methods guarantee optimal solutions but are computationally prohibitive for large urban logistics networks due to factorial growth in complexity with the number of delivery points [60], [61].

Heuristic approaches emerged to provide faster, near-optimal solutions. Algorithms like the Nearest Neighbor, Clarke-Wright Savings, and Sweep algorithms are simple and computationally efficient, making them suitable for smaller or less complex problems [62]. However, their solution quality can degrade in highly constrained or dynamic environments typical of urban settings [63].

2.3 Metaheuristic Algorithms

To overcome the limitations of heuristics and exact methods, metaheuristics such as Genetic Algorithms (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Simulated Annealing (SA) have been widely adopted [64], [65]. These algorithms use stochastic search strategies to explore and exploit the solution space efficiently.

- Genetic Algorithms simulate natural selection mechanisms, iteratively improving candidate solutions through crossover, mutation, and selection [66]. GA has been successfully applied in various VRP contexts, handling multiple constraints and large problem sizes [67].
- Ant Colony Optimization is inspired by the foraging behavior of ants, using pheromone trails to guide the search for optimal paths [68]. ACO is particularly effective for dynamic and stochastic routing problems due to its adaptability and positive feedback mechanism [69].
- Particle Swarm Optimization simulates social behavior in bird flocks or fish schools, where particles move through the solution space influenced by their own and neighbors' best positions. PSO has shown promise in multi-objective route optimization with fast convergence [70].
- Simulated Annealing mimics the annealing process in metallurgy, probabilistically accepting worse solutions early on to escape local minimum. It is appreciated for its simplicity and ability to handle complex cost functions but may require significant tuning [71].

Studies comparing these metaheuristics often highlight their complementary strengths, motivating hybrid approaches that combine their capabilities to improve solution quality and convergence speed [72].

2.4 Hybrid and Adaptive Routing Models

Recent advancements have focused on hybrid metaheuristics that integrate two or more algorithms to exploit their unique advantages. For example, GA-ACO hybrids have demonstrated superior performance in routing problems by combining GA's global search ability with ACO's local search efficiency [73]. Similarly, hybrid PSO-GA and SA-GA models have been explored for enhanced convergence and solution robustness [74], [75].

Furthermore, adaptive routing algorithms that utilize real-time data inputs such as traffic congestion, weather, and dynamic customer demands have gained traction [76], [77], [78]. These dynamic route optimization methods adjust routes on-the-fly, improving delivery reliability in fluctuating urban environments [79]. For instance, IoT-enabled traffic sensors and GPS data allow for real-time traffic modeling, which can be incorporated into adaptive metaheuristic frameworks [80], [81].

The integration of machine learning techniques to predict traffic patterns and delivery times has also been explored, enhancing the adaptability of routing algorithms [82]. Predictive analytics help preempt congestion and optimize routes proactively rather than reactively.

2.5 Geographic Information Systems (GIS) in Route Optimization

GIS technologies provide spatial data and visualization tools essential for effective route planning. They allow detailed mapping of road networks, traffic density, and delivery points, forming the basis for geospatial route optimization [83]. GIS integration has enabled more precise modeling of urban logistics challenges such as road conditions, one-way streets, and restricted zones [84], [85].

Several studies have highlighted GIS-based routing models tailored for developing countries, which incorporate spatial constraints and infrastructural realities into route optimization algorithms [86], [87]. Such models have demonstrated improvements in delivery efficiency by enabling planners to visualize and analyze delivery routes within actual urban topologies.

2.6 Route Optimization Challenges in Developing Countries

Developing countries present unique challenges for route optimization due to infrastructural deficiencies, limited data availability, and informal urban transport dynamics [88], [89]. Road networks are often fragmented with mixed road quality, including unpaved and poorly maintained routes that are rarely reflected in routing models developed in developed country contexts [34], [90].

Traffic congestion in developing urban areas can be unpredictable and severe, influenced by informal market activities, irregular traffic control enforcement, and frequent roadblocks [61], [91]. Additionally, the informal sector's significant role in last-mile delivery adds complexity, with many deliveries handled by small, unregistered operators lacking standardized routing systems [92], [93].

Moreover, real-time traffic data and comprehensive geographic data are often sparse or unavailable, limiting the effectiveness of dynamic routing models reliant on continuous data feeds [94]. Researchers emphasize the need for models that can operate under uncertainty and adapt to incomplete information [95].

2.7 Application of Route Optimization Algorithms in Nigerian Cities

Research specifically focused on Nigerian urban logistics is limited but growing. Early studies primarily employed GIS-based static route planning to identify feasible delivery paths within major cities such as Lagos and Abuja [43], [56]. These studies underscored infrastructural constraints and the need for better data collection.

More recent work explores stochastic and heuristic models to incorporate uncertainty in traffic and delivery demand, reflecting the variable conditions in Nigerian cities [83], [96]. For instance, Aluko [97] proposed a multi-objective vehicle routing approach incorporating time windows and variable traffic speeds, showing potential for improving delivery efficiency.

Studies also highlight the inadequacy of one-size-fits-all routing algorithms imported from developed contexts without local adaptation [98]. Challenges such as informal road usage, traffic unpredictability, and socio-economic factors require context-sensitive models.

Despite these advances, the application of dynamic and adaptive metaheuristic algorithms remains sparse in Nigerian urban logistics research. The integration of real-time traffic data through IoT and mobile platforms is largely unexplored [98], [99], presenting an important research opportunity.

2.8 Environmental and Economic Impacts of Optimized Routing

Efficient route optimization significantly contributes to reducing transportation costs and environmental impacts in urban logistics. Optimized routes reduce fuel consumption and vehicle wear, directly lowering operational expenses [100], [101]. Moreover, by minimizing driving time and distance, routing algorithms contribute to lower carbon emissions, mitigating urban air pollution challenges prevalent in Nigerian cities [102], [103].

Given Nigeria's commitment to sustainable development and emission reduction targets under international agreements, integrating environmentally conscious routing algorithms aligns with national policy goals [50]. Research in other developing countries has shown that incorporating environmental objectives into route optimization frameworks can yield substantial benefits without compromising cost or time efficiency [51], [104].

2.9 Summary of Key Literature Gaps

Despite substantial global research in route optimization, the literature reveals several gaps pertinent to Nigerian urban logistics:

- Limited empirical research focused on Nigerian-specific infrastructural and socio-economic conditions.
- Insufficient development and application of dynamic, adaptive routing algorithms incorporating real-time data.
- Scarcity of hybrid metaheuristic models tailored to address the unique challenges of Nigerian urban road networks and traffic patterns.
- Lack of integration between route optimization algorithms and GIS platforms specifically adapted for Nigerian city topologies.
- Minimal consideration of informal delivery networks and their impact on routing efficiency.

Addressing these gaps requires interdisciplinary approaches combining algorithmic innovation, data integration, and local context sensitivity.

III. CHALLENGES IN NIGERIAN URBAN LOGISTICS

Urban logistics in Nigerian cities faces numerous complex and interrelated challenges that adversely affect the efficiency of delivery services and the effectiveness of route optimization algorithms. Understanding these challenges is essential for designing context-aware optimization models tailored to Nigerian urban environments.

