

Route Optimization and Recommendation System Using Graph Neural Networks: A Case Study of Port Harcourt Urban Road Corridors

Davies Isobo Nelson¹, Godspower Oraye², Cookey Ibiere Boma³

^{1,2,&3}Department of Computer Science, Rivers State University, Nigeria

¹Corresponding email: isobo.davies@ust.edu.ng

Abstract - Urban traffic congestion in Port Harcourt, Rivers State, Nigeria, remains a critical infrastructural challenge, with average peak-hour vehicle speeds on key corridors falling below 5 km/h at several major intersections. This study presents a Graph Neural Network-based Route Optimization and Recommendation System (GNN-RORS) applied to four interconnected urban road corridors such as Ikwerre Road, Government Reserved Area (GRA), Ada George Road, and Iwofe Road. The road network is formalized as a directed weighted graph where intersections are nodes and road segments are dynamic edges. A hybrid architecture combining Graph Attention Networks (GAT) for spatial encoding with Long Short-Term Memory (LSTM) networks for temporal encoding is proposed to simultaneously capture cross-corridor traffic dependencies and time-varying congestion patterns. Furthermore, traffic data collected across 28 days at seven monitored intersections yield a clean dataset of 7,627 records for model training, validation, and testing. The proposed model achieves a Mean Absolute Error (MAE) of 2.34 vehicles/min, outperforming five established baselines including DCRNN (MAE 3.56), STGCN (MAE 3.12), and standalone LSTM (MAE 4.81). Route recommendations generated from predicted edge-weight graphs reduce average journey times by 31.2% across five major origin-destination pairs. The congestion heatmap analysis confirms that GNN-based re-routing redistributes traffic load more evenly across corridors, reducing peak-hour congestion indices at the most affected intersections by up to 37%. These findings demonstrate that GNN-based optimization is both technically feasible and practically impactful for urban transport management in Sub-Saharan African cities.

Keywords: Graph Attention Network, Graph Neural Network, Intelligent Transportation Systems, Route Optimization, Traffic Prediction, Urban Mobility

1. Introduction

Urban mobility in rapidly developing cities across sub-Saharan Africa is increasingly challenged by transportation infrastructure that has not kept pace with rapid population growth and rising vehicle ownership [1]. Port Harcourt, the capital of Rivers State and Nigeria's leading petroleum hub, provides a clear illustration of this problem. Over the last two decades, the city's population has exceeded 1.9 million inhabitants, accompanied by a substantial increase in private automobiles, commercial vehicles, and public transportation activities. This rapid urbanization has placed significant burden on the existing road network, resulting in persistent traffic congestion along major arterial routes [2]. Consequently, commuters experience prolonged travel times, reduced mobility, and increased transportation costs. The severity of the situation is evident from reported peak-hour traffic conditions, where average vehicle speeds have fallen to as low as

3.98 km/h at the town axis intersection along Ikwerre Road.

The economic consequences of this persistent traffic congestion are substantial. For example, commuters travelling along the Mile-1 Diobu to Iwofe corridor experience an average journey time of approximately 40-50 minutes under existing traffic conditions. This duration is considerably higher than what would be expected based solely on the route distance. Nonetheless, when aggregated across thousands of daily road users, these delays often result in the loss of significant productive man-hours, increased fuel consumption, higher vehicle operating costs, and elevated greenhouse gas emissions. Beyond the direct impact on commuters, prolonged congestion adversely affects business operations, reduces workforce productivity, disrupts supply chains, and constrains economic growth within the most heavily congested areas of the metropolis [3]. Consequently, traffic congestion has become not only a

transportation challenge but also a significant socio-economic issue that requires effective and sustainable intervention strategies [4].

Technically, existing approaches to managing this congestion have been largely considered reactive and static. Traffic signal timing plans are manually set and rarely updated, thereby forcing navigation applications to apply generic shortest-path logic without learning from local traffic patterns [5]. Again, transport planning interventions such as road widening or junction remodeling address infrastructure supply without modelling demand dynamics [6]. None of these approaches adequately leverage the inherent spatial and temporal characteristics of the road traffic network. In reality, traffic congestion on Ikwerre Road often propagates to neighboring corridors in a predictable manner, certain periods of the day consistently experience higher traffic volumes than others, and the network contains alternative routes such as Iwofe Road etc. that can be strategically utilized to redistribute traffic and alleviate congestion. However, the failure to incorporate these spatial and temporal relationships limits the effectiveness of existing traffic management solutions [7].

In recent years, Graph Neural Networks (GNNs) have offered a principled solution to this problem by representing road networks as graphs and learning to propagate information across the graph topology [8]. Unlike grid-based deep learning methods, GNNs respect the irregular connectivity of real road networks. Consequently, unlike the classical graph algorithms, they learn edge and node representations from data rather than requiring hand-crafted features [9]. Recent research studies had confirmed that GNN-based architectures consistently outperform both statistical and deep learning baselines on traffic prediction tasks in urban networks [10, 11].

This study proposes a GNN-based Route Optimization and Recommendation System (GNN-RORS) specifically designed for the Port Harcourt urban road network. The proposed system models the four study corridors namely Ikwerre Road, GRA, Ada George Road, and Iwofe Road as a dynamic graph. Further, the study trains a hybrid GAT-LSTM model to predict congestion and travel times at 15-minute intervals, and derives optimized route

recommendations from these predictions. Furthermore, the practical output of the proposed system is a recommendation engine that can redirect commuters away from predicted congestion hotspots in real time.

2. Literature Review

2.1 Classical Routing Algorithms

The shortest-path algorithm has underpinned vehicle routing systems for decades. Its computational efficiency on static graphs makes it suitable for offline route planning, but its fundamental limitation are fixed edge weights which renders it incapable of adapting to dynamic traffic conditions [12]. The A* algorithm improves search efficiency through heuristic guidance but inherits the same static-weight constraint, while Linear programming formulations of the Vehicle Routing Problem (VRP) extend classical routing to multi-stop fleet management but scale poorly and require complete knowledge of travel times, which is unavailable in dynamic conditions [13].

