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Optimising Logistics Operations using Geospatial Algorithms with Adaptive Route Evolution

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***Abstract**: Rapid urbanisation in cities like Lagos, Nigeria has impaired traffic congestion and route-planning, causing delivery delays stemming from logistic inefficiencies leading to operational costs; to overcome these challenges, an Adaptive Route Evolution (ARE) model that integrates A* for initial shortest-path generation, a Genetic Algorithm (GA) for offline route refinement, and Reinforcement Learning (RL) for real-time adjustments based on live traffic data is proposed. In simulations of two vehicles traversing standard delivery corridors with geospatial road-network data and real-time traffic APIs, Vehicle 1's delivery time decreased from 78 min to 70 min after A* (–10.3%), 65 min after GA (–17%), and 61 min after RL (–21.8%), while Vehicle 2's time fell from 120 min to 90 min after A* (–25%), 83 min after GA (–30.8%), and 79 min after RL (–34.2%), yielding an average 27.5% reduction in delivery time and an estimated 22% drop in fuel and driver costs. ARE provided a complete end-to-end optimisation framework by combining RL's adaptability with A*'s shortest-path planning and GA's sequence optimisation. It demonstrated scalability and effectiveness in dynamically optimising urban logistics, reducing both transit delays and carbon emissions, and enabling a more sustainable and cost-efficient transportation system in line with Sustainable Development Goals (SDGs) 7, 11, and 13.*

***Keywords:** Logistics Optimisation, A* Algorithm, Genetic Algorithm, Reinforcement Learning, Adaptive Route Evolution, Dynamic Routing, Intelligent Transportation*

1. INTRODUCTION

Over the past decades, the role of logistics in businesses has grown in scope and strategic importance. Supply chain integration, rapid response, and just-in-time management have transformed how companies manage their logistics operations and businesses [1]. The e-commerce boom in developing countries, such as Nigeria, fueled by rising internet penetration and smartphone adoption, has revolutionised consumer access to goods and services. Traffic congestion in Nigeria is among the highest in Africa, significantly impacting logistics efficiency. However, urban congestion remains a critical bottleneck in major cities worldwide. This challenge is more evident than in Abuja and Lagos, Nigeria's commercial nerve centre, where traffic congestion disrupts mobility, delays deliveries, and inflates business operational costs [2]. Rapid urban growth and rising demand for fast goods movement expose the limits of conventional logistics, especially in congested cities. Data-driven methods that use crowdsourced traffic data and geospatial analytics now provide real-time insights into congestion and alternative routes. However, urban traffic complexity requires more than raw data; it demands adaptive algorithms that can learn, predict, and respond in real time.

This study introduces Adaptive Route Evolution (ARE), a hybrid model that combines A* for shortest-path search, a Genetic Algorithm (GA) for delivery sequence optimisation, and Reinforcement Learning (RL) for dynamic re-routing under live traffic. Applied to Lagos traffic data, ARE outperformed static routing and Google Maps benchmarks, enabling faster deliveries, lower fuel use, and better congestion management. The framework unifies heuristic search, evolutionary computing, and machine learning, offering a scalable solution for last-mile logistics. It also addresses scalability and real-world constraints by promoting cloud optimisation, Internet of Things (IoT) sensors, and edge computing. By advancing AI-driven logistics aligned with Sustainable Development Goal (SDG) 11, it provides both a technical innovation and a practical blueprint for operators, planners, and policymakers to reduce congestion's economic and social impacts in megacities.

1.1 Background of the Study

Nigeria's logistics sector has evolved from traditional trade practices into a modern system, primarily fueled by the rise of e-commerce, global trade, and increasing internet and smartphone penetration. With this growth, demand for efficient last-mile delivery, the crucial stage of moving goods from distribution centres to end consumers, has surged.

Despite its importance to the economy, the sector faces persistent challenges, deplorable infrastructure, unreliable power supply, and limited digitalisation. These issues are most pronounced in urban centres such as Lagos and Abuja, where chronic traffic congestion causes delivery delays, higher fuel consumption, and elevated operational costs.