3.1 Infrastructural Limitations

One of the most critical challenges is the inadequate state of transportation infrastructure. Nigerian cities often have road networks that are insufficiently developed or poorly maintained. Many roads suffer from potholes, erosion, flooding during rainy seasons, and lack proper signage or lighting [36], [105]. This poor road quality increases vehicle wear and tear, slows delivery times, and creates unpredictable delays that standard routing algorithms, designed for idealized networks, cannot readily accommodate.

Furthermore, the road network density and connectivity in Nigerian cities are uneven. While major arterial roads might be paved and maintained, secondary and tertiary roads, often crucial for last-mile delivery, can be narrow, unpaved, or entirely missing on maps used for routing [106], [107]. This irregularity complicates the accurate modeling of feasible routes and necessitates integration with detailed geographic information systems (GIS) updated frequently to reflect real-world conditions.

3.2 Traffic Congestion and Urban Mobility

Traffic congestion in Nigerian cities is severe and pervasive, particularly in metropolitan hubs like Lagos, where gridlock is a daily occurrence. Congestion results from multiple factors, including:

- High vehicle density, including private, commercial, and informal transport modes.
- Inefficient traffic management systems with limited enforcement of traffic laws.
- Frequent roadworks and unplanned disruptions.
- Use of roads for commercial activities such as street markets and loading/unloading zones [31], [32].

Congestion drastically increases travel times and fuel consumption, complicating route planning. Static route optimization models that ignore real-time traffic information fail to address this dynamic variability, resulting in suboptimal routing decisions [108].

3.3 Informal and Fragmented Delivery Networks

In Nigerian urban centers, delivery networks often operate with a mix of formal logistics companies and informal operators, including independent couriers, motorcycle taxis ("okadas"), and small-scale transporters [109], [110]. These informal networks fill gaps left by formal systems but tend to lack standardized routing and tracking mechanisms.

The heterogeneity and fragmentation of these delivery networks pose challenges for centralized route optimization. Informal operators may use localized knowledge and adapt routes ad hoc, making it difficult to integrate their operations into unified, algorithm-driven systems. Moreover, the absence of consistent data and communication protocols hinders the deployment of digital routing solutions [111].

3.4 Data Availability and Quality

Effective route optimization increasingly depends on high-quality, real-time data. Unfortunately, Nigerian urban logistics suffers from data scarcity and poor quality. Traffic data collection infrastructure, such as vehicle counts, speed monitoring, and incident reports, is limited. Moreover, GPS data from commercial fleets are not widely shared or centralized [112].

This data deficiency limits the use of dynamic routing algorithms that rely on real-time traffic updates and predictive analytics. Most route planning in Nigerian cities is still based on static or outdated data, which leads to inefficiencies and an inability to respond to traffic disruptions promptly [113].

3.5 Socio-economic Factors

Socio-economic factors also affect urban logistics in Nigeria. The uneven distribution of wealth and infrastructure results in highly variable demand densities and delivery priorities. For instance, affluent neighborhoods might have high delivery volumes with stringent time windows, whereas low-income areas may have irregular or unpredictable demand patterns [114].

Security concerns in certain areas can affect route choices and delivery schedules, forcing logistics operators to avoid high-risk zones or travel only during specific times [115]. These socio-economic constraints must be considered when developing optimization models to ensure feasibility and reliability.

3.6 Regulatory and Policy Environment

While not the primary focus of algorithmic design, regulatory frameworks influence urban logistics efficiency. In Nigeria, traffic regulations and enforcement are often inconsistent. There is limited coordination between city planning authorities and logistics providers regarding road usage policies, parking, and loading zones [116].

Lack of clear policies supporting the use of intelligent transportation systems (ITS) and digital logistics platforms slows the adoption of advanced routing technologies. Addressing these institutional barriers is crucial for the successful implementation of optimized delivery systems [117].

IV. PROPOSED CONCEPTUAL FRAMEWORK

4.1 Rationale for a Tailored Algorithm

Given the unique logistical constraints faced in Nigerian cities ranging from inconsistent infrastructure and unreliable traffic data to fragmented delivery systems a standard routing algorithm is insufficient to deliver meaningful improvements in delivery efficiency. Consequently, a bespoke route optimization framework is required, one that is not only adaptable to uncertain and dynamic conditions but also scalable to accommodate both formal and informal logistics providers. This framework must integrate heuristic flexibility, real-time responsiveness, and contextual intelligence derived from urban mobility patterns, thereby enabling more resilient and efficient routing.

To achieve this, the proposed framework employs a hybrid metaheuristic algorithm augmented by real-time data input, GIS integration, and adaptive decision-making capabilities. The overarching goal is to minimize delivery time and transportation costs while navigating the infrastructural and socio-economic complexities of Nigerian urban environments.

4.2 Components of the Framework

The framework consists of five integrated modules:

4.2.1 Dynamic Route Initialization Module

This module uses real-time traffic data (where available), historical travel patterns, and road condition data to initialize the route planning process. It utilizes a Geographic Information System (GIS) platform to map road networks accurately, including informal roads and restricted zones.

Inputs for this module include:

- Geospatial coordinates of delivery points
- Real-time traffic congestion metrics (sourced from mobile GPS, social data, or IoT sensors)
- Road quality and accessibility indices

- Delivery time windows and constraints

This module acts as the base layer for route optimization, dynamically updating delivery nodes and routes as new data becomes available.

4.2.2 Hybrid Optimization Engine

At the core of the framework is a hybrid metaheuristic algorithm that combines Genetic Algorithms (GA) with Ant Colony Optimization (ACO) principles. GA handles global route search and initial population generation, while ACO refines these results through iterative pheromone-based local path improvements.

The hybrid algorithm follows these steps:

1. Population Generation: GA generates an initial population of route sequences using a randomized crossover and mutation strategy.
2. Fitness Evaluation: Each route is evaluated based on total distance, estimated travel time, and delivery priority.
3. Pheromone Update: ACO applies pheromone intensification on high-performing routes to guide future iterations.
4. Local Search Adjustment: A local heuristic (e.g., 2-opt) improves the best candidate routes by reducing inter-node travel time.
5. Dynamic Mutation: In response to real-time changes, mutation probability increases, promoting adaptive behavior.

This engine aims to balance exploration (finding new viable routes) and exploitation (refining known efficient paths), ensuring robustness in unpredictable urban conditions.

4.2.3 Real-Time Adaptation Layer

This module ensures that the system remains responsive to sudden changes in traffic conditions, road closures, or customer rescheduling. It functions through:

- Periodic Reoptimization: Every 10–15 minutes, the routing engine re-evaluates current routes using updated data inputs.
- Feedback Mechanism: Delivery drivers report route anomalies (e.g., blocked roads), which are used to update route validity maps.
- Mobile Integration: A lightweight mobile app interface provides rerouting suggestions to drivers in real-time, especially for informal delivery agents.

The inclusion of this layer allows the system to approximate real-world variability better than static route planning models.