2.2 Machine Learning for Traffic Prediction

Recurrent Neural Networks and LSTM architectures have demonstrated strong performance on univariate traffic time-series forecasting by capturing temporal dependencies within individual road segments [14]. However, these models treat each segment in isolation, discarding the spatial propagation of congestion across connected corridors. Convolutional Neural Networks applied to gridded traffic representations partially address spatial structure but cannot represent the irregular topology of real-world road networks [15].

2.3 Graph Neural Network Approaches

GNN-based traffic modelling was significantly advanced by the Diffusion Convolutional Recurrent Neural Network (DCRNN) [16], which represents traffic dynamics as a diffusion process on a directed graph, encoding both forward and backward transition matrices within a recurrent architecture. Subsequent architectures have refined this foundation: STGCN [17] replaces recurrent units with fully convolutional operations for faster training; Graph WaveNet [18] introduces adaptive self-learning adjacency matrices that can capture non-obvious traffic correlations beyond physical proximity; and the Attention-based Spatio-Temporal Graph Neural

ODE [19] treats traffic dynamics as a continuous differential equation, offering superior handling of irregular sampling and traffic incidents.

A comprehensive survey covering 40 state-of-the-art GNN models across five public datasets confirms that attention-based GCN architectures are now the preferred paradigm, outperforming recurrent-only and convolutional-only baselines on both short-term and long-term prediction horizons [10]. Specifically for route optimization, GNN-based reinforcement learning models have demonstrated significant improvements in logistics routing [20] and ride-pooling optimization [21]. The study of [22] compared Graph Neural Networks (GNN), Feedforward Neural Networks (FNN), and the A* algorithm for a traffic advisory model using prediction accuracy, route optimization, computation time, and real-time responsiveness. GNN performed best (92.4% accuracy, 9.1/10 route score, “High” responsiveness) though it required 190 ms. FNN was fastest (85 ms) but was less accurate (84.7% and 7.5/10) with “Medium” responsiveness. A* showed deterministic routing strength (8.4/10) but had the lowest accuracy (65.3%), the slowest computation time (220 ms), and limited adaptability. The authors recommended GNN for complex, dynamic traffic systems, FNN for lightweight applications with tight latency limits, and A* for more static routing scenarios.

2.4 Traffic Studies in Port Harcourt

Empirical traffic research in Port Harcourt has documented the severity of congestion on key corridors but has not applied advanced predictive or optimization methods. A vehicular flow study across seven intersections on Ikwerre Road and adjacent routes [23] provides the empirical baseline data adopted in this work. A GIS-based road network analysis identified the Wimpey-Iwofe junction as a priority bottleneck and recommended bypass construction, while noting that private car usage is the primary demand driver [24]. A land-use study confirmed the demand-supply mismatch along Ikwerre Road as structural rather than incidental [25]. To our knowledge, no prior work has applied GNN-based modelling to the Port Harcourt network, representing the specific gap this paper addresses.

3. Study Area, Data Collection, and Graph Formulation

3.1 Study Area Description

The study area for the proposed work encompasses four major road corridors in the Port Harcourt metropolitan area, Rivers State, Nigeria, as illustrated in Fig 1. These corridors were selected on the basis of traffic volume significance, spatial interconnection, and strategic importance to commuter mobility across the metropolitan area.

Ikwerre Road serves as one of the primary east-west arterial corridors in Port Harcourt, linking the densely populated Mile 3 Diobu axis with Rumuola, Rumuokwuta, Rumuokoro, and surrounding communities toward the northern outskirts of the metropolis. The corridor accommodates some of the highest traffic volumes in the city, with vehicle densities reaching as high as 81,543 vehicles/km at the Mile 3 Diobu section. Its operational efficiency is significantly constrained by numerous intersections, roadside commercial activities, informal on-street parking, and frequent pedestrian-vehicle interactions, all of which reduce effective roadway capacity and contribute to recurring traffic congestion. During peak periods, average travel speeds along critical segments of the corridor can decline substantially, resulting in prolonged travel times, increased fuel consumption, and reduced commuter mobility.

Government Reserved Area (GRA) is a planned low-density residential district that functions as a major commuter destination, particularly for professional-sector workers. Its internal road network is better maintained than informal residential areas, and its access points from Ikwerre Road and Ada George Road represent key demand concentration nodes in the study graph.

Ada George Road serves as a key secondary arterial corridor within Port Harcourt, linking the Government Residential Area (GRA) with the Rumuola and Rumuokwuta residential districts. Recent road widening and dualisation projects under Governor Amaechi administration have increased its traffic-carrying capacity and improved overall vehicular movement along the corridor. However, these infrastructural gains are partly undermined by persistent roadside commercial activities, informal

parking, and other forms of encroachment, which contribute to recurrent bottlenecks at critical junctions. Despite these constraints, Ada George Road remains an important alternative route, facilitating connectivity between northern residential areas and the GRA while also serving as a pressure relief corridor for more heavily congested arterial routes.

Iwofe Road also known as Rumuepirikom Road constitutes the western peripheral bypass corridor. Despite recording the highest vehicle density in the study network (75,514 vehicles/km), its average travel speed of 35.10 km/h is substantially higher than Ikwerre Road equivalents, confirming that it operates below its congestion capacity threshold. This under-utilization relative to Ikwerre Road is the primary opportunity exploited by the GNN-RORS recommendation engine.