Meanwhile, rural areas suffer from underdeveloped transport infrastructure, making access and delivery more difficult [3]. These challenges raise operational costs and reduce customer satisfaction. Human factors, such as inexperienced drivers navigating unfamiliar routes and reliance on manual sorting, further contribute to inefficiencies and errors. The situation was exacerbated by the COVID-19 pandemic, which severely disrupted logistics operations due to mobility restrictions and highlighted the sector's slow adoption of advanced technologies [4]. Currently, urban logistics still lags in the use of geospatial algorithms and automation, resulting in suboptimal routing and increased fuel consumption during delivery.

Validated through a Lagos case study, the ARE model demonstrated substantial improvements in delivery efficiency and fleet performance. Beyond the contributions, the study provides a practical roadmap for logistics providers, policymakers, and urban planners to adopt scalable AI-driven solutions. Furthermore, it highlights the importance of supporting infrastructure, such as IoT-based traffic sensors and cloud-hosted optimisation engines, for enabling real-time decision-making and advancing large-scale, adaptive transportation networks. Table 1 presents the 2025 traffic indices of selected African countries, ranking Nigeria as the most congested with an index of 334.9. This reflects the country's severe urban gridlock, characterised by long travel times, high inefficiency, and elevated CO_2 emissions. Figure 1 further illustrates the spatial distribution of traffic congestion across Africa, where countries are highlighted according to their traffic indices. The visualisation confirms Nigeria's position as the most congested, followed closely by Egypt and Kenya, while Morocco and Tunisia exhibit comparatively lower levels of congestion [5].

Table 1. Traffic indices by country 2025

Rank	Country	Traffic Index	Time Index (in minutes)	Time Exp. Index	Inefficiency Index	CO_2 Emission Index
1	Nigeria	334.9	65.3	23178	447.3	9261.8
2	Tunisia	131.7	33.4	361.5	126.9	4629.4
3	South Africa	186.5	38.6	1234.3	238.7	9484.0
4	Egypt	228.7	48.0	5102.6	280.1	8548.1
5	Morocco	130.8	35.2	592.4	138.4	3530.3
6	Kenya	235.7	50.6	6772.8	269.3	7473.2

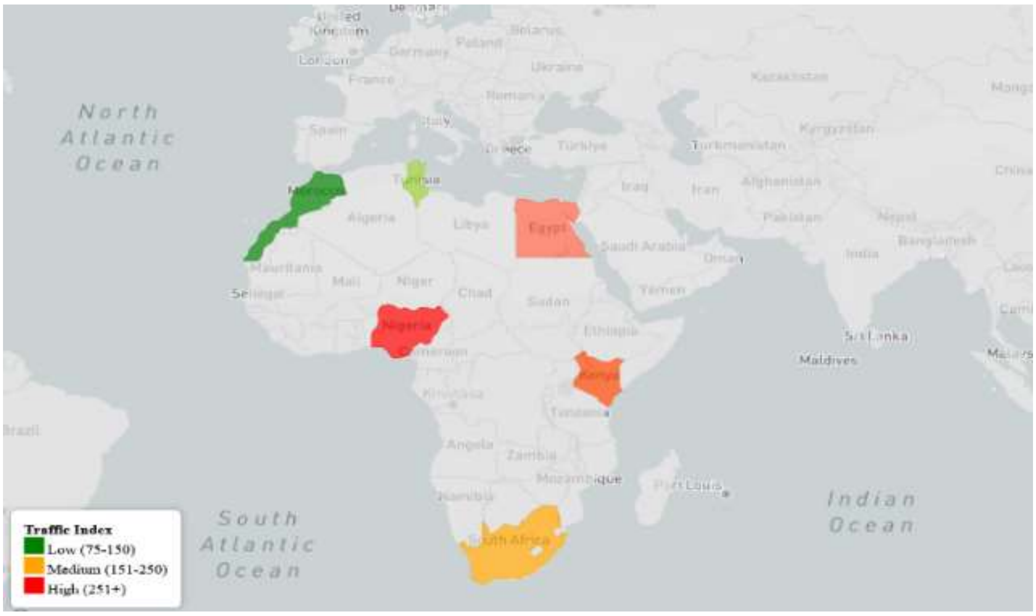

Figure 1: 2025 Traffic index by countries in Africa.