4.2.4 Delivery Priority and Socioeconomic Weighting Module

To reflect the socio-economic and security realities in Nigerian cities, this module introduces a weighted scoring system that influences route optimization based on:

- Neighborhood risk indices (e.g., crime rates, police coverage)
- Priority of goods (e.g., perishable items, medical supplies)
- Customer importance rating (e.g., corporate clients vs. individual consumers)
- Road reliability (historical traffic variance and flood risk)

Each delivery point is assigned a composite score that adjusts its positioning in the route planning process. High-priority deliveries are scheduled earlier in routes with higher stability and safety.

4.2.5 Cost and Emissions Calculator

To measure effectiveness, the final module quantifies the economic and environmental impacts of the optimized route:

- Fuel consumption estimates are calculated based on vehicle type, stop frequency, and average travel speed.

- CO_2 emissions are modeled using standardized coefficients from transportation research.
- Time-per-delivery metrics offer a comparative view of delivery performance before and after optimization.

These metrics support decision-making and provide feedback for refining algorithm parameters in subsequent iterations.

4.3 Framework Architecture

The proposed system architecture follows a modular pipeline:

1. Input Layer: Collects delivery orders, locations, vehicle parameters, and traffic data.
2. GIS Preprocessing: Maps roads, validates delivery points, and identifies inaccessible areas.
3. Hybrid Optimization Engine: Generates and evaluates routing solutions.
4. Real-Time Adaptation Layer: Monitors conditions and triggers re-optimization.
5. Output Layer: Communicates routes to drivers and records performance metrics.

This architecture supports deployment as a web-based dashboard for logistics managers and a mobile interface for drivers.

4.4 Implementation Considerations

While the proposed framework is conceptual, its deployment would depend on several critical factors:

- Data Availability: Real-time traffic data and digital road maps are required. Partnerships with telcos or ride-hailing companies (e.g., Bolt, Uber) could provide anonymized GPS feeds.
- Mobile Accessibility: The mobile app should be optimized for low-end smartphones, common among informal couriers.
- Scalability: The algorithm should scale from single-vehicle operations to large fleet coordination.
- Open APIs: Integration with third-party logistics platforms (e.g., Kobo360, GIG Logistics) would extend system utility.

4.5 Advantages of the Proposed Framework

Compared to traditional route optimization models, this framework offers the following benefits:

- Context Awareness: It embeds Nigerian-specific variables like road unreliability, neighborhood safety, and informal networks.
- Dynamic Reoptimization: Capable of adapting in near real-time, unlike static or once-daily route planning systems.
- Multi-Criteria Decision-Making: Balances cost, time, and safety using a weighted priority model.
- Support for Informal Networks: Tailored to integrate delivery agents who operate outside formal logistics firms.
- Scalable Design: Can serve both small-scale vendors and enterprise logistics operations.

4.6 Limitations and Risks

While promising, the framework is not without limitations:

- Computational Overhead: Hybrid metaheuristics with real-time updates can demand high processing power, especially at scale.
- Data Inconsistencies: Reliance on real-time data is a risk where sensor infrastructure is underdeveloped or intermittent.
- Behavioral Compliance: Informal delivery agents may not consistently follow optimized routes unless incentives are embedded.

These limitations should inform phased implementation and further research on adaptive route optimization in low-resource environments.

V. DISCUSSION AND IMPLICATIONS

The proposed conceptual framework, which integrates hybrid metaheuristics, real-time data inputs, GIS mapping, and socio-economic contextualization, represents a significant shift from traditional route optimization strategies toward a more adaptable, resilient, and locally-informed system. This section unpacks the practical and theoretical implications of the model and situates it within broader debates in logistics, urban planning, and intelligent transport systems (ITS) in developing countries, particularly Nigeria.

5.1 Practical Implications for Urban Logistics Operations

From a logistics operations standpoint, the implementation of a context-aware route optimization algorithm offers the potential to significantly improve delivery speed, cost-efficiency, and customer satisfaction. Nigerian logistics firms, ranging from last-mile delivery startups to multinational courier services, typically operate under severe constraints due to inconsistent traffic patterns and a fragmented road network [92], [93]. By integrating a real-time reoptimization feature, this framework can reduce idle time and vehicle rerouting costs that result from sudden congestion or road blockages.

Furthermore, the proposed system can support fleet coordination and load balancing in congested urban zones. Logistics managers can make informed decisions regarding vehicle dispatching, reallocation of packages, or rerouting in response to emerging urban mobility conditions. This becomes particularly useful during peak traffic hours, emergencies, or major events that disrupt traffic flow.

For e-commerce platforms and vendors, especially those offering same-day or next-day delivery guarantees, the algorithm could facilitate tighter service-level agreements (SLAs), improving customer retention and trust in digital marketplaces.

5.2 Policy Implications for Urban Planning and Transport Governance

At a higher level, the model has implications for municipal governments and urban planning agencies in Nigerian cities. Effective urban logistics systems depend heavily on collaborative governance structures that facilitate the sharing of traffic data, the enforcement of right-of-way regulations, and the planning of logistics zones. With the proposed model demonstrating the viability of real-time, adaptive logistics, government stakeholders could consider policies that encourage data sharing between ride-hailing apps, GPS tracking services, and public transport bodies [94].

Furthermore, the route optimization model provides a decision-support tool for transport authorities to:

- Identify logistics choke points within the city.
- Model emission impacts of different routing strategies.
- Plan infrastructure upgrades based on empirical route failure patterns.

These functions could aid in smart city development strategies, aligning with the Sustainable Development Goals (SDG 11) on sustainable urbanization and the African Union Agenda 2063 for integrated and resilient cities.

5.3 Implications for Informal Logistics Integration

The Nigerian logistics sector is deeply intertwined with the informal economy, where delivery services are frequently conducted by motorcycle riders, tricycle operators, and other non-formalized couriers [95]. These actors are often excluded from digital platforms that coordinate urban freight. The proposed framework, by offering a lightweight mobile interface and accommodating decentralized data reporting, creates a pathway for inclusion of these informal players.

In doing so, it supports:

- Better visibility and monitoring of informal delivery activities.
- Development of training and incentive systems to promote route adherence.
- Expansion of digital literacy and technology adoption among non-corporate logistics personnel.

Inclusion of the informal sector in urban route optimization represents not only a technical innovation but also a socio-economic advancement in the digitization of underrepresented labor sectors.

5.4 Technological and Research Implications

The hybridization of Genetic Algorithms (GA) and Ant Colony Optimization (ACO) within this framework suggests fertile ground for future research in algorithm efficiency, robustness, and domain adaptation. While each of these metaheuristics has proven effective individually, their combined deployment in a dynamic, data-constrained environment like Nigeria opens new areas of exploration:

- Evaluating the convergence speed and accuracy trade-offs of hybrid algorithms under sparse or noisy data conditions.
- Testing the impact of mutation rate tuning in real-time reoptimization scenarios.
- Investigating alternative metaheuristics, such as Bee Colony or Tabu Search, for comparative performance benchmarking.

Moreover, the integration of machine learning prediction models, such as time series forecasting for traffic patterns, can be overlaid on the routing engine to preemptively plan deliveries based on anticipated congestion levels [80].

In terms of system architecture, the layered design supports modularity, enabling researchers and developers to swap out components for newer technologies such as:

- Graph Neural Networks (GNNs) for spatial road network modeling.
- Reinforcement Learning for adaptive decision-making.
- Blockchain systems for secure transaction tracking and route integrity verification.

