

Traffic Control and Management Implications of an Optimised Route-Generation Framework for Urban Road Networks: A Port Harcourt Case

Fun-Akpo Pere Kormane¹; Thankgod Ode²; Captain Gospel Otto^{3*};
Kemejika Ichechi Amadi-Oparaeli⁴

^{1,2,3,4}Department of Civil Engineering, Rivers State University, Port Harcourt, Nigeria

*Corresponding Authors: Captain Gospel Otto^{3*}

³ORCID: 0000-0001-6855-6871

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Abstract: Traffic agencies in developing cities must manage recurrent congestion on networks where demand is concentrated on a few corridors and where independent alternative routes are scarce. This article examines what an optimised route-generation framework, in which machine learning supplies traffic-state predictions to an engineering cost and allocation process, implies for traffic control and management in Port Harcourt, Nigeria. Aggregate morning and evening observations from seven locations, a directed road network of 48,504 nodes and 111,839 edges, and high-resolution Padua traffic and travel-time data were used to diagnose demand patterns, network structure, bottlenecks and resilience. Total peak flow rose by only 5.04% from morning to evening, but Mile 3 Diobu and Choba rose by 40.68% and 37.60% while four other locations fell, so the constrained corridor changes with the period. Although the network is almost fully connected (99.85% of nodes in the largest strongly connected component), 41 of 42 directed origin-destination pairs had only one sufficiently distinct route, which limits what route guidance can achieve: five routing strategies differed by about 0.01% in network travel time at base demand. The framework was more useful as a management tool than as a routing tool. It identified bottleneck corridors (including segments of Rumuola/Rumuokwuta Road and the Port Harcourt–Aba Expressway), showed total travel time rising by about 54% and critical links rising from 31 to 203 in the evening when demand reached 1.5 times base, kept route rankings stable under $\pm 20\%$ systematic forecast error, and exposed five Choba-bound emergency diversions that need field verification. The following phases are proposed: validation of data and sites, coordination of signals and management of junctions and access at recurrent bottlenecks, preparation of incident diversions, implementing the live data feeds with human intervention, and planning redundancy when structural importance and limited alternatives are met. All route flows, capacities and loads are model-derived and require field validation before operational use.

Keywords: Traffic Management; Traffic Control; Route Generation; Incident Management; Network Resilience; Bottleneck Corridors; Port Harcourt.

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I. INTRODUCTION

Congestion delays travellers, wastes fuel, delays emergency response and weakens road safety, and it is most severe where urban growth has outpaced infrastructure (Faheem et al., 2024; Oloyede et al., 2026). Studies of Addis Ababa, Enugu and Lagos describe unstable flow, concentrated corridor loading and limited capacity to absorb disturbance (Chukwurah et al., 2025; Imoh & Rad, 2025; Sokido, 2024). Because large-scale road expansion is often

constrained by funding, land and environmental limits (World Bank Group, 2024), agencies must get more from existing networks through traffic control, traffic management and better use of route choice.

Intelligent transport systems and data-driven analytics are increasingly proposed for this purpose (Adeniran et al., 2026; Brocchini et al., 2025). Much of the machine-learning literature, however, stops at prediction, and engineering guidance on how predictions should inform control and

management decisions in data-constrained cities remains thin (Kebrawi et al., 2025). A manager needs to know not only what traffic will do, but where intervention is warranted, which measure fits which location, how much relief re-routing can really deliver, and what happens when a critical link fails.

This article uses the results of an optimised route-generation study to answer those management questions for Port Harcourt, Nigeria. In the underlying framework, machine learning predicts future traffic conditions but does not select routes; an engineering layer combines the predictions with distance, congestion, relative loading and structural risk to rank routes and allocate demand. The article's aim is to translate the findings into traffic control and management implications. Specifically, it:

- Shows how temporal and spatial demand patterns determine when and where control is needed;
- Explains how network structure and route redundancy limit what route guidance can achieve;
- Identifies bottleneck corridors and links them to candidate control and management measures;
- Uses demand, forecast-error and disruption scenarios to indicate when operational measures are enough and when capacity or Redundancy investment is needed; and
- Proposes a phased action programme for agencies, with the evidence required before each step.