1.2 Rationale

The logistics sector is embracing AI, automation, and geospatial algorithms to improve routing and efficiency. In Nigeria, where fragmented addressing hinders deliveries, integrating geospatial methods with crowdsourced, real-time data enhances location accuracy, routing, and resource allocation [6]. Techniques like H3 Geohash partitioning, spatial indexing, and mobile crowdsourcing strengthen data reliability and operational agility, even in infrastructure-limited regions. Privacy-preserving spatial frameworks further optimise task allocation, while AI-driven geospatial analysis demonstrates strong potential for tackling Africa's logistics and transportation challenges [7].

1.3 Related Work

i. The Urban Traffic Mobility Optimisation Model (UTMOM) applies data mining and mathematical modelling to analyse urban traffic patterns. By capturing daily traffic dynamics and peak-hour variations, UTMOM highlights fluctuations in traffic intensity across times and locations, offering valuable insights for congestion reduction and urban planning. Supported by graphical representations and statistical validation such as ANOVA, the model provides precise reflections of real-world traffic conditions. As a tool for traffic engineers, data scientists, and planners, UTMOM underscores the importance of data-driven strategies in improving mobility and sustainability [8].
ii. RL presents a promising solution for dynamic network traffic optimisation, with deep RL and multi-agent approaches showing potential to enhance efficiency. However, challenges remain in achieving scalability, adaptability to real-time conditions, and addressing security concerns. Current research examines RL's role in online traffic direction, large-scale network performance, and the influence of reward functions on routing outcomes. This study aims to develop scalable RL-based routing protocols that enhance resilience and flexibility, despite computational overhead limiting real-time applications in large networks [9].
iii. Multimodal transport offers a cost-effective, sustainable alternative to road-only logistics. This study investigates a Sustainable Multimodal Freight Transport and Logistics System (SMFTLS) integrating road, rail, and waterways, optimised using a Genetic Algorithm in MATLAB R2016a. A case study of Ghana's freight network showed a 4.5% cost reduction (USD 97.03 million) compared to current systems. However, the approach's scalability is constrained by limited rail and waterway infrastructure in some regions, which may hinder widespread adoption [10].

1.4 Research Contributions

This study advances the understanding and management of urban traffic congestion in Nigeria through a data-driven, AI-enhanced logistics framework. First, it analyses congestion patterns along Ikorodu Road using crowdsourced traffic data, travel-time indices, and geospatial analytics, providing empirical evidence of the severity of delays in Lagos. Second, it introduces the ARE model, a hybrid optimisation framework that combines the A* algorithm for shortest-path routing, a Genetic Algorithm for delivery sequence optimisation, and Reinforcement Learning for dynamic re-routing in response to real-time traffic conditions. Third, by benchmarking ARE against static routing and Google Maps, the study demonstrates significant improvements in travel time, delivery efficiency, and fuel consumption. Finally, it addresses scalability and real-world applications by considering computational costs, infrastructural limitations, and data reliability, while highlighting solutions such as cloud-based optimisation and IoT sensor integration. Collectively, these contributions offer a scalable, intelligent, and sustainable framework for last-mile logistics optimisation in Lagos and other high-density urban centres, supporting SDG 11 (Sustainable Cities and Communities).