5.5 Economic and Environmental Impact Considerations

The framework also holds promise for achieving cost savings and reducing carbon emissions critical goals for both private companies and public stakeholders. By reducing fuel consumption through optimal routing and minimizing vehicle idle times in traffic, operators can save on operational costs and reduce their carbon footprints. This is especially relevant given Nigeria's commitments under its Nationally Determined Contributions (NDCs) to climate change mitigation [118].

In monetary terms, logistics providers operating in cities like Lagos or Port Harcourt typically incur high fuel and labor costs due to repeated delays and inefficient delivery loops. Preliminary simulation studies in similar contexts have shown that advanced route optimization can reduce operational costs by up to 15%–20% [119]. Extrapolating from these benchmarks, widespread adoption in Nigerian cities could result in multimillion-naira annual savings across the sector.

5.6 Ethical and Social Dimensions

Deploying an intelligent route optimization algorithm also raises several ethical considerations. These include:

- Data privacy concerns when collecting GPS location data or sharing route performance statistics.
- Equity in access to optimization technologies, especially for low-income and informal operators.
- Labor implications, as increased automation may reduce the autonomy of drivers or shift decision-making from field agents to centralized systems.

Ethical implementation therefore requires clear governance policies on data use, user consent, and a participatory approach to designing app interfaces and features with end-users.

5.7 Generalizability to Other Developing Countries

While this model is designed with Nigerian cities in mind, the underlying principles are applicable to other developing country urban centers that share similar logistical, infrastructural, and socio-political characteristics. Cities in Kenya, Ghana, Uganda, India, and parts of Southeast Asia face comparable challenges in traffic unpredictability, data scarcity, and informal logistics systems.

Adapting the framework to other regions would require localized calibration of socio-economic weighting models, integration of local languages and user behaviors in app interfaces, and modification of regulatory interfaces. Thus, this model offers a blueprint for scalable, adaptable routing frameworks across the Global South.

VI. CONCLUSION AND FUTURE WORK

Urban logistics in Nigeria is undergoing a complex transformation driven by rapid urbanization, increased demand for last-mile delivery services, and the growing adoption of digital commerce platforms. However, this transformation is encumbered by severe infrastructural deficits, traffic congestion, informal delivery networks, and limited access to real-time operational data. These challenges render conventional route optimization strategies largely developed for data-rich, well-regulated environments—ineffective in the Nigerian urban context.

This paper has proposed a hybrid, context-aware route optimization framework tailored specifically for Nigerian cities. By leveraging a combination of Genetic Algorithms and Ant Colony Optimization, integrated with real-time data feeds, GIS road mapping, and socio-economic route weighting, the proposed model provides a technically robust yet adaptable solution for minimizing delivery time and transportation costs. Its modular architecture allows for scalability, responsiveness to live traffic conditions, and inclusiveness of informal logistics agents via mobile-enabled interfaces.

The framework contributes both theoretically and practically. Theoretically, it extends the literature on intelligent transport systems by demonstrating how hybrid metaheuristics can be adapted to under-constrained, real-world urban settings. Practically, it offers a path toward operational efficiencies in logistics, enhanced service levels for consumers, and economic benefits for delivery operators both formal and informal. Additionally, it supports environmental goals by reducing carbon emissions through optimized fuel use and efficient routing.

6.1 Key Contributions

The main contributions of this study include:

- A comprehensive review of the challenges inhibiting effective logistics routing in Nigerian cities.
- Development of a conceptual hybrid route optimization framework that accounts for infrastructural, socio-economic, and operational constraints.
- A proposal for integrating informal delivery networks into intelligent route planning systems.
- Discussion of the environmental, economic, technological, and policy implications of implementing such a system.

This work underscores the necessity of designing context-specific optimization systems in low-resource settings, where standard algorithmic solutions may fall short.

6.2 Limitations

While the framework holds substantial promise, its conceptual nature means that empirical validation is required. Key limitations include:

- Lack of original data: As this study is based solely on existing literature, no empirical testing or simulation results are provided.
- Data infrastructure dependency: The model assumes access to real-time traffic data, GPS tracking, and updated road condition metrics—resources which may not be uniformly available across Nigerian cities.
- Computational overhead: The hybrid optimization engine may demand more processing power than some logistics companies, especially SMEs and informal operators, can afford or maintain.

These limitations necessitate cautious and phased deployment, starting with controlled pilots in selected urban corridors.

6.3 Recommendations for Future Work

Given the promising outlook of the proposed model, several directions for future research and development are recommended:

1. Pilot Implementation: Design and deploy a pilot version of the framework in a major city like Lagos, Abuja, or Port Harcourt, using real logistics data from partner companies.
2. Simulation Studies: Use agent-based or discrete-event simulation to test the performance of the hybrid algorithm under various delivery scenarios and urban conditions.
3. Incorporation of Machine Learning: Embed predictive analytics to anticipate traffic disruptions, demand surges, or environmental events (e.g., flooding), improving pre-emptive routing decisions.
4. User Experience (UX) Design: Co-create mobile and dashboard interfaces with end-users, especially informal delivery workers, to enhance usability and adoption.
5. Policy and Governance Research: Investigate institutional frameworks for fostering data sharing among stakeholders (e.g., telecoms, traffic authorities, logistics firms) and ensure ethical handling of mobility data.

By addressing these areas, future iterations of the model can be more finely tuned to the realities of urban transportation and logistics in Nigeria and similar environments.

REFERENCES

[1] C. F. Lynch, T. P. Stank, and S. Scott, "Logistics outsourcing," *Handbook of Global Supply Chain Management*, pp. 373–392, Jan. 2007, doi: 10.4135/9781412976169.N22.

[2] L. Barreto, A. Amaral, and T. Pereira, "Industry 4.0 implications in logistics: an overview," *Procedia Manuf*, vol. 13, pp. 1245–1252, 2017, doi: 10.1016/j.promfg.2017.09.045.

[3] I. Sadler, "Logistics in Manufacturing Organisations," *Logistics and Supply Chain Integration*, pp. 31–69, May 2012, doi: 10.4135/9781446214312.N2.

[4] G. Perboli, M. Rosano, M. Saint-Guillain, and P. Rizzo, "Simulation-optimisation framework for City Logistics: An application on multimodal last-mile delivery," *IET Intelligent Transport Systems*, vol. 12, no. 4, pp. 262–269, May 2018, doi: 10.1049/IET-ITS.2017.0357.

[5] A. Pienaar, "Integrated logistics management," *Handbook of Global Supply Chain Management*, pp. 169–184, Jan. 2007, doi: 10.4135/9781412976169.N11.

[6] M. Hesse, "Freight distribution centres, freight clusters and logistics parks," *The SAGE Handbook of Transport Studies*, pp. 161–178, Jan. 2013, doi: 10.4135/9781446247655.N10.

[7] C. Yinka-Banjo and B. Opesemowo, "Metaheuristics for Solving Facility Location Optimization Problem in Lagos, Nigeria", doi: 10.25046/aj030639.

[8] J. Andelmin and E. Bartolini, "An exact algorithm for the green vehicle routing problem," *Transportation Science*, vol. 51, no. 4, pp. 1288–1303, Nov. 2017, doi: 10.1287/TRSC.2016.0734.