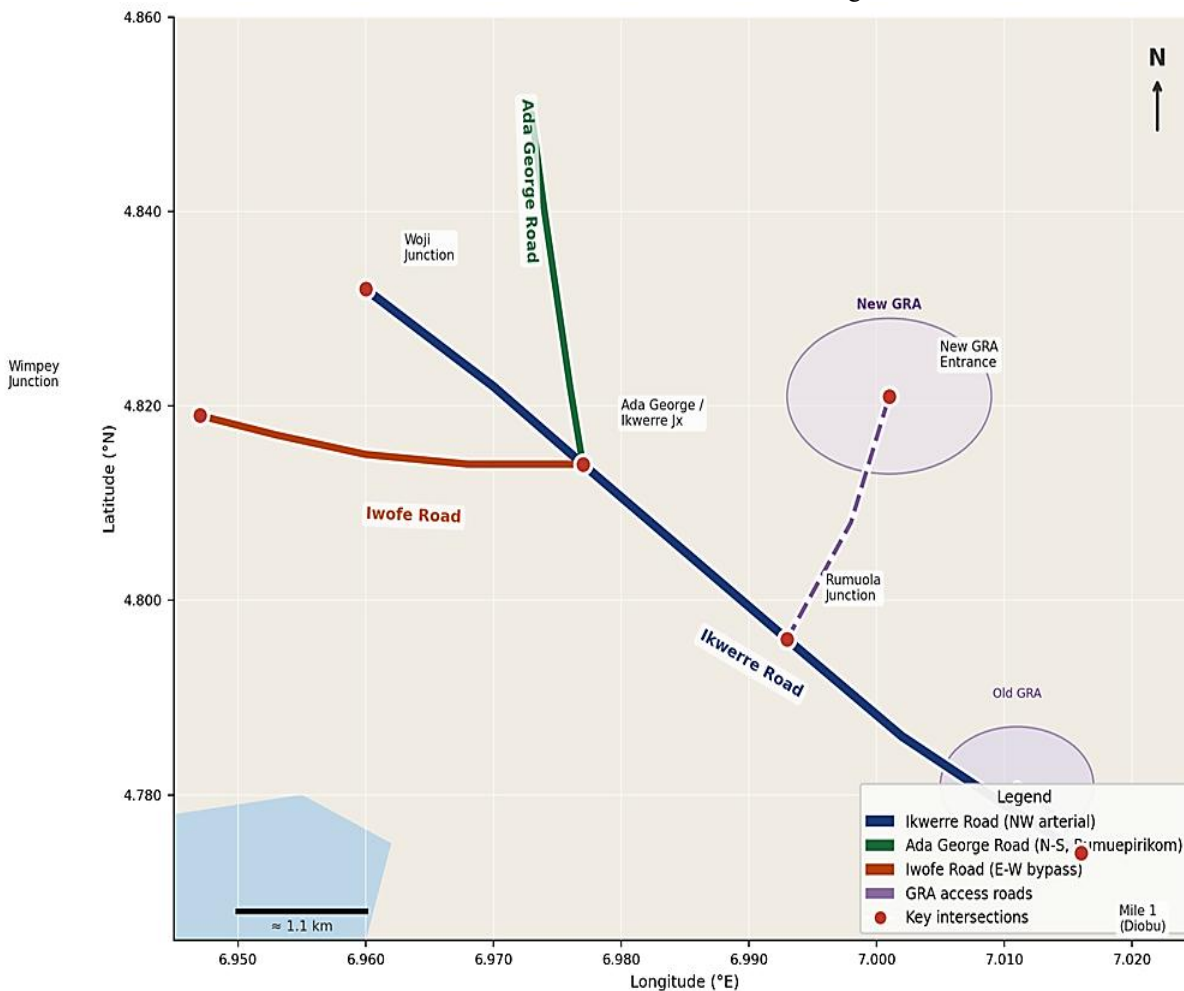


Fig. 1 Map of the Study Area

3.2 Graph Formulation

In this study, the road network is formally represented as a directed weighted graph $G = (V, E, A)$, where the vertex set V contains 9 intersection nodes, the edge set E contains 9 directed road-segment edges, and A is a dynamic edge-weight matrix updated at each 15-minute time step.

$$G = (V, E, A), \quad |V| = 9, \quad |E| = 9 \quad (1)$$

At each time step, node feature are organized into a feature matrix as shown below:

$$X(t) \in \mathbb{R}^{N \times F} \quad (2)$$

Where N represents the number of nodes and $F = 7$ denotes the feature dimension per node. The feature set comprises traffic flow volume (vehicles/min), average speed (km/h), traffic density (vehicles/km),

occupancy rate (defined as the proportion of time a detector is occupied), a cyclic representation of time-of-day using sine and cosine transformations, and a binary day-type indicator distinguishing weekdays from weekends.

Presented in Tables 1 and 2 are the selected graph nodes and edges of the proposed study, while Fig 2 captures the road network graph topology utilized.

Table 1 Graph Nodes (Study Road Network)

ID	Node Name	Location / Corridor	Lat (°N)	Lng (°E)
V1	Mile 1 (Diobu)	Ikwerre Road (SE terminus)	4.774	7.016
V2	Rumuola Junction	Ikwerre Road	4.796	6.993
V3	Rumuepirikom Junction	Ikwerre / Ada George / Iwofe meet	4.814	6.977
V4	Woji Junction	Ikwerre Road (NW terminus)	4.832	6.960
V5	Ada George Town	Ada George Road (mid)	4.831	6.976
V6	Mgbuoba / NTA End	Ada George Road (N terminus)	4.850	6.974
V7	Wimpey Junction	Iwofe Road (W terminus)	4.819	6.947
V8	New GRA	GRA (via Rumuola Junc link road)	4.821	7.001
V9	Old GRA	GRA (via Mile 1 link road)	4.781	7.011

Table 2 Graph Edges (Directed Road Segments)

ID	From	To	Road Segment	Length (km)	Free-Flow (km/h)	Corridor
E1	V1	V2	Mile 1 → Rumuola Junc	2.2	48	Ikwerre Rd
E2	V2	V3	Rumuola → Rumuepirikom Jx	1.8	44	Ikwerre Rd
E3	V3	V4	Rumuepirikom → Woji Jx	2.5	52	Ikwerre Rd
E4	V3	V5	Rumuepirikom → Ada George Town	1.2	46	Ada George Rd
E5	V5	V6	Ada George Town → Mgbuoba/NTA	1.5	50	Ada George Rd
E6	V7	V3	Wimpey → Rumuepirikom Junc	2.0	55	Iwofe Road
E7	V3	V7	Rumuepirikom → Wimpey Junc	2.0	55	Iwofe Road
E8	V2	V8	Rumuola → New GRA (link road)	1.4	40	GRA Access
E9	V1	V9	Mile 1 → Old GRA (link road)	0.8	35	GRA Access