➤ Background

- Signal control and active traffic management. Intelligent traffic control strategies have been organised into taxonomies by method and application (Brocchini et al., 2025), and active traffic management guidance covers planning and evaluation of operational strategies on existing roads (National Academies of Sciences, Engineering, and Medicine, 2024). Signal retiming is a long-established way to improve corridor performance (Yue et al., 2021), and recent work applies reinforcement learning and predictive analytics to adaptive signal control (Almomany et al., 2025; Elharoun et al., 2025; Nautiyal et al., 2025). These approaches presuppose reliable detection and communications, which are often limited in the cities that most need them.
- Re-routing and assignment. Route guidance operates within the logic of traffic assignment, in which user-equilibrium and system-optimal behaviour differ and can be reconciled only under conditions that must be checked (Morandi, 2024; Wardrop, 1952). Re-routing algorithms have been proposed to mitigate congestion by moving vehicles away from loaded links (Pala et al., 2026; Wang et al., 2023), and data-driven routing frameworks have been applied in African cities including Kampala and Calabar (Solomon et al., 2026; Tamale et al., 2026). A recurring practical question is whether the network offers alternatives that are genuinely independent of the congested link; urban network capacity is itself shaped by network structure and demand distribution (Loder et al., 2019).

- Vulnerability and resilience. Transport resilience research distinguishes the likelihood of disruption from the consequences of losing a link and the ability of the network to absorb diverted flow (Mattsson & Jenelius, 2015). Graph-based vulnerability assessment and machine-learning identification of critical links have been proposed to prioritise protection and monitoring (Bachir et al., 2025; Marian et al., 2025).
- Gap addressed here. Prediction, routing, signal control and resilience are usually studied separately. Few studies show, for a data-constrained developing-city network, how predicted conditions, route redundancy, bottleneck structure and disruption scenarios combine into concrete control and management priorities. This article draws that link from one integrated study.

➤ Study Area, Data and Framework

Port Harcourt is the administrative, commercial and industrial centre of Nigeria's Niger Delta, with arterial routes, distributors, local streets and busy junctions serving residential, commercial and industrial areas. Seven locations (Abuloma, Artillery, Borikiri, Choba, Iwofe, Mile 3 Diobu and Woji) served as calibration points. For each, a four-week survey of morning and evening peak traffic (originally recorded per 15 minutes and expressed as hourly equivalents) and a reported operating speed were available, giving 14 location-period observations. The motor-vehicle road network was extracted from OpenStreetMap as a directed graph. Because Port Harcourt lacks a dense detector record, high-resolution traffic-volume and travel-time series from Padua, Italy (40 junctions, ten-minute intervals, 6 February–1 April 2026) were used to train prediction models. The Padua data were not used for Port Harcourt demand, but relationships learned at Padua were simply imported to Port Harcourt, with the relative values of traffic states as traffic-state multipliers anchored to the speeds and flows found in the Padua data set.

The framework has nine steps in a fixed order:

- Acquire traffic, travel-time, network and calibration inputs.
- Engineer features: current value, three lags, cyclical hour and weekday, location and regime.
- Identify traffic regimes by K-Means clustering (two regimes were selected).
- Train and compare Linear Regression, Random Forest and Gradient Boosting on chronological splits.
- Predict future traffic state and travel time (Gradient Boosting was selected for both tasks).
- Compute dynamic link costs from five equally weighted (0.20) components: predicted travel time, normalised length, congestion penalty, relative loading and loading-dependent structural risk.
- Generate candidate routes between 42 directed origin–destination (OD) pairs, rejecting alternatives that overlap an accepted route by 0.80 or more.
- Allocate model-derived OD demand over accepted routes, conserving flow.