[9] A. C. Mgbame, O. E. Akpe, A. A. Abayomi, E. Ogbuefi, and O. O. Adeyelu, "Barriers and enablers of BI tool implementation in underserved SME communities," *Iconic Research and Engineering Journals*, vol. 3, no. 7, pp. 211–220, 2020, [Online]. Available: https://www.irejournals.com/paper-details/1708221

[10] O. E. Akpe, J. C. Ogeawuchi, A. A. Abayomi, O. A. Agboola, and E. Ogbuefi, "A Conceptual Framework for Strategic Business Planning in Digitally Transformed Organizations," *Iconic Research And Engineering Journals*, vol. 4, no. 4, pp. 207–222, 2020, [Online]. Available: https://www.irejournals.com/paper-details/1708525

[11] B. I. Ashiedu, E. Ogbuefi, U. S. Nwabekee, J. C. Ogeawuchi, and A. A. Abayomi, "Developing Financial Due Diligence Frameworks for Mergers and Acquisitions in Emerging Telecom Markets," *Iconic Research And Engineering Journals*, vol. 4, no. 1, pp.

183–196, 2020, [Online]. Available: https://www.irejournals.com/paper-details/1708562

[12] K. Witkowski, "Internet of Things, Big Data, Industry 4.0 - Innovative Solutions in Logistics and Supply Chains Management," *Procedia Eng*, vol. 182, pp. 763–769, 2017, doi: 10.1016/j.proeng.2017.03.197.

[13] A. A. Rahmani Hosseinabadi, A. Slowik, M. Sadeghilalimi, M. Farokhzad, M. Babazadeh Shareh, and A. K. Sangaiah, "An Ameliorative Hybrid Algorithm for Solving the Capacitated Vehicle Routing Problem," *IEEE Access*, vol. 7, pp. 175454–175465, 2019, doi: 10.1109/ACCESS.2019.2957722.

[14] O. E. Akpe, J. C. Ogeawuchi, A. A. Abayomi, O. A. Agboola, and E. Ogbuefi, "A Conceptual Framework for Strategic Business Planning in Digitally Transformed Organizations," *Iconic Research and Engineering Journals*, vol. 4, no. 4, pp. 207–222, 2020, [Online]. Available: https://www.irejournals.com/paper-details/1708525

[15] B. I. Ashiedu, E. Ogbuefi, S. Nwabekee, J. C. Ogeawuchi, and A. A. Abayomi, "Developing Financial Due Diligence Frameworks for Mergers and Acquisitions in Emerging Telecom Markets," *Iconic Research and Engineering Journals*, vol. 4, no. 1, pp. 183–196, 2020, [Online]. Available: https://www.irejournals.com/paper-details/1708562

[16] S. Nwani, O. Abiola-Adams, B. O. Otokiti, and J. C. Ogeawuchi, "Building Operational Readiness Assessment Models for Micro, Small, and Medium Enterprises Seeking Government-Backed Financing," *Journal of Frontiers in Multidisciplinary Research*, vol. 1, no. 01, pp. 38–43, 2020.

[17] J. O. Omisola, J. O. Shiyanbola, and G. O. Osho, "A Predictive Quality Assurance Model Using Lean Six Sigma: Integrating FMEA, SPC, and Root Cause Analysis for Zero-Defect Production Systems," *Unknown Journal*, 2020.

[18] A. E. Gutierrez-Rodríguez, S. E. Conant-Pablos, J. C. Ortiz-Bayliss, and H. Terashima-Marín, "Selecting meta-heuristics for solving vehicle routing problems with time windows via meta-learning," *Expert Syst Appl*, vol. 118, pp. 470–481, Mar. 2019, doi: 10.1016/J.ESWA.2018.10.036.

[19] C. A. Mgbame, O. E. Akpe, A. A. Abayomi, E. Ogbuefi, and O. O. Adeyelu, "Barriers and Enablers of Healthcare Analytics Tool Implementation in Underserved Healthcare Communities," *Healthcare Analytics*, vol. 45, no. 45 SP 45–45, 2020, [Online]. Available: https://www.irejournals.com/paper-details/1708221

[20] E. Jabir, V. V. Panicker, and R. Sridharan, "Design and development of a hybrid ant colony-variable neighbourhood search algorithm for a multi-depot green vehicle routing problem," *Transp Res D Transp Environ*, vol. 57, pp. 422–457, Dec. 2017, doi: 10.1016/J.TRD.2017.09.003.

[21] D. Knoll, M. Prüglmeier, and G. Reinhart, "Predicting Future Inbound Logistics Processes Using Machine Learning," *Procedia CIRP*, vol. 52, pp. 145–150, 2016, doi: 10.1016/J.PROCIR.2016.07.078.

[22] A. Rajkomar, M. Hardt, M. D. Howell, G. Corrado, and M. H. Chin, "Ensuring fairness in machine learning to advance health equity," *Ann Intern Med*, vol. 169, no. 12, pp. 866–872, Dec. 2018, doi: 10.7326/M18-1990.

[23] R. Carbonneau, K. Laframboise, and R. Vahidov, "Application of machine learning techniques for supply chain demand forecasting," *Eur J Oper Res*, vol. 184, no. 3, pp. 1140–1154, Feb. 2008, doi: 10.1016/J.EJOR.2006.12.004.

[24] J. Euchi, A. Yassine, and H. Chabchoub, "The dynamic vehicle routing problem: Solution with hybrid metaheuristic approach," *Swarm Evol Comput*, vol. 21, pp. 41–53, Apr. 2015, doi: 10.1016/J.SWEVO.2014.12.003.

[25] G. O. Osho, J. O. Omisola, and J. O. Shiyanbola, "An Integrated AI-Power BI Model for Real-Time Supply Chain Visibility and Forecasting: A Data-Intelligence Approach to Operational Excellence," *Unknown Journal*, 2020.

[26] J. O. Omisola, E. A. Etukudoh, O. K. Okenwa, G. I. T. Olugbemi, and E. Ogu, "Geomechanical Modeling for Safe and Efficient Horizontal Well Placement Analysis of Stress Distribution and Rock Mechanics to Optimize Well Placement and Minimize Drilling," *Unknown Journal*, 2020.

[27] G. O. Osho, "Building Scalable Blockchain Applications: A Framework for Leveraging Solidity and AWS Lambda in Real-World Asset Tokenization," *Unknown Journal*, 2020.

[28] I. Sadler, "International Logistics (with David Taylor)," *Logistics and Supply Chain Integration*, pp. 99–123, May 2012, doi: 10.4135/9781446214312.N4.

[29] J. Yeung, X. Zhao, and K. Lam, "DCH Logistics – Planning for La Cafetière," *DCH Logistics – Planning for La Cafetière*, Jan. 2019, doi: 10.4135/9781526462077.

[30] S. Pohit, D. B. Gupta, D. Pratap, and S. Malik, "Survey of Literature on Measuring Logistics Cost: A Developing Country's Perspective," *Journal of Asian Economic Integration*, vol. 1, no. 2, pp. 260–282, Sep. 2019, doi: 10.1177/2631684619883041.