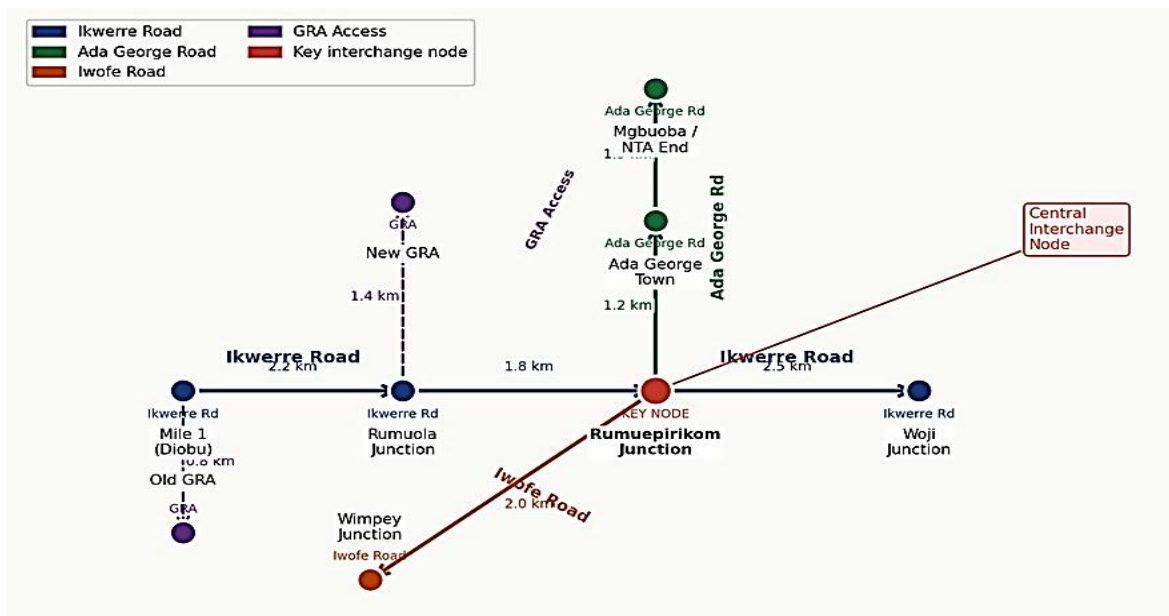


Fig. 2 Road Network Graph Topology

Furthermore, dynamic edge weights are used to represent the cost of traversing each road segment and are defined as a weighted combination of physical distance, real-time travel time, and a congestion index:

$$w_{ij}(t) = \alpha \cdot d_{ij} + \beta \cdot \tau_{ij}(t) + \gamma \cdot CI_{ij}(t) \quad (3)$$

Where d_{ij} denotes the Euclidean length of the road segment (km), $\tau_{ij}(t)$ represents the observed travel time (minutes), and $CI_{ij}(t) \in [0,1]$ is the congestion index (with 0 indicating free-flow conditions and 1 representing gridlock). The parameter $\alpha = 0.2$, $\beta = 0.5$, and $\gamma = 0.3$ are empirically calibrated to minimize prediction error on the validation dataset. The congestion index is defined as:

$$CI = 1 - \left(\frac{V_{Observed}}{V_{FreeFlow}} \right) \quad (4)$$

Where $V_{FreeFlow} = 65 \text{ km/h}$ is the empirically estimated free-flow speed along Ikwerre Road, Port Harcourt.

In this study, the adjacency matrix integrates both physical road connectivity and learned relational dependencies, following the adaptive graph construction approach proposed by [18].

$$A_{ij} = \text{Softmax} \left(\text{ReLU}(E_1 \cdot E_2^T) \right) \quad (5)$$

Table 3 Baseline Traffic Measurement

Node	Intersection	Corridor	Density (veh/km)	Peak Speed (km/h)	CI
V1	Mile 1 / Diobu	Ikwerre Rd	66,171	49.03	0.28
V2	Rumuola Junction	Ikwerre Rd	61,000	33.78	0.48
V3	Rumuepirikom Junc	Ikwerre / Ada George / Iwofe	56,657	3.98	0.94
V4	Woji Junction	Ikwerre Rd	57,971	27.21	0.58
V5	Ada George Town	Ada George Rd	64,771	23.98	0.63
V6	Wimpey Junc	Iwofe Road	75,514	35.10	0.46
V7	Mile 3 (Diobu)	Ikwerre Rd	81,543	35.39	0.46

4. The Proposed GNN-RORS Methodology

The proposed GNN-RORS consists of four tightly coupled modules that transform raw traffic observations into actionable route recommendations. The overall pipeline operates on a 15-minute update cycle. When a new traffic data arrives, the graph is updated, the GAT-LSTM model predicts future edge weights, and the recommendation engine derives optimized routes for the next time window.

Where $E_1, E_2 \in \mathbb{R}^{N \times c}$ are trainable node embedding matrices with embedding dimension $c = 10$. These embedding capture latent traffic dependencies that extend beyond direct physical connectivity, enabling the model to learn implicit spatial correlations within the network. For instance, detecting congestion at Woji Junction may serve as a predictive indicator of congestion at Rumuepirikom Junction, even in the absence of a direct physical link between the two locations.