- Output performance indicators, bottleneck rankings and planning priorities.

The design deliberately separates prediction from decision: machine learning estimates conditions, while engineering rules decide how those estimates affect route cost and allocation. This helps to ensure that the outputs are interpretable and allows the manager to make control decisions. The assessment was based on the following traffic-engineering indicators: total travel time, mean travel time, delay, speed, utilization, utilization dispersion, severity of bottlenecks, flow and demand accommodated on critical links, and compared to the following baselines: a calibrated distribution (B0), distance-only routing (B1), current travel-time routing (B2), and ML minimum-cost routing (B3). The scenarios included demand variations (0.8–1.5 times base demand), systematic forecast error (SFE) (–20% to +20%), and capacity reductions and closure of critical links (50% reduction). All OD demand and route flows, capacities and link loads for Port Harcourt are estimates based on models and not observations of links.

II. DEMAND PATTERNS AND WHERE CONTROL IS NEEDED

➤ Time Dependence

The network flow showed a strong diurnal cycle in the Padua series, with a secondary morning surge in flow followed by a more pronounced afternoon surge: At 17:00 the network flow was 32,955.32 vehicles per hour, while at 03:00

it was 897.60 vehicles per hour. The weekday flow was 24.49% greater than the weekend flow and the evening trend was repeated throughout the week, not on single days. There was greater variability in date during active hours, meaning that different loads of material could be transported during the same hour on different days. For control, the following means that if one plan were developed for the morning and then adopted in the evening, this would be conservative and that fixed plans would be least reliable during critical peaks of load. Adaptive or frequently changed plans are more suitable for time-of-day plans, when they are based on observed behavior. Traffic was also very persistent, with a correlation between 10-minute totals of network traffic being 0.994 and 0.973 after 30 minutes. This allows managers to have a short warning time before a rising flow becomes a severe peak to trigger a signal adjustment, a route guidance and/or incident staffing. For known peaks, 7-day recurrence ($r = 0.981$) will help to pre-plan weekly schedules.

➤ Spatial Shifts Between Peaks

The overall recorded peak flow at Port Harcourt increased by 5.04% from 4,271 to 4,486.27 vehicles per hour, but the changes at individual traffic counters ranged from a low of –19.74% to a high of +40.68% (Table 1). Mile 3 Diobu (996 veh/h) and Choba (849 veh/h) were the major receiving corridors in the evening with lesser at Borikiri (828 veh/h), Woji (810 veh/h), Iwofe (799 veh/h) and Abuloma (784 veh/h). A corridor that helps during the morning may be the main bottle neck during the evening and an evening-only solution may be of little value on a site whose evening flow is low.

Table 1 Peak-Period Change and Congestion Index (CI) by Location, with Indicative Management Emphasis

Location	AM to PM change (%)	AM CI	PM CI	Indicative emphasis (for field confirmation)
Mile 3 Diobu	+40.68	0.631	0.639	Evening-peak management; CI moves from moderate to high
Choba	+37.60	0.685	0.682	Severe in both periods; priority for both peaks
Artillery	+8.48	0.656	0.547	Moderate in both periods; monitor and tune
Borikiri	–19.74	0.889	0.708	Severe in both periods, but re-measure speed first
Woji	–19.70	0.663	0.478	Morning attention; moderate in the evening
Iwofe	–17.31	0.411	0.303	Low congestion; routine monitoring
Abuloma	–8.83	0.410	0.270	Low congestion; routine monitoring

High congestion does not only relate to the flow and is based on loading and relative speed deficit, which are both normalised. The flow of Borikiri is moderate in both periods (618 veh/h and 496 veh/h) and the speed is the lowest (3.98 km/h) in both periods but the highest CI is recorded in both periods (0.889 and 0.708). This was also reported with the same speed, but flagged as it is very low and is in contradiction with the source discussion; it should be re-measured prior to the design of any Borikiri-specific measure. The general finding that Choba and Mile 3 Diobu have high loads and that sites vary significantly from time to time does not rely on that one value. There was also an increase in flow concentration in the evening at all seven sites. The Herfindahl index increased from 0.1468 to 0.1598 while the normalised concentration increased from 0.0046 to 0.0198 which means that a small number of destinations had increased evening traffic relative to their total share. The period specific pattern should then be followed instead of an average across the city.