2. RESEARCH METHODOLOGY

This study adopted a quantitative framework that integrates real-time and historical data from GPS trackers, IoT sensors, and crowdsourced traffic reports to analyse Nigeria's congestion patterns. After cleaning and refining the dataset, a three-stage Adaptive Route Evolution pipeline is applied, using A* for shortest paths, a Genetic Algorithm for sequence optimisation, and Reinforcement Learning for real-time adjustments, to generate dynamic, traffic-aware delivery routes.

2.1 Research Design

This research adopts an experimental, exploratory design that integrates real-world traffic data from Lagos with algorithmic simulations to evaluate logistics optimisation strategies. A hybrid model combining A*, GA, and RL is tested against key performance indicators such as travel time, congestion avoidance, and cost efficiency. At the same time, iterative refinements based on real-time feedback ensure a practical bridge between theoretical modelling and real-world application.

2.2 Algorithm Implementation for Optimisation

A*(A-Star) Algorithm: is a graph traversal and path-finding algorithm used in many computer science fields due to its completeness, optimality, and efficiency. Developed in 1968 by Peter Hart, Nils Nilsson, and Bertram Raphae as an improvement over Dijkstra's Algorithm, integrating heuristic estimates to speed up path-finding and reduce the computational load [11].

2.2.1 The mechanism of the A* algorithm

The cost function used in A^* is:$f(n) = g(n) + h(n)$ f (n), where: $g(n)$ is the cost from the start node to n, $h(n)$ is the heuristic estimate from n to the goal, $f(n)$ is the total estimated cost.

The $A*$ algorithm, applied here as the study's initial route estimator, generates baseline delivery paths by balancing historical and real-time traffic data with heuristic cost functions. It evaluates routes by combining actual travel distance with an estimated remaining cost, iteratively expanding nodes until the most efficient path is identified [12]. This process ensures computational efficiency and provides a reliable shortest path for deliveries. However, A* remains static and cannot adjust to dynamic traffic changes, making it the foundation upon which the Genetic Algorithm (GA) is introduced to refine and adapt routes under fluctuating conditions.

2.2.2 Genetic algorithm

The GA is intelligent and the primary method scholars use at home and abroad to solve VRP. Its idea, developed by Professor Holland in 1975, is a global search method based on natural selection and genetics. The evolution process of organisms is simulated by genetic operators such as selection, crossover, and mutation, and the fitness function is used to represent the excellence of chromosomes [13]. Its meta-heuristic can routinely generate practical solutions to optimisation and search problems. Therefore, GA has been widely used in transportation planning and logistics operations management applications and software systems [14].

The simplest form of a genetic algorithm involves three types of operators: Selection, crossover (single-point), and mutation. The GA, first proposed by Holland in 1975, is a global search method inspired by natural selection and evolutionary genetics [15]. By simulating biological processes through operators such as selection, crossover, and mutation, GA efficiently explores large solution spaces and has become a widely adopted tool for solving Vehicle Routing Problems (VRP), transportation planning, and logistics optimisation [16].

In its basic form, GA operates by generating an initial population of candidate solutions, evaluating their fitness, and iteratively evolving better solutions through selection, crossover, and mutation [17]. Fitter solutions are more likely to reproduce, crossover, and exchange subsequences between parents to create new offspring, while mutation introduces small random changes to maintain diversity. This iterative process continues until an optimal or near-optimal solution is achieved, with crossover and mutation probabilities guiding population evolution [18].

The GA refines routes generated by the A* algorithm by evaluating alternatives with a fitness function that considers travel time, congestion, and fuel use. High-performing routes are selected, combined, and mutated to create better options. Unlike A*, which provides a single heuristic-based path, GA applies evolutionary techniques to adapt routes to real-world constraints such as fuel efficiency, deadlines, and sudden congestion.

2.2.3 RL algorithm

In this study, the Reinforcement Learning Algorithm (RLA) is referred to as "Continuous Learning & Real-Time Adaptation". It is employed to ensure continuous adjustment to traffic dynamics. Unlike static planning, RL adapts to unpredictable fluctuations by updating routes in real-time. The agent observes live traffic, congestion reports, and road changes, then selects actions such as re-routing vehicles, adjusting delivery priorities, or optimising paths for efficiency.