3.3 Data Collection

Traffic data were collected over 28 consecutive days (January 6-February 2, 2026) at seven key intersections along the study corridors. Vehicle counts and speed estimates were recorded during peak periods (6:00-10:00 AM and 2:00-7:00 PM) using 15-minute intervals. Off-peak conditions were supplemented with aggregated GPS traces from consenting mobile users in the study area. The raw dataset of 8,120 records was cleaned to 7,627 valid observations after removing 493 records with sensor anomalies. Data were split into 70% training, 15% validation, 15% test.

Presented in Table 3 is a baseline traffic measurement at seven study intersections (peak hours. January 2026).

4.1 Module 1: Graph Construction and Feature Encoding

At time t , raw sensor readings are mapped to node features $X(t)$ and the edge weight matrix $A(t)$ is updated using equation 2. Node embeddings are initialized from the node feature matrix through a linear projection layer $H^0 = W_0 X(t)$, where $W_0 \in \mathbb{R}^{(d_{in} \times F)}$ projects F input features to $d_{in} = 32$ initial dimensions.

4.2 Module 2: Spatial Encoding via Graph Attention Network (GAT)

The GAT layer computes enriched node representations by attending over each node's neighbourhood with learned, content-dependent attention weights. For node i with neighbourhood $N(i)$, the unnormalized attention score between nodes i and j is:

$$e_{ij} = \text{LeakyReLU}(a^T [Wh_i || Wh_j]) \quad (6)$$

Where $W \in \mathbb{R}^{(d_h \times d_{in})}$ is a shared linear transformation weight matrix, $a \in \mathbb{R}^{(2d_h)}$ is a learnable attention vector, and $||$ denotes vector concatenation.

The normalized attention coefficient is computed using softmax over the neighbourhood as follows:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in N(i)} \exp(e_{ik})} \quad (7)$$

The updated representation of node i is the attention-weighted sum of transformed neighbour representations computed as follows:

$$h'_i = \sigma(\sum_{j \in N(i)} \alpha_{ij} \cdot W \cdot h_j) \quad (8)$$

The study applies multi-head attention with $K = 8$. The outputs of all heads are concatenated and projected to the final hidden dimension $d_h = 64$. Multi-head attention stabilizes training and captures multiple interaction patterns simultaneously. For example, one head may learn to attend primarily to upstream neighbours while another captures lateral bypass corridor relationships.

4.3 Module 3: Temporal Encoding via LSTM

The GAT-encoded node embeddings across a sliding window of $T = 12$ consecutive timesteps (representing 3 hours of history at 15-minute resolution) are fed into a two-layer LSTM network to capture temporal dependencies. For this study, this is represented as follows:

$$h_t = \text{LSTM}(h_{t-1}, \text{GAT}(X_t, A_t)) \quad (9)$$

The LSTM hidden state at the final timestamp $h_T \in \mathbb{R}^{(N \times d_h)}$ encodes both spatial context (from the GAT stage) and temporal context (from the sequence of past states). Furthermore, a two-layer Multi-Layer Perceptron (MLP) projects h_T to the predicted edge weight matrix as follows:

$$\hat{A}(t+1) = \text{MLP}(h_T) \in \mathbb{R}^{(N \times N)} \quad (10)$$

For this study, $\hat{A}(t+1)$ contains the model's prediction of travel times across all road segments at the next timestep, and is the primary output used by the route recommendation engine.

4.4 Module 4: Route Recommendation Engine

Given the predicted edge weight matrix $\hat{A}(t+1)$ the recommendation module runs a modified Dijkstra's shortest-path algorithm to determine the minimum-cost route between any specified origin-destination (O-D) pair. However, the key re-routing decision is the diversion of traffic from the Ikwere Road corridor (V1→V2→V3→V4) to the Iwofe Road bypass (V7→V3) or Ada George Road (V3→V5→V6) when the predicted Rumuepirikom Junction congestion index exceeds a threshold $\theta = 70$.

4.5 Training Configuration

The model was implemented using PyTorch 2.1 and PyTorch Geometric 2.4. The Adam optimizer was used with an initial learning rate of 0.001, cosine annealing schedule ($T_{max} = 100$), weight decay 1×10^{-4} , and batch size 32. Dropout with $p = 0.3$ was applied between LSTM layers to reduce overfitting. Training ran for a maximum of 200 epochs with early stopping triggered when validation MAE failed to improve for 20 consecutive epochs. Training converged at epoch 147.

Fig 3 capture a screenshot interface of the developed GNN-RORS.