III. NETWORK STRUCTURE, ROUTE REDUNDANCY AND BOTTLENECK CORRIDORS

➤ Connected, But Dependent on a Limited Backbone

The extracted Port Harcourt graph has 48,504 nodes and 111,839 directed edges. All nodes are connected in one weakly connected component, and the largest strongly connected component contains 48,431 nodes (99.85%) with the remaining 73 nodes in small directionally constrained components (e.g. one way access branches) where return movement is not possible. Local-access roads dominate the length: 65.80% of the directed length is on residential roads, 14.03% on service roads and 10.24% on unclassified roads, while primary, secondary and trunk roads account for only 5.83% (3.22%, 2.11% and 0.50%). The links with the top 1% of normalised edge betweenness (threshold value 0.284) connect in continuous bands, indicating that cross-city

mobility relies on a small number of “arterial” links, while local mobility is well developed. This hierarchy has two implications for management. Local streets provide access but are not ideal substitutes for loaded arterials as they have less functional capacity, turning friction and discontinuity. The functional use of each road class is important for management, because if the link is disrupted on an increasing level, that congestion and safety pressure will be pushed onto roads designed for local use, potentially creating congestion in residential neighbourhoods (Tsigdinos et al., 2024; U.S. Federal Highway Administration, 2013).

➤ *Route Redundancy*

The most important structural outcome for route guidance is the lack of alternative routes that are independent. Across the 42 directed OD pairs among the seven control locations, applying direction, motor-vehicle access and the 0.80 overlap rule produced 43 accepted routes: 41 pairs (97.62%) had one route and only Iwofe–Artillery had two. Accepted routes ranged from 3.42 to 34.34 km (median 13.76 km). Apparent alternatives on a dense street map typically

converged onto the same arterial sections and so offered no real separation from the original path. Re-allocating vehicles to such a nominal alternative changes the route label without relieving the shared bottleneck.

➤ *Bottleneck and Critical Links*

Critical links were identified by combining structural importance (edge betweenness) with model-derived loading and operating condition. In both periods 2,904 directed edges were loaded; 724 were classed as critical in the morning and 720 in the evening, and 291 were severe candidates in each, suggesting that the most exposed part of the network is structurally persistent while the wider critical set varies with loading. The mean bottleneck index was 0.259 (morning) and 0.241 (evening), the 90th-percentile thresholds were 0.376 and 0.348, and the maximum was 0.690 and 0.680. The top namesd results were along Rumuola/Rumuokwuta Road and Port Harcourt – Aba Expressway (Table 2). They rank above links that were heavily loaded but served fewer network-wide paths, because delay on a high-betweenness arterial raises costs for many OD movements at once.

Table 2 Leading Named Model-Derived Bottleneck Corridors

Corridor	Class	Period	Model flow (veh/h)	Normalised betweenness	Bottleneck index
Rumuola/Rumuokwuta Road	Primary	Morning	476.6	0.769–0.775	0.600–0.602
Rumuola/Rumuokwuta Road	Primary	Evening	510.8	0.769–0.775	0.554–0.556
Port Harcourt–Aba Expressway	Trunk	Morning	377.9	0.849–0.859	0.579–0.583

These values are analytical assignments from the derived OD matrix, not counted link flows, so they identify candidates for field validation rather than confirmed bottlenecks. High betweenness alone shows exposure, not congestion; the corridors above matter because exposure coincides with high modelled loading and with limited alternatives. Such links are candidates for signal coordination, incident-management priority, access control and junction improvement and, where operational measures are insufficient, corridor-capacity or alternative-link intervention.