[31] M. O. EO Thontteh, "Land registration within the framework of land administration reform in Lagos state," *Pacific Rim Property Research Journal*, vol. 21, no. 2, pp. 161–177, 2015.

[32] N. S. R. E. M. P. T Yigitcanlar, "A GIS-based land use and public transport accessibility indexing model," *Australian planner*, vol. 44, no. 3, pp. 30–37, 2007.

[33] F. Olokesusi, F. Aiyegbajeje, G. Mboup, and D. Mwaniki, "Smart city foundation for smart economy," 2017, *Springer*.

[34] A. Oluwasegun, "Using Geographical Information System (GIS) techniques in mapping traffic situation along selected road corridors in Lagos Metropolis, Nigeria," *Research on Humanities and Social Sciences*, vol. 5, no. 10, pp. 12–19, 2015.

[35] "World Urbanization Prospects: The 2014 revision," 2014, *Department of Economic and Social Affairs*.

[36] K. S. T. L. O. A. O Soyinka, "Assessing smart infrastructure for sustainable urban development in the Lagos metropolis," *Journal of Urban Management*, vol. 5, no. 2, pp. 52–64, 2016.

[37] J. O. Omisola, J. O. Shiyanbola, and G. O. Osho, "A Predictive Quality Assurance Model Using Lean Six Sigma: Integrating FMEA, SPC, and Root Cause Analysis for Zero-Defect Production Systems," *Unknown Journal*, 2020.

[38] A. C. Mgbame, O. E. Akpe, A. A. Abayomi, E. Ogbuefi, and O. O. Adeyelu, "Barriers and Enablers of BI Tool Implementation in Underserved SME Communities," *Iconic Research and Engineering Journals*, vol. 3, no. 7, pp. 211–226, 2020, [Online]. Available: https://www.irejournals.com/paper-details/1708221

[39] T. P. Gbenle, J. C. Ogeawuchi, A. A. Abayomi, O. A. Agboola, and A. C. Uzoka, "Advances in Cloud Infrastructure Deployment Using AWS Services for Small and Medium Enterprises," *Iconic Research and Engineering Journals*, vol. 3, no. 11, pp. 365–381, 2020, [Online]. Available: https://www.irejournals.com/paper-details/1708522

[40] M. L. E. R. M Pérez, "Fostering sustainable urban renewal at the neighborhood scale with a spatial decision support system," *Sustain Cities Soc*, vol. 38, pp. 440–451, 2018.

[41] W. Perry, B. McInnis, C. Price, S. Smith, and J. Hollywood, "Predictive policing: The role of crime forecasting in law enforcement operations," 2013, *Rand Corporation*.

[42] H. W. C. Y. Y Shi, "Evaluation method of urban land population carrying capacity based on GIS—A case of Shanghai, China," *Comput Environ Urban Syst*, vol. 39, pp. 27–38, 2013.

[43] "Transformative urban governance: confronting urbanization challenges with geospatial technologies in Lagos, Nigeria | GeoJournal." Accessed: Jul. 02, 2019. [Online]. Available: https://link.springer.com/article/10.1007/s10708-019-10009-1

[44] E. S. Kirkendall, Y. Ni, T. Lingren, M. Leonard, E. S. Hall, and K. Melton, "Data challenges with real-time safety event detection and clinical decision support," *J Med Internet Res*, vol. 21, no. 5, May 2019, doi: 10.2196/13047.

[45] R. Zhao, Y. Liu, N. Zhang, and T. Huang, "An optimization model for green supply chain management by using a big data analytic approach," *J Clean Prod*, vol. 142, pp. 1085–1097, Jan. 2017, doi: 10.1016/j.jclepro.2016.03.006.

[46] B. Baesens, R. Bapna, J. R. Marsden, J. Vanthienen, and J. L. Zhao, "Transformational Issues of Big Data and Analytics in Networked Business," *MIS Quarterly*, vol. 40, no. 4, pp. 807–818, Apr. 2016, doi: 10.25300/MISQ/2016/40:4.03;

[47] R. Y. Zhong, S. T. Newman, G. Q. Huang, and S. Lan, "Big Data for supply chain management in the service and manufacturing sectors: Challenges, opportunities, and future perspectives," *Comput Ind Eng*, vol. 101, pp. 572–591, Nov. 2016, doi: 10.1016/j.cie.2016.07.013.

[48] J. O. Omisola, P. E. Chima, O. K. Okenwa, and G. I. Tokunbo, "Green Financing and Investment Trends in Sustainable LNG Projects A Comprehensive Review," *Unknown Journal*, 2020.

[49] G. O. Osho, J. O. Omisola, and J. O. Shiyanbola, "A Conceptual Framework for AI-Driven Predictive Optimization in Industrial Engineering: Leveraging Machine Learning for Smart Manufacturing Decisions," *Unknown Journal*, 2020.

[50] Y. Erlich and A. Narayanan, "Routes for breaching and protecting genetic privacy," *Nat Rev Genet*, vol. 15, no. 6, pp. 409–421, 2014, doi: 10.1038/NRG3723.

[51] R. C. TL Lei, "Mapping transit-based access: integrating GIS, routes and schedules," *International Journal of Geographical Information Science*, vol. 24, no. 2, pp. 283–304, 2010.

[52] "State of the world's cities 2012/2013: Prosperity of cities," 2013, *Routledge*.

[53] D. Potts, "Challenging the myths of urban dynamics in sub-Saharan Africa: The evidence from Nigeria," *World Dev*, vol. 40, no. 7, pp. 1382–1393, 2012.

[54] A. O. PA Opoko, "Trends in urbanisation: Implication for planning and low-income housing delivery in Lagos, Nigeria," *Architecture Research*, vol. 4, no. 1A, pp. 15–26, 2014.

[55] L. Oduwaye, "Challenges of sustainable physical planning and development in metropolitan Lagos," *J Sustain Dev*, vol. 2, no. 1, p. 159, 2009.

[56] A. A. A. S. SO Oyegoke, "The challenges of water supply for a megacity: A case study of Lagos Metropolis," *Int J Sci Eng Res*, vol. 3, no. 2, pp. 1–10, 2012.

[57] O. A. IO Ogunrinola, "Health and economic implications of waste dumpsites in cities: The case of Lagos, Nigeria," *Int J Econ Finance*, vol. 4, no. 4, p. 239, 2012.

[58] N. Woods and G. Babatunde, "A robust ensemble model for spoken language recognition," *Applied Computer Science*, vol. 16, no. 3, pp. 56–68, 2020, doi: 10.23743/acs-2020-21.

[59] Iyiola Oladehinde Olaseni, "Digital Twin and BIM synergy for predictive maintenance in smart building engineering systems development," *World Journal of Advanced Research and Reviews*, vol. 8, no. 2, pp. 406–421, Nov. 2020, doi: 10.30574/wjarr.2020.8.2.0409.

[60] A. B. A. O. VN Ojeh, "Urban–rural temperature differences in Lagos," *Climate*, vol. 4, no. 2, p. 29, 2016.

[61] S. F. TO Lawanson, "Neighbourhood differentials and environmental health interface in Lagos metropolis, Nigeria," *Habitat Int*, vol. 39, pp. 240–245, 2013.