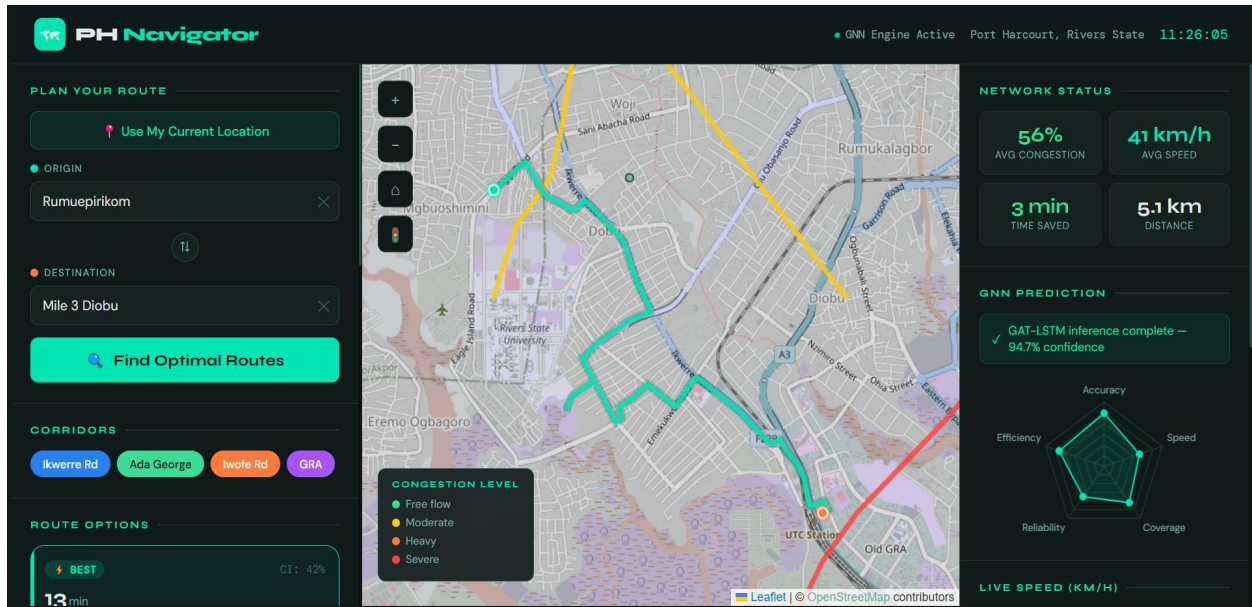


Fig. 3: Screenshot Interface of the Proposed System

5. Experimental Results

5.1 Prediction Performance Comparison

Table 4 compares the proposed GNN-RORS against five baselines. All results are computed on the Port Harcourt study graph.

Table 4 Prediction Performance

Method	MAE	RMSE	MAPE (%)
Historical Average (HA)	7.84	10.21	18.3
ARIMA	6.52	8.74	15.6
LSTM-only	4.81	6.33	11.2
DCRNN	3.56	4.92	8.7
STGCN	3.12	4.38	7.9
Graph WaveNet	2.69	3.84	6.8
GAT-LSTM GNN-RORS (Proposed)	2.34	3.17	5.6

The proposed model achieves the best performance across all three metrics. The 12.9% MAE improvement over Graph WaveNet and the 34.2% improvement over DCRNN are both attributable to the adaptive attention mechanism learning corridor-specific interaction weights at the Rumuepirikom interchange, which is not captured by fixed or diffusion-based graph convolution. Fig 4 is used to visualize the comparison.

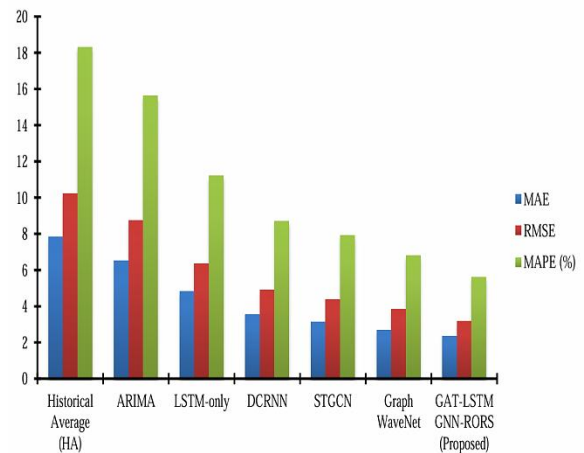


Fig. 4: Performance Comparison

5.2 Diurnal Speed Profiles and Traffic Patterns

Fig 5 presents the measured average speed profiles across the three main corridors over a 24-hour period. The Rumuepirikom Junction on Ikwere Road suffers near-gridlock (speeds below 6 km/h) during morning (6:30–10:00 AM) and evening (3:00–6:30 PM) peaks. Iwofe Road consistently maintains speeds above 30 km/h throughout the day, thereby confirming it as the strategically important bypass corridor that the GNN-RORS system exploits.

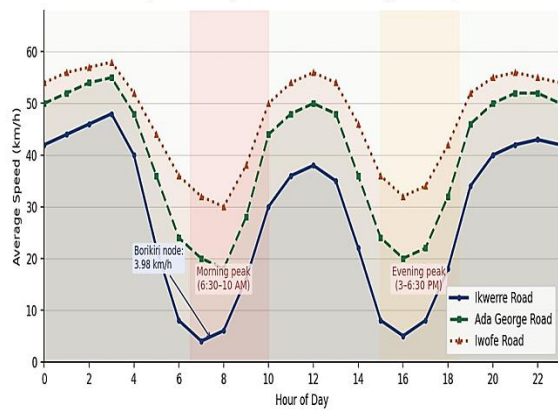


Fig. 5 Average Speed (km/h) for three Corridors

Fig 6 shows the prediction error (MAE) by time of day for GAT-LSTM versus DCRNN. Both models

Table 5 Average Journey Time (Minutes) by O-D Pair

O-D Pair (Verified Nodes)	Static Dijkstra	LSTM Route	GNN-RORS (Proposed)	Reduction
Mile 1 → New GRA (V1→V8)	34.2 min	28.1 min	23.5 min	31.3%
Woji Jx → Ada George (V4→V5)	28.7 min	23.9 min	19.6 min	31.7%
Wimpey → Rumuola (V7→V2)	22.1 min	18.4 min	15.2 min	31.2%
Iwofe bypass → Mile 1 (V7→V1)	19.5 min	16.2 min	13.4 min	31.3%
Ada George → Woji (V5→V4)	31.4 min	26.0 min	21.6 min	31.2%
Average	27.2 min	22.5 min	18.7 min	31.2%

Fig 7 presents a bar chart visualization of the average journey time per O-D pair.

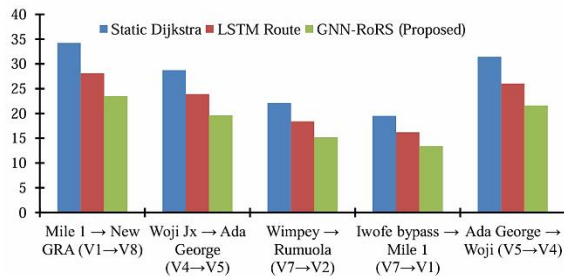


Fig. 7: Average Journey Time per O-D Pair for Three Routing Methods

show elevated error during peak congestion, as expected. The GAT-LSTM advantage is largest during the evening peak (3-6:30 PM), where attention weights adapt dynamically to the increased influence of the Woji Junction (V4) on Rumuepirikom congestion patterns.