IV. PREDICTIVE INFORMATION, DYNAMIC COSTS AND DEMAND ALLOCATION

➤ *What the Predictions can Support*

On held-out Padua data, Gradient Boosting predicted next ten-minute junction volume with RMSE = 12.704 vehicles and $R^2 = 0.977$, and next-hour directed-pair travel time with RMSE = 218.274 seconds and $R^2 = 0.673$. Short-horizon volume can therefore be forecast with high consistency, whereas roughly one-third of travel-time variance was unexplained and unusually long travel times were the least predictable. Current and lagged observations dominated permutation importance for both tasks, and the traffic-regime variable added little once they were included. The operational lesson is that forecasts are only as good as the freshness of the measurements feeding them: a deployment needs reliable, regularly updated detector or probe data even if the fitted model is retained. Predicted travel times should be communicated to the public and to operators as ranges.

Only 14 observations of location-period of the aggregates were seen in Port Harcourt and this is presented as Padua accuracy. They do not show that the method works on a dense record, they do not show that the forecasts of Port Harcourt have been independently validated.

➤ *Dynamic Costs*

Relative loading and loading dependent structural risk were added to length and congestion penalty to provide composite link costs. Although the mean predicted link time was larger during the evening (11.368 s) than during the morning (6.820 s), the mean link cost was higher during the morning (0.186) than in the evening (0.171). The increase in mean relative loading in the evening (0.239 vs. 0.295), however, was more than offset by the increase in structural exposure in the morning. If the links are ranked based on distance or time only, links that are important to the system, but are expensive, may be overlooked.

➤ *Allocation and Operational Performance*

All specified demand was accommodated and flow was conserved for every OD pair, but redistribution was possible for only one movement. For Iwofe–Artillery, the lower-cost second route received 80.44% of demand and the first route 19.56% in both periods (morning 57.63 and 14.01 veh/h; evening 48.19 and 11.72 veh/h). All other movements had a single route. Consequently, the five routing strategies (B0 to B3 and the proposed allocation) differed in network travel time by about 0.01%, and the proposed allocation removed no flow from critical links (Table 3).

Table 3 Operational Performance of the Proposed Framework at Base Demand

Indicator	Morning	Evening
Mean travel time (min)	21.73	37.67
Mean delay (min)	8.67	24.22
Mean speed (km/h)	41.08	24.89
Maximum link utilisation	1.034	1.251
Utilisation coefficient of variation	0.710	0.743
Critical-flow reduction (%)	0.000	0.000
Bottleneck relief (%)	0.036	0.019
Demand accommodated (%)	100.0	100.0

It was the period that had an impact on performance, not the routing strategy: the evening mean delay was almost three times that of the morning (24.22 versus 8.67 minutes). This is a substantive management finding or decision. Route guidance doesn't offer significant base-condition savings in this network of its own, it's there to raise issues of where and when loads are being concentrated, play out futures and to better inform disruption planning – not to promise instant travel-time benefit.

V. CONTROL SCENARIOS

Scenarios test operational control being adequate and when it is not. All results have been derived from a model.

➤ Demand Growth

As the OD demand increased from 0.8 to 1.5 times base demand (Table 4), the performance gradually became poor.

The total travel time for the network during the morning and evening peak periods were 54.21% and 54.12% respectively of base travel time and the maximum utilisation was 1.551 and 1.876 respectively. The number of critical links had also increased significantly in the morning (from 6 to 59) and in the evening (from 31 to 203 links), while the percentage of congested loaded links had increased from 0.241% to 3.340% in the morning and from 0.999% to 2.824% in the evening. However, demand was still met as there was no rejection of flow along links, but excess demand came through as utilisation greater than one, delay and severity of bottlenecks.