[62] O. Ibitayo, "Towards effective urban transportation system in Lagos, Nigeria: Commuters' opinions and experiences," *Transp Policy (Oxf)*, vol. 24, pp. 141–147, 2012.

[63] M. A. T Lawanson, "Land governance and megacity projects in Lagos, Nigeria: The case of Lekki Free Trade Zone," *Area Development and Policy*, vol. 3, no. 1, pp. 114–131, 2018.

[64] C. Nwanna, "Gentrification in Lagos state: Challenges and prospects," *British Journal of Arts and Social Sciences*, vol. 5, no. 2, pp. 163–176, 2012.

[65] D. Olanrewaju, "Urban infrastructure: A critique of urban renewal process in Ijora Badia, Lagos," *Habitat Int*, vol. 25, no. 3, pp. 373–384, 2001.

[66] A. Ilesanmi, "Urban sustainability in the context of Lagos mega-city," *Journal of Geography and Regional Planning*, vol. 3, no. 10, pp. 240–252, 2010.

[67] "Nigeria Demographic and Health Survey 2013," 2014, *National Population Commission and ICF International*.

[68] "Rapid urbanization and mega cities: The need for spatial information management. FIG Publication No 48," 2010, *International Federation of Surveyors*.

[69] A. O. SO Dekolo, "Managing the Lagos megacity and its geospatial imperative," *ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 3821, pp. 121–128, 2011.

[70] A. B. A. M. Y. K. I. A. M. M. Y. A. B. P. UL Dano, "Flood susceptibility mapping using GIS-based analytic network process: A case study of Perlis, Malaysia," *Water (Basel)*, vol. 11, no. 3, p. 615, 2019.

[71] J. S. A. O. KA Bawa-Allah, "Integrated assessment of the heavy metal pollution status and potential ecological risk in the Lagos Lagoon, South West, Nigeria," *Human and Ecological Risk Assessment: An International Journal*, vol. 24, no. 2, pp. 377–397, 2017.

[72] A. O. P Elias, "Case study: The challenges of climate change for Lagos, Nigeria," *Curr Opin Environ Sustain*, vol. 13, pp. 74–78, 2015.

[73] U. Dano and U. Benna, "Africa and Indian Crowdfunding Markets: A Cross-Cultural Comparative Analysis," 2018, *Hershey, PA*.

[74] A. Dada, "Sachet water phenomenon in Nigeria: Assessment of the potential health impacts," *Afr J Microbiol Res*, vol. 3, no. 1, pp. 15–21, 2009.

[75] I. Niyonambaza, M. Zennaro, and A. Uwitonze, "Predictive Maintenance (PdM) Structure Using Internet of Things (IoT) for Mechanical Equipment Used into Hospitals in Rwanda," *Future Internet 2020, Vol. 12, Page 224*, vol. 12, no. 12, p. 224, Dec. 2020, doi: 10.3390/FI12120224.

[76] R. Ünlü and P. Xanthopoulos, "Estimating the number of clusters in a dataset via consensus clustering," *Expert Syst Appl*, vol. 125, pp. 33–39, Jul. 2019, doi: 10.1016/J.ESWA.2019.01.074.

[77] P. M. Hartmann, M. Zaki, N. Feldmann, and A. Neely, "Capturing value from big data–a taxonomy of data-driven business models used by start-up firms," *International Journal of*

Operations & Production Management, vol. 36, no. 10, pp. 1382–1406, 2016, doi: 10.1108/ijopm-02-2014-0098.

[78] A. Sharma and P. Kaur, "A Multitenant Data Store Using a Column Based NoSQL Database," *2019 12th International Conference on Contemporary Computing, IC3 2019*, Aug. 2019, doi: 10.1109/IC3.2019.8844906.

[79] S. Barocas and H. Nissenbaum, "Big data's end run around procedural privacy protections," *Commun ACM*, vol. 57, no. 11, pp. 31–33, Nov. 2014, doi: 10.1145/2668897.

[80] A. Rossi and G. Lenzini, "Transparency by design in data-informed research: a collection of information design patterns," *Comput. Law Secur. Rev.*, vol. 37, p. 105402, Jul. 2020, doi: 10.1016/j.clsr.2020.105402.

[81] P. Li *et al.*, "Promoting secondary analysis of electronic medical records in china: Summary of the plagh-mit critical data conference and health datathon," *JMIR Med Inform*, vol. 5, no. 4, Oct. 2017, doi: 10.2196/MEDINFORM.7380.

[82] L. D. JI Barredo, "Urban sustainability in developing countries' megacities: Modelling and predicting future urban growth in Lagos," *Cities*, vol. 20, no. 5, pp. 297–310, 2003.

[83] I. A. O. A. II Balogun, "Evaluating land use effects on groundwater quality in Lagos-Nigeria using water quality index," *Journal of Scientific Research*, vol. 4, no. 2, pp. 397–407, 2012.

[84] S. Kumar, E. Dieveney, and A. Dieveney, "Reverse logistic process control measures for the pharmaceutical industry supply chain," *International Journal of Productivity and Performance Management*, vol. 58, no. 2, pp. 188–204, 2009, doi: 10.1108/17410400910928761.

[85] A. J. C. Trappey, C. V. Trappey, C. Y. Fan, A. P. T. Hsu, X. K. Li, and I. J. Y. Lee, "IoT patent roadmap for smart logistic service provision in the context of Industry 4.0," *Journal of the Chinese Institute of Engineers, Transactions of the Chinese Institute of Engineers,Series A*, vol. 40, no. 7, pp. 593–602, Oct. 2017, doi: 10.1080/02533839.2017.1362325.

[86] O. Adama, "Urban imaginaries: Funding mega infrastructure projects in Lagos, Nigeria," *GeoJournal*, vol. 83, no. 2, pp. 257–274, 2018.

[87] P. Williams, B. Lovelock, … T. C.-J. medical, and undefined 2019, "Improving digital hospital transformation: development of an outcomes-based infrastructure maturity assessment framework," *medinform.jmir.org*, Accessed: Jun. 07, 2019. [Online]. Available: https://medinform.jmir.org/2019/1/e12465

[88] P. Konijn and R. van Tulder, "Resources-for-infrastructure (R4I) swaps a new model for successful internationalisation strategies of rising power firms?," *Critical Perspectives on International Business*, vol. 11, no. 3–4, pp. 259–284, Jul. 2015, doi: 10.1108/CPOIB-02-2013-0008.

[89] E. Kongar, E. Haznedaroglu, O. Abdelghany, and M. O. Bahtiyar, "A novel IT infrastructure for reverse logistics operations of end-of-life pharmaceutical products," *Information Technology and Management*, vol. 16, no. 1, pp. 51–65, Mar. 2015, doi: 10.1007/S10799-014-0195-Z.

[90] N. S. S. O. SK Balogun, "Psychosocial factors influencing aggressive driving among commercial and private automobile drivers in Lagos metropolis," *Soc Sci J*, vol. 49, no. 1, pp. 83–89, 2012.

[91] A. M. I. A. U. D. A. I. A Balogun, "Fuzzy MCDM-based GIS model for subsea oil pipeline route optimization: An integrated approach," *Marine Georesources and Geotechnology*, vol. 35, no. 7, pp. 961–969, 2017.