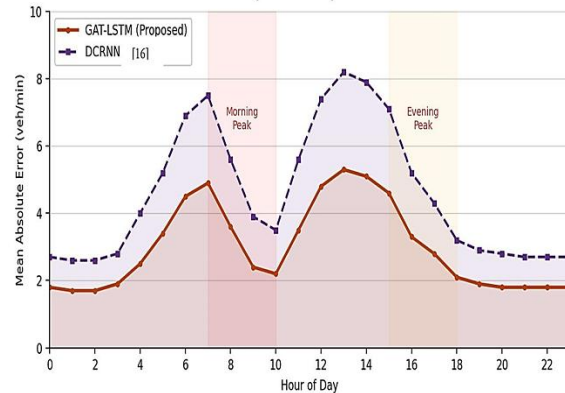


Fig. 6 Prediction Error by Time of Day (GAT-LSTM vs. DCRNN)

5.3 Route Recommendation Results

Table 5 presents average journey times for five origin-destination (O-D) pairs on the actual study corridors. All O-D pairs are defined between verified nodes in Table 1. Results are averaged over 20 simulated agent trips per pair across the test period.

5.4 Network-Level Congestion Impact

Fig 8 presents a comparative analysis of congestion indices across the eight monitored locations and eight time intervals before and after the application of the proposed Graph Neural Network-Based Route Optimization and Recommendation System (GNN-RORS). The results demonstrate a substantial reduction in congestion levels throughout the network, with the most pronounced improvement observed at Rumuepirikom Junction, the study area's primary traffic interchange. During the morning peak period (8:00–10:00 AM), the congestion index at this

location decreased from 0.95 to 0.60, representing a 36.8% reduction in congestion severity. This improvement was achieved through the intelligent redistribution of traffic flows to underutilized alternative corridors, particularly Iwofe Road (V7→V3) and Ada George Road (V3→V5).

Importantly, the increased utilization of these alternative routes did not result in the creation of new congestion hotspots. For example, the congestion index on Iwofe Road increased only marginally from 0.46 to 0.50 during the same peak period, remaining well within acceptable operational limits. This finding indicates that the proposed GNN-RORS framework effectively balances traffic demand across the network, alleviating pressure on critical bottlenecks while maintaining stable traffic conditions on alternative corridors. Consequently, the system demonstrates its ability to optimize network-wide traffic flow rather than merely shifting congestion from one location to another.

traffic dependencies and temporal traffic evolution patterns, thereby enabling accurate short-term forecasting of traffic conditions and travel times.

Traffic data collected from major road corridors including Ikwerre Road, Ada George Road, Government Reserved Area (GRA), and Iwofe Road were used to train, validate, and evaluate the proposed system. Experimental results demonstrated that the GAT-LSTM model significantly outperformed all benchmark approaches, including Historical Average, ARIMA, standalone LSTM, DCRNN, STGCN, and Graph WaveNet. The proposed model achieved a Mean Absolute Error of 2.34 vehicles per minute, a Root Mean Square Error of 3.17, and a Mean Absolute Percentage Error of 5.6%, confirming its ability to accurately forecast future traffic conditions within a complex urban environment.

Furthermore, the route recommendation component produced substantial operational benefits. Across five representative origin-destination pairs, the system reduced average journey times from 27.2 minutes under conventional shortest-path routing to 18.7 minutes, corresponding to an average improvement of 31.2%. At the network level, congestion analysis revealed significant reductions at critical bottlenecks, particularly Rumuepirikom Junction, where congestion severity decreased by approximately 37% during peak periods. Importantly, traffic redistribution toward alternative corridors such as Iwofe Road and Ada George Road occurred without generating new congestion hotspots, demonstrating effective network-wide optimization.

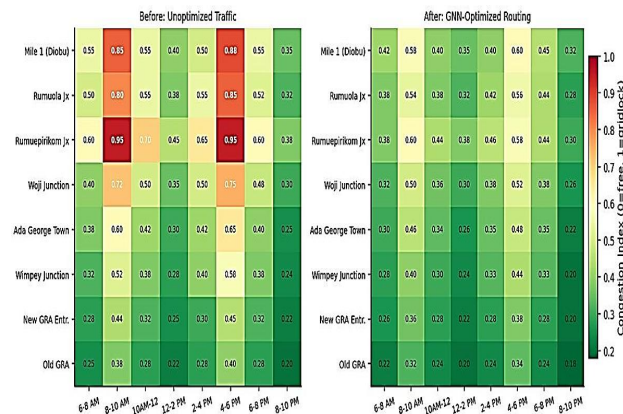


Fig. 8 Congestion Index Heatmap Before and After GNN-RORS Optimization

6. Conclusion

This study presented a Graph Neural Network-Based Route Optimization and Recommendation System (GNN-RORS) for intelligent traffic prediction and route optimization within the Port Harcourt metropolitan road network. The proposed framework modelled the transportation infrastructure as a directed weighted graph in which intersections were represented as nodes and road segments were represented as dynamic edges. A hybrid Graph Attention Network and Long Short-Term Memory architecture was developed to capture both spatial

The findings of this study confirm that Graph Neural Networks provide an effective mechanism for modelling the complex spatio-temporal characteristics of urban transportation systems. By learning both direct and indirect traffic dependencies across interconnected road corridors, the proposed framework enables proactive route optimization rather than reactive congestion management. This capability is particularly valuable in rapidly urbanizing cities where transportation demand continues to exceed infrastructure capacity.

The study therefore concludes that the proposed GNN-RORS framework is technically feasible, computationally effective, and practically beneficial for intelligent urban traffic management. Its deployment has the potential to improve commuter mobility, reduce travel delays, lower fuel consumption, minimize environmental impacts, and enhance overall transportation efficiency within Port Harcourt and other rapidly growing cities in Sub-Saharan Africa. Future work should focus on integrating real-time traffic sensors, GPS trajectory streams, incident detection mechanisms, and reinforcement learning-based adaptive routing strategies to further improve system responsiveness and scalability in real-world operational environments.