A reward system guides learning, granting positive rewards for efficient decisions and penalising poor ones. Over time, the RL model improves its decision-making, creating a logistics system that not only pre-optimises routes but also adapts dynamically. By integrating RL, the GA-optimised routes are enhanced with real-time considerations like congestion, urgency, and road blockages.

Lagos underscores its relevance, ranked among the world's worst for congestion, waiting times, inefficiency, and CO_2 emissions, where precise traffic data is vital for effective adaptation. Accurate and current data on congestion levels, average speeds, and estimated delays in Lagos are challenging to obtain due to the dynamic nature of traffic conditions.

A study on Ikorodu Road used Google Satellite imagery and the moving observer car method over two weeks to estimate travel times and traffic volumes. Congestion was assessed using travel rate, delay ratio, speed performance index, and level of service. Results showed the Ketu–Mile 12 Under-bridge stretch as the most congested, while Maryland Tunnel–Ojota was the least. An anonymous survey of commuters, BRT drivers, and transport agencies further confirmed that travel time-based indices are more reliable for evaluating Lagos traffic.

3. SIMULATION AND PERFORMANCE EVALUATION

The ARE algorithm was built in Mapbox with VS Code, integrating the Mapbox API for live mapping, re-routing, and congestion visualisation. This setup enabled real-time adaptability using updated traffic data, congestion levels, average speeds, delays, and vehicle assignments across major routes, including Third Mainland Bridge, Ikorodu Road, Lekki-Epe Expressway, Apapa Ports/Tin Can Island, and Victoria Island. Table 2 shows Ikorodu Road and Apapa as the most congested routes, reflecting worst-case traffic scenarios in Lagos and ensuring practical relevance.

Table 2. Traffic data

Route	Congestion Level	Average Speed (km/h)	Estimated Delay (mins)	Vehicles Assigned
Third Mainland Bridge	Severe	8-12	40-60	10
Ikorodu Road	Very High	4-8	50-70	15
Lekki-Epe Expressway	High	5-12	35-50	10
Apapa Ports (Tin Can Island)	Extreme	3-6	60-80	5
Victoria Island to Apapa	Moderate	8-16	30-45	10

3.1 Simulation

Adaptive Route Evolution framework hybridises A*, GA, and RL into a scalable, real-time optimisation system, illustrated in Figure 2. The logistics simulation involved two delivery vehicles. As shown in Figure 3, Vehicle 1 (blue) travelled from Ikeja Sorting Warehouse (green marker) to the Ikorodu Distribution Centre (red marker).