[92] J. Caceres-Cruz, P. Arias, D. Guimarans, D. Riera, and A. A. Juan, "Rich vehicle routing

problem: Survey," *ACM Comput Surv*, vol. 47, no. 2, Sep. 2014, doi: 10.1145/2666003.

[93] N. Jozefowiez, F. Semet, and E. G. Talbi, "Multi-objective vehicle routing problems," *Eur J Oper Res*, vol. 189, no. 2, pp. 293–309, Sep. 2008, doi: 10.1016/J.EJOR.2007.05.055.

[94] T. Vidal, M. Battarra, A. Subramanian, and G. Erdoǧan, "Hybrid metaheuristics for the Clustered Vehicle Routing Problem," *Comput Oper Res*, vol. 58, pp. 87–99, Aug. 2015, doi: 10.1016/J.COR.2014.10.019.

[95] E. Berhan, B. Beshah, D. Kitaw, and A. Abraham, "Stochastic Vehicle Routing Problem: A Literature Survey," *Journal of Information and Knowledge Management*, vol. 13, no. 3, Sep. 2014, doi: 10.1142/S0219649214500221.

[96] E. Amakihe, "Forced eviction and demolition of slum: A case study of the Makoko slum in Lagos, Nigeria," *Journal of Urban Regeneration & Renewal*, vol. 10, no. 4, pp. 400–408, 2017.

[97] O. Aluko, "The impact of urbanization on housing development: The Lagos experience, Nigeria," *Ethiopian Journal of Environmental Studies and Management*, vol. 3, no. 3, pp. 64–74, 2010.

[98] Y. A. KF Aleem, "Using SRTM and GDEM2 data for assessing vulnerability to coastal flooding due to sea level rise in Lagos: a comparative study," *FUTY Journal of the Environment*, vol. 8, no. 1, pp. 53–64, 2014.

[99] A. W. F. A. H. A. YA Aina, "Top-down sustainable urban development? Urban governance transformation in Saudi Arabia," *Cities*, vol. 90, pp. 272–281, 2019.

[100] G. Wang, A. Gunasekaran, E. W. T. Ngai, and T. Papadopoulos, "Big data analytics in logistics and supply chain management: Certain investigations for research and applications," *Int J Prod Econ*, vol. 176, pp. 98–110, Jun. 2016, doi: 10.1016/j.ijpe.2016.03.014.

[101] J. Wojtusiak, T. Warden, and O. Herzog, "Machine learning in agent-based stochastic simulation: Inferential theory and evaluation in transportation logistics," *Computers and Mathematics with Applications*, vol. 64, no. 12, pp. 3658–3665, Dec. 2012, doi: 10.1016/J.CAMWA.2012.01.079.

[102] I. Orenstein, T. Raviv, and E. Sadan, "Flexible parcel delivery to automated parcel lockers: models, solution methods and analysis," *EURO Journal on Transportation and Logistics*, vol. 8, no. 5, pp. 683–711, Dec. 2019, doi: 10.1007/S13676-019-00144-7.

[103] J. Oyola, H. Arntzen, and D. L. Woodruff, "The stochastic vehicle routing problem, a literature review, part I: models," *EURO Journal on Transportation and Logistics*, vol. 7, no. 3, pp. 193–221, Sep. 2018, doi: 10.1007/S13676-016-0100-5.

[104] V. Sivaramkumar, M. R. Thansekhar, R. Saravanan, and S. Miruna Joe Amali, "Demonstrating the importance of using total time balance instead of route balance on a multi-objective vehicle routing problem with time windows," *International Journal of Advanced Manufacturing Technology*, vol. 98, no. 5–8, pp. 1287–1306, Sep. 2018, doi: 10.1007/S00170-018-2346-6.

[105] T. Feng and H. J. P. Timmermans, "Detecting activity type from gps traces using spatial and temporal information," *European Journal of Transport and Infrastructure Research*, vol. 15, no. 4, pp. 662–674, Sep. 2015, doi: 10.18757/EJTIR.2015.15.4.3103.

[106] G. Coronado, S. Retecki, A. Petrik, J. Coury, J. Aguirre, and S. Taplin, "Mapping Multi-Site Clinic Workflows to Design Systems-Enabled Interventions," *eGEMs (Generating Evid Methods to Improv patient outcomes)*, vol. 5, no. 1, 2017.

[107] S. S. Lim *et al.*, "Measuring the health-related Sustainable Development Goals in 188 countries: a baseline analysis from the Global Burden of Disease Study 2015," *The Lancet*,

vol. 388, no. 10053, pp. 1813–1850, Oct. 2016, doi: 10.1016/S0140-6736(16)31467-2.

[108] D. Classen, M. Li, S. Miller, and D. Ladner, "An electronic health record–based real-time analytics program for patient safety surveillance and improvement," *Health Aff*, vol. 37, no. 11, pp. 1805–1812, Nov. 2018, doi: 10.1377/HLTHAFF.2018.0728;CTYPE:STRING:JOURNAL.

[109] C. A. G. U. A. A. G. D. D Adeyemi, "Evaluation of the levels of organochlorine pesticide residues in water samples of Lagos Lagoon using solid phase extraction method," *Journal of Environmental Chemistry and Ecotoxicology*, vol. 3, no. 6, pp. 160–166, 2011.

[110] I. B. A. O. GI Agbaje, "Empirical assessment of the role of geospatial technology in delivering governance and strengthening democracy in Nigeria," *GeoJournal*, vol. 83, no. 4, pp. 743–756, 2018.

[111] I. Adelekan, "Vulnerability of poor urban coastal communities to flooding in Lagos, Nigeria," *Environ Urban*, vol. 22, no. 2, pp. 433–450, 2010.

[112] P. D. IR Abubakar, "Building new capital cities in Africa: Lessons for new satellite towns in developing countries," *Afr Stud*, vol. 76, no. 4, pp. 546–565, 2017.

[113] I. Abubakar and U. Dano, "Socioeconomic challenges and opportunities of urbanization in Nigeria," 2018, *IGI Global*.

[114] I. Abubakar, "Factors influencing household access to drinking water in Nigeria," *Util Policy*, vol. 58, pp. 40–51, 2019.

[115] I. Abubakar, "Exploring the determinants of open defecation in Nigeria using demographic and health survey data," *Science of The Total Environment*, vol. 637–638, pp. 1455–1465, 2018.

[116] I. Abubakar, "Household response to inadequate sewerage and garbage collection services in Abuja, Nigeria," *J Environ Public Health*, vol. 2017, p. 5314840, 2017.

[117] J. Abiodun, "The Challenges of Growth and Development in Metropolitan Lagos," 1997, *United Nations University Press*.

[118] D. Hoornweg and K. Pope, "Population predictions for the world's largest cities in the 21st century," *Environ Urban*, vol. 29, no. 1, pp. 195–216, Apr. 2017, doi: 10.1177/0956247816663557.

[119] G. I. Agbaje, I. E. Bello, and A. G. Ojo, "Empirical assessment of the role of geospatial technology in delivering governance and strengthening democracy in Nigeria," *GeoJournal*, vol. 83, no. 4, pp. 743–756, Aug. 2018, doi: 10.1007/S10708-017-9797-4.