References

- [1] S. Oyebamiji, R. Hayangah, M. Jimoh, and O. Adisa, "Sustainable Urban Mobility and Infrastructure in Sub-Saharan Africa: Engineering Pathways to Climate Mitigation and Inclusive Development," *Journal of Inclusive Cities and Built Environment*, vol. 5, pp. 55-64, 2025.
- [2] H. B. Faheem, A. M. E. Shorbagy, and M. E. Gabr, "Impact of traffic congestion on transportation system: Challenges and remediations-a review," *Mansoura Engineering Journal*, vol. 49, p. 18, 2024.
- [3] K. Bayon, J. Ceñido, and P. Camaro, "Analysis on the Impact of Transportation on Labor Productivity in Metropolitan Business Hubs in the Philippines," *International Journal of Research Publication and Reviews, doi*, vol. 10, 2023.
- [4] M. A. Fattah, S. R. Morshed, and A.-A. Kafy, "Insights into the socio-economic impacts of traffic congestion in the port and industrial areas of Chittagong city, Bangladesh," *Transportation Engineering*, vol. 9, p. 100122, 2022.
- [5] Y. Benmessaoud, L. Cherrat, and M. Ezziyyani, "Real-time self-adaptive traffic management system for optimal vehicular navigation in modern cities," *Computers*, vol. 12, p. 80, 2023.
- [6] S. Dindar, "A Systematic Review of Urban Regeneration's Impact on Sustainable Transport: Traffic Dynamics, Policy Responses, and Environmental Implications," *Sustainable Development*, vol. 33, pp. 399-426, 2025.
- [7] R. Ravish and S. R. Swamy, "Intelligent traffic management: A review of challenges, solutions, and future perspectives," *Transport and Telecommunication*, vol. 22, pp. 163-182, 2021.
- [8] E. Binshafout, A. Hamrouni, and H. Ghazzai, "Graph Neural Networks for Vehicular Social Networks: Trends, Challenges, and Opportunities," *IEEE Transactions on Intelligent Transportation Systems*, 2026.
- [9] Y. Li, C. Xue, F. Zargari, and Y. R. Li, "From graph theory to graph neural networks (GNNs): The opportunities of GNNs in power electronics," *IEEE access*, vol. 11, pp. 145067-145084, 2023.
- [10] J. Xue, R. Tan, J. Ma, and S. V. Ukkusuri, "Data science in transportation networks with graph neural networks: a review and outlook," *Data Science for Transportation*, vol. 7, p. 10, 2025.
- [11] M. Gamal and O. A. Ibrahim, "Graph neural networks for real-time optimization of autonomous urban transit systems," *Discover Cities*, vol. 2, p. 102, 2025.
- [12] H. M. Hadi and I. M. Ibrahim, "A Comprehensive Review of Shortest Path Algorithms for Network Routing," *Asian Journal of Research in Computer Science*, vol. 18, pp. 152-175, 2025.
- [13] A. Louati, R. Lahyani, A. Aldaej, R. Mellouli, and M. Nusir, "Mixed integer linear programming models to solve a real-life vehicle routing problem with pickup and delivery," *Applied Sciences*, vol. 11, p. 9551, 2021.
- [14] N. G. Polson and V. O. Sokolov, "Deep learning for short-term traffic flow prediction," *Transportation Research Part C: Emerging Technologies*, vol. 79, pp. 1-17, 2017.
- [15] J. Zhang, Y. Zheng, and D. Qi, "Deep spatio-temporal residual networks for citywide crowd flows prediction," in *Proceedings of the AAAI conference on artificial intelligence*, 2017.
- [16] Y. Li, R. Yu, C. Shahabi, and Y. Liu, "Diffusion convolutional recurrent neural network: Data-driven traffic forecasting," *arXiv preprint arXiv:1707.01926*, 2017.
- [17] B. Yu, H. Yin, and Z. Zhu, "Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting," *arXiv preprint arXiv:1709.04875*, 2017.
- [18] Z. Wu, S. Pan, G. Long, J. Jiang, X. Chang, and C. Zhang, "Connecting the dots: Multivariate time series forecasting with graph neural networks," in *Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery & data mining*, 2020, pp. 753-763.

- [19] W. Zhong, H. Meidani, and J. Macfarlane, "Attention-based spatial-temporal graph neural ode for traffic prediction," *arXiv preprint arXiv:2305.00985*, 2023.
- [20] E. A. Aldahri, A. A. Almazroi, M. H. Alkinani, M. Alqarni, E. A. Alghamdi, and N. Ayub, "GNN-RMNet: Leveraging graph neural networks and GPS analytics for driver behavior and route optimization in logistics," *Plos one*, vol. 20, p. e0328899, 2025.
- [21] X. Xing, Y. Peng, L. Wan, and F. Luo, "Optimization of two-passenger ride-pooling orders based on ST-GNN and path optimization," *PLoS One*, vol. 20, p. e0337415, 2025.
- [22] A. T. Basse, I. N. Davies, and A. I. Akintunde, "Comparative Analysis of AI Techniques in a Traffic Advisory Model: GNN, FNN, and A*," *International Journal of Mathematics and Computer Research*, vol. 13, pp. 5576-5581, 2025.
- [23] E. O. Iwo and S. E. Egop, "Evaluation and Prediction of Vehicular Flow in Port Harcourt," *Journal of Transportation Engineering and Traffic Management*, vol. 6, pp. 33-38, 2025.
- [24] L. Amadi and G. Pepple, "Development of GIS-Based Road Network Map of Port Harcourt to Resolve Issues with Road Network.," *Global Science Research Journals*, vol. 10, 2022.
- [25] F. B. C. Nwoburuke, N. C. Bridget, E. E. Chidozie, R. A. O. Abdul, H. O. Olumide, and S. O. Akegbeyale, "An Assessment of Urban Road Transportation on Land Use Pattern in Ikwerre Road Port Harcourt," *IEEE-SEM*, vol. 12, pp. 1-8, 2024.