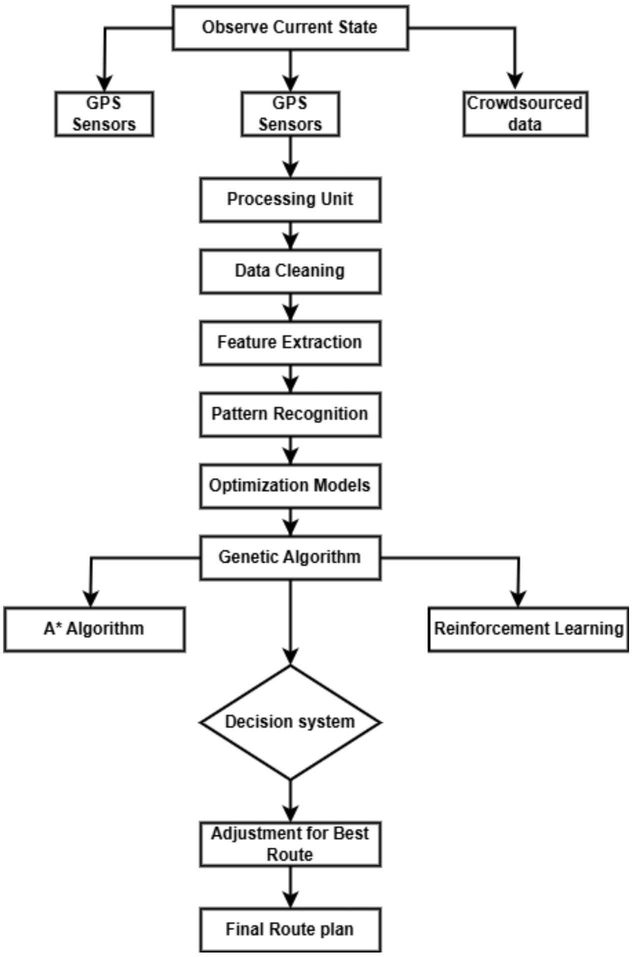

Figure 2. Schematic diagram of ARE

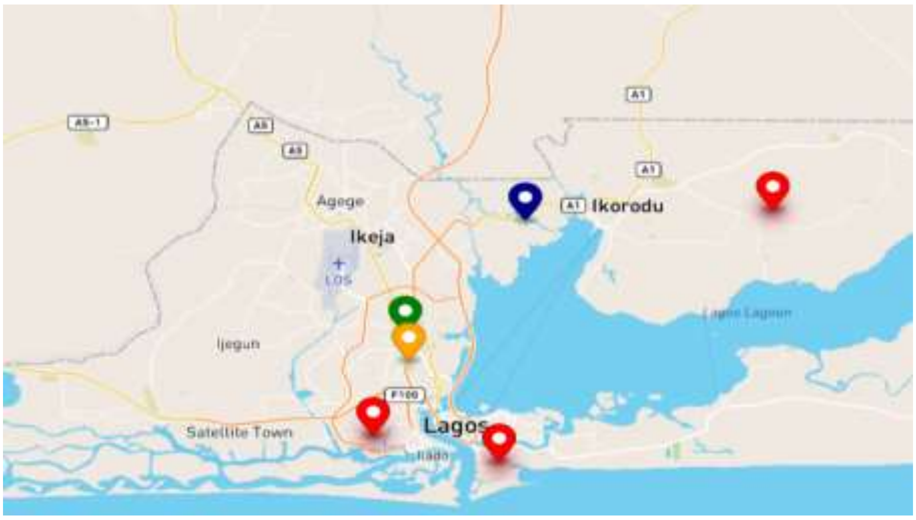

Figure 3: Route strategy for logistics vehicles.

In contrast, Vehicle 2 (orange) followed Ikeja → Victoria Island → Apapa Tin Can Island (red markers). Vehicle 1 used Ikorodu Road directly, reaching its destination in 78 minutes, whereas Vehicle 2 passed through the Third Mainland Bridge and Victoria Island, arriving at Apapa in 120 minutes. This is shown clearly in Table 3.

Table 3. Initial routes (Before optimisation)

Vehicle	**Route**	**Congestion Impact**	**Estimated Time (A)* (mins)**
Vehicle 1	Ikeja → Ikorodu Distribution Centre	High congestion on Ikorodu Road (4-8 km/h)	78
Vehicle 2	Ikeja → Victoria Island → Apapa	Severe congestion on Third Mainland Bridge (8-12 km/h) & Apapa Ports (3-6 km/h)	120

The simulation followed three key steps:
Step 1: Initial Route Planning with A*
The A* algorithm calculates the shortest delivery paths, taking into account real-time traffic delays.
The road network is modelled as a graph with weighted edges. Using Euclidean Distance between the destinations, Euclidean Distance (n, destination) nodes as an estimate of the remaining cost:
Where: $f(n)$ = estimated total cost;
$g(n)$ = actual cost to reach the current node,
$h(n) = \text{ Euclidean Distance } (n\,, \text{destination})$