Table 4 Effect of Demand Scaling on the Proposed Framework

Demand	Period	Total time vs base (%)	Max utilisation	Congested links (%)	Critical links
0.8 Q ₀	Morning	-20.33	0.827	0.207	0
1.0 Q ₀	Morning	0.00	1.034	0.241	6
1.2 Q ₀	Morning	+20.89	1.240	0.413	6
1.5 Q ₀	Morning	+54.21	1.551	3.340	59
0.8 Q ₀	Evening	-20.32	1.001	0.034	1
1.0 Q ₀	Evening	0.00	1.251	0.999	31
1.2 Q ₀	Evening	+20.87	1.501	1.033	44
1.5 Q ₀	Evening	+54.12	1.876	2.824	203

The management reading is that the network is already at or above nominal capacity on some evening links at base demand (maximum utilisation 1.251), and that the range between 1.2 and 1.5 times base demand is where operational management alone becomes increasingly insufficient and capacity or redundancy investment becomes more important.

➤ Forecast Error

Systematic travel-time errors of -20% to +20% scaled total network travel time almost proportionally (morning 1,237.41 to 1,856.11 vehicle-hours; evening 2,253.50 to 3,380.25), but the Iwofe–Artillery allocation stayed at a route-1 share of 0.196 throughout. Route recommendations were therefore stable in ranking, because a common proportional error preserves the order of route costs under equal weights, while predicted burden changed with the error. This applies to systematic error only; link-specific errors were not tested. Operators should issue recommendations that

are stable but present predicted times and delays as ranges and refresh forecasts on a schedule.

➤ Link Degradation and Closure

The chosen critical link was an unnamed segment of a service-road, part of the evening network (OSM nodes 11397139192 to 5401575857), and the identity of this link needs to be verified in the field prior to intervention. Doubling its analytical power, it doubled its maximum usage (1.251 to 2.501), but added only 0.100% to total travel time – a very strong local effect that is hidden by a network average. Full closure caused five Choba-bound movements to be rerouted through the full directed graph; all demand remained serviceable, modelled total time fell by 2.494% and maximum utilisation fell to 0.943, and the number of loaded edges fell from 2,904 to 2,795 (Table 5).

Table 5 Critical-Link Disruption Results (Evening)

Scenario	Total time (veh-h)	Max utilisation	Congested links (%)	Change in total time (%)
Normal	2,816.87	1.251	0.999	0.000
Capacity reduced by 50%	2,819.70	2.501	0.999	+0.100
Closure	2,746.62	0.943	0.572	-2.494

The improvement under closure does not support closing links. It shows that paths excluded from the normal screened set by cost or overlap rules can become useful during an incident, but their pavement, width, junction control, safety, community impact and usable capacity are unknown. Resilience depends on more than the existence of a graph path: relief traffic must avoid the failed link without relocating unacceptable congestion onto unsuitable roads (Mattsson & Jenelius, 2015). Candidate emergency routes should be inspected and pre-planned, and kept under separate protocols from routine route guidance.

VI. MANAGEMENT IMPLICATIONS

➤ Corridor Priorities

Repeated link loading, delay, bottleneck severity, structural importance and scenario persistence were combined into planning-priority scores that point to different types of intervention rather than one remedy (Table 6). The highest numerical score belonged to an unnamed service link whose assumed class-based capacity was low relative to its assigned demand; that ranking should trigger field verification of its name, lanes and capacity, not construction.

Table 6 Selected Model-Derived Corridor Priorities

Corridor	Class	Max utilisation	Mean delay (s)	Priority score	Indicated response
Glory Land Drive Roundabout to East West Road	Primary	0.680	267.85	0.529	Traffic management and junction improvement
Ship Builders Road	Service	1.551	49.66	0.497	Future capacity-investment priority
Ship Builders Road (second segment)	Service	1.545	47.37	0.488	Future capacity-investment priority
Port Harcourt–Aba Expressway	Trunk	0.297	29.43	0.413	Network-resilience and alternative-link priority
Mission Road	Residential	1.415	19.68	0.408	Future capacity-investment priority

➤ A Phased Programme

The findings support a hierarchy of responses by horizon (Table 7). They are screening directions and do not replace the traffic surveys, geometric and safety assessments and stakeholder consultation required before physical or operational intervention.

