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(Review Article)

Urban traffic congestion in African cities: A mathematical review

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Abstract

Accelerated urbanisation, poor infrastructure, private vehicle ownership and land-use planning have made traffic congestion a significant challenge confronting African cities. Beyond creating daily delays, congestion hampers economic productivity, increases the risk of infrastructure projects, and compromises environmental sustainability. This paper adopts a systematic mathematical review approach to show how mathematical modelling has a solid arsenal for diagnosing and addressing these challenges. Techniques such as network theory, agent-based models (ABMs), and epidemic-inspired Susceptible–Infected–Recovered (SIR) models have been found to model the propagation of traffic congestion in urban networks, even with sparse data. Applications in some African cities, such as Lagos, Dar es Salaam, Cai and Johannesburg, demonstrate how these models can identify systemic bottlenecks, estimate tipping points, and assess resilience based on various policies or infrastructure options. Significantly, SIR-inspired models enable the calibration of epidemiological parameters, such as the basic reproduction number, to quantify under what conditions traffic congestion spreads or dies out. The article continues to discuss the potential application of hybrid models that integrate mathematical models with emerging real-time data sources, such as mobile phones and GPS data, to enhance predictive accuracy. These models not only provide understanding of short-term congestion behaviour but also inform long-term planning, allowing policymakers to align transport strategies with sustainable development goals like infrastructure delays and cost overruns. By building integrated, evidence-based modelling techniques, this research reviews and shows future direction in the building of adaptable and context-specific transport models that can respond to the unique realities of Africa's rapidly urbanising cities.

Keywords*:* Mathematical Model; Agent-Based Simulation; SIR Model; Urban Traffic Congestion; Infrastructure Risk; African Cities.

1. Introduction

More people now view traffic congestion as a systemic urban risk as well as a transportation problem. Congestion has permeated every aspect of daily life in African cities like Dar es Salaam, Lagos, and Nairobi, from clogged highways to jammed intersections and packed terminals.

According to Nyirajana et al. [1], the problem has been characterised as an unavoidable aspect of urban life, with traffic jams stretching from the airport to junctions, frequently surpassing the capacity of infrastructure. Congestion persists despite a variety of measures, such as road extensions, Bus Rapid Transit (BRT) systems, and unofficial regulation by motorbike taxis (boda-bodas) and minibuses (dala-dala). Also, traffic congestion creates artificial barriers to the movement of goods and people, raising logistics costs and impeding economic productivity [2].

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This is especially true in cities like Dar es Salaam, where traffic is directed into the CBD by a monocentric structure, and where planning organisations like LATRA are unable to perform predictive analysis and real-time modelling. According to World Bank data, urban centres in Africa face increasing traffic congestion due to rapid urbanisation and rising motorisation. Recent reports [3] show that a 30-minute trip now takes up to 70 minutes, with commuters losing 2.5 hours daily due to congestion, worsened by flooding at known bottlenecks like Jangwani Valley. Project delivery is hampered by congestion, which results in poor service, delays, and cost overruns [4]. Because it delays deliveries, raises transportation costs, and messes up labour schedules, congestion has a direct effect on infrastructure projects. These interruptions enhance the risk profile of urban development initiatives, particularly those depending on just-in-time logistics. Research from Kenya and Nigeria confirms that reactive traffic planning and inadequate traffic predictions are frequently linked to project delays.

Road traffic congestion has serious economic repercussions in African cities, especially in fast-urbanising towns like Dar es Salaam, according to recent studies. [5] identified several factors, including narrow roads, inadequate infrastructure, frequent rainfall, and insufficient traffic control systems, such as broken lights and a lack of feeder roads, that contribute to traffic congestion in Dar es Salaam. In addition to raising operating expenses (public drivers pay Tsh. 32,167.00 a month for fuel), these conditions also lower productivity, with formal workers losing an average of 2.5 hours each day. Additionally, because of inefficiencies caused by traffic, low-income earners spend about 39% of their income on erratic transportation. These findings emphasise how traffic congestion erodes business turnover, profit margins, and overall regional economic activity, necessitating urgent infrastructure and policy interventions [5].

The effectiveness of hybrid deep learning models, especially Graph Convolutional Networks (GCNs), in anticipating urban congestion has been shown in recent studies [6]. Both the time dynamics of congestion and the geographical architecture of road networks are captured by these models. In short-and medium-term forecasts, GCNs can perform better than conventional techniques when paired with recurrent neural architecture such as GRU. This holds special promise for African cities, where widespread GPS coverage might replace traditional traffic sensors and enable real-time modelling without infrastructure expenditure.

The use of simulation-based and mathematical models is becoming more popular as a solution to this problem. These models offer instruments to evaluate infrastructure stress, model the spread of congestion, and direct strategic solutions. Reviewing such models is the main goal of this paper, especially those that are appropriate for the urban environment of Africa, where adaptive planning is essential despite the lack of formal data [7, 8, 9, 10].

Figure 1 Typical scenes of urban traffic congestion in an African city. [3]

2. Methodology

This study adopts a structured review methodology, incorporating both qualitative and quantitative analyses of mathematical approaches used in urban traffic congestion modelling and infrastructure risk management. The review is based on government reports, case studies, and peer-reviewed journal articles about African cities, especially Nairobi, Lagos, and Dar es Salaam [11, 12,13]. The following quantitative methods were highlighted in the inclusion criteria:

- Models of compartmental epidemics (SIR/SEIR and variations)
- Cellular automata and simulations based on agents.
- Frameworks from network and graph theory for node/junction analysis.
- Models of stochastic processes and queuing theory.

- Combining data-driven approaches with machine learning.

2.1. Data Sources and Selection Criteria

Databases like Scopus, Google Scholar, JSTOR, and Web of Science were used to find pertinent literature. The following inclusion criteria were used:

- Pay attention to African cities that face significant traffic issues.
- Using computational or mathematical models.
- Discussion of project management, transportation policy ramifications, or infrastructure risk.
- Publications starting in 2000.
- The keywords used were urban congestion, infrastructure risk, traffic modelling, African cities, SIR models, and game theory in transport, along with project risk assessment.

2.2. Thematic Categorisation

The selected research was categorised into the following thematic areas:

- Deterministic vs. Stochastic Models.
- Compartmental Models Inspired by Epidemics.
- Models of Optimisation.
- Models Based on Simulation and Agents.
- Methods for Quantifying Risk.

The methodological presumptions, computational strategies, and applicability for crowded urban settings of each theme were examined.

3. Literature Review Findings

Traffic congestion and risk in infrastructure development are among the most pressing challenges for African cities. Even as the scenario varies from region to region, some of the common themes across regions are quick motorisation, inadequate transport planning, and inadequate public transport. Research efforts–ranging from mathematical queue models, micro-