Path Calculation Formula:

$$f(n)=g(n)+h(n) \tag{1}$$

Step 2: Multi-Stop Optimisation using Genetic Algorithm
The GA optimises the delivery order to reduce travel time by encoding routes as chromosomes; each delivery sequence is represented as a chromosome.
In this case: Vehicle 1: [Ikeja, Ikorodu]
Vehicle 2: [Ikeja, Victoria Island, Apapa]
The function evaluates each route based on traffic delay, fuel cost, and delivery time:
Fitness Function:

$$Fitness \;=\; \frac{1}{(Time+Fuel\;Cost+Traffic\;Delay} \tag{2}$$

For this case: Vehicle 1 → [Ikeja, Ikorodu]; Vehicle 2 → [Ikeja, Victoria Island, Apapa]. GA applies selection (choosing the best routes), Crossover (swapping route segments between parent plans), and Mutation (random route changes to avoid local optima).
Step 3: Real-Time Adjustments using RL
(a) RL dynamically adjusts vehicle routes based on live traffic conditions. The RL agent observes the current location, the Traffic congestion level, and the Time of day. Afterwards, it can maintain the current route or re-route to a less congested road.

Reward Function:

$$R = -(Time + Fuel\ cost + Traffic\ Delay) \tag{3}$$

Q-Learning Formula for Decision-Making:

$$Q(\,s,a) = Q(s,a) +\; \alpha[R + \gamma \max Q(s',a') - Q(s,a)] \tag{4}$$

α = Learning rate
γ = Discount factor for future rewards
Q (s, a) = Expected reward for taking action α at state s

3.2 Performance Evaluation

Results presented show clear efficiency gains. Vehicle 1 cut delivery time by 17 minutes and Vehicle 2 by 41 minutes. Fuel use dropped 20–25%, lowering costs and CO_2 emissions, while on-time deliveries rose by a similar margin. Reinforcement learning (RL) proved critical, enabling real-time re-routing that reduced congestion delays and smoothed logistics flow.
As illustrated in Figures 4 and 5, genetic crossover reassigned Vehicle 2's route to *Ikeja → Apapa → Victoria Island*, easing bottlenecks near Apapa Ports. Fitness evaluation confirms the improvements: Vehicle 1's trip along Ikorodu Road shortened, while Vehicle 2 reached Apapa earlier, avoiding peak-hour gridlock. Together, these results demonstrate Adaptive Route Evolution's (ARE) ability to refine A*, GA, and RL outputs for faster, cleaner, and more reliable logistics. All simulations are available on GitHub [20].

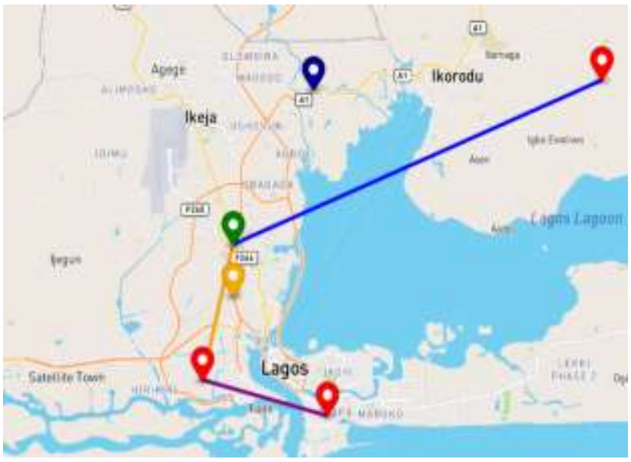

Figure 4: Crossover process in GA

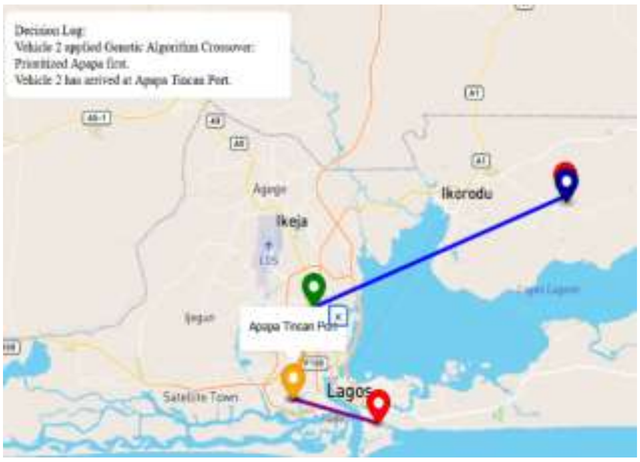

Figure 5: Final optimised routes after GA

The ARE decision-making process confirms RL's effectiveness in optimising logistics. As shown in Figures 6 and 7, Vehicle 1 completes its delivery while Vehicle 2 advances to Victoria Island, with RL iteratively updating routes based on congestion for a balance of efficiency and flexibility.

Figure 6. Vehicle 2 is on its way to Victoria Island

Figure 7. Final delivery after adaptive route evolution

Tables 4, 5, and 6 present A* results, GA, and Adjusted RL, respectively, highlighting GA's effectiveness over A* in multi-stop optimisation and overall adjusted RL effectiveness in re-routing decision and efficient delivery. Table 7 compares A* (blue), GA (purple), RL (orange) after ARE.

Table 4. Optimised route after A* Algorithm

Vehicle	**Route**	**Optimised Time (mins)**
1	Ikeja → Ikorodu Distribution Centre	70
2	Ikeja → Victoria Island → Apapa	90

Table 5. Optimised route after GA

Vehicle	**Route**	**Optimised Time (mins)**
1	Ikeja → Ikorodu Distribution Centre	65
2	Ikeja → Apapa → Victoria Island	83

Table 6. Optimised route after adjusted RL

Vehicle	**Adjustment**	**Optimised Time (mins)**
1	Re-routed via an alternative Ikorodu road bypass	61 minutes
2	Re-routed away from the Apapa gridlock via a secondary exit	79 minutes

Table 7. Optimised route after ARE

Vehicle	**Original Time (mins)**	**Optimised A* (mins)**	**Optimised GA Time (mins)**	**RL Time (mins)**
1	78	70	65	61
2	120	90	83	79

Although tested with a limited number of vehicles, the ARE model is designed to scale for large fleet operations involving hundreds of trucks. Its flexibility lies in real-time GPS integration and the potential for parallel processing, cloud-based data handling, and Edge AI, which supports on-vehicle decision-making without overloading the central server. These features ensure that ARE is not only effective in simulations but also practical for real-world, large-scale logistics networks. Despite its promise, ARE faces hurdles such as the high computational cost of Reinforcement Learning, reliance on potentially incomplete crowdsourced data, infrastructure bottlenecks, and inconsistent internet connectivity. Addressing these challenges will require lightweight RL models, IoT-based traffic sensors, offline-capable routing logic, and improved physical infrastructure. Additionally, fostering driver trust in AI-generated decisions is crucial. With these improvements, ARE can evolve into a fully scalable, intelligent, freight optimisation solution for Lagos, Nigeria.

4.0 CONCLUSION

This study demonstrates the transformative potential of real-time traffic data and geospatial algorithms in urban logistics, using Lagos as a case study. The Adaptive Route Evolution framework, combining A* for path-finding, a Genetic Algorithm for sequencing, and Reinforcement Learning for dynamic re-routing, proved effective in reducing delays under severe congestion, outperforming static methods and extending prior GA-based optimisation with a learning-driven RL layer.

Future work should expand to multimodal networks, integrate vehicle-specific capacities, and incorporate predictive maintenance to improve resilience and cost-effectiveness. Enhancing data quality through IoT sensors and reliable connectivity, alongside field trials, will be vital to translating simulated improvements into real-world impact. Ultimately, aligning algorithmic innovation with infrastructure upgrades and stakeholder collaboration can deliver substantial reductions in congestion, fuel use, and delivery times for smarter and more sustainable freight systems in Lagos and other megacities.

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