Table 7 Phased Traffic Control and Management Programme

Horizon	Action	Evidence from this study	Condition before proceeding
Immediate	Verify control locations, snapped nodes, unnamed critical links and the Borikiri speed	Coordinates carry a map-review flag; Borikiri speed of 3.98 km/h conflicts with the source discussion	Field and map review
Immediate	Establish continuous or repeated link-level counts, speeds and travel times; record lanes, turning movements, discharge rates and usable capacity	Link flows and capacities are model-derived and class-based	Replaces assumptions and allows validation
Near term	Monitor and respond first on links where structural importance coincides with high loading or limited alternatives; assess signal coordination, channelisation, lane and access management at recurrent-delay sites	Rumuola/Rumuokwuta Road and Port Harcourt–Aba Expressway rank highest; Glory Land Drive Roundabout to East West Road has the greatest delay among named links	Detailed corridor studies; avoid shifting congestion into residential or service roads
Near term	Use time-of-day control with short-horizon adjustment, prioritising evening operations at Mile 3 Diobu and Choba	Evening shift of +40.68% and +37.60%; 0.994 ten-minute persistence	Fresh detector or probe data
Near term	Inspect the five Choba-bound emergency paths and issue a separate diversion protocol	Closure rerouted five movements and lowered modelled total time by 2.494%	Pavement, width, junction control, safety, community impact and capacity checks

Medium term	Pilot the framework on live or regularly updated data, refreshing inputs, calibration factors and link costs on a schedule, with engineering review before recommendations are issued	Forecast accuracy depends on current and lagged observations; rankings stable under $\pm 20\%$ systematic error	Communicate predictions as ranges
Medium term	Study Ship Builders Road, Mission Road, Glory Land Drive Roundabout to East West Road and the Port Harcourt–Aba Expressway; test any relief corridor under diverted demand	Capacity, junction-delay or resilience concerns identified	Expand the OD sample beyond seven locations
Long term	Invest in redundancy where structural importance coincides with limited alternatives, favouring genuinely independent links over alternatives that rejoin the same bottleneck	41 of 42 OD pairs have one distinct route; critical links rise from 31 to 203 at 1.5 times base demand	Appraisal of independence, usability in disruption and absorbed diverted demand
Institutional	Integrate the framework into intelligent transport system, corridor-investment appraisal and incident-management processes with defined responsibilities for data, model maintenance, review and public communication	Automated outputs must remain accountable and operationally credible	Periodic validation

There are two principles which form the backbone of the programme. First, Operational measures are implemented in advance of construction where they are supported by the evidence; where the evidence shows that they are not sufficient, the demand-growth scenarios are implemented. Second, redundancy needs to be true: additional capacity on a link that is combined with the same bottleneck does not provide resiliency.

VII. CONCLUSION

The key points of the study for traffic control and management are that structure defines the constraints and data defines the priorities. Demand in Port Harcourt is spatially varying and temporally persistent, the constrained corridor varies with the period, with the total flow increasing by 5.04% while at Mile 3 Diobu the increase is 40.68% and at Choba is 37.60%. The network is almost 100% connected but route guidance was not effective as it was constrained to a limited arterial backbone with 41 out of 42 OD pairs having only one route with significant distinctness, leading to differences of approximately 0.01% in network travel time. The framework was nevertheless found to be beneficial for management purposes as it identifies bottleneck corridors, identified the increase of travel time around 54% at 1.5 times the base evening demand, identified a rise in critical links from 31 to 203 at 1.5 times the base evening demand and highlighted emergency diversions for Choba-bound traffic at $\pm 20\%$ systematic forecast error. Agencies need to confirm data and sites, reinforce signal, junction and access management and incident preparedness at regular bottlenecks, test live-data operation under engineering supervision and ensure a genuine route redundancy before overloads become an issue. The next steps are field validation, and link-level counts and origin-destination data from the local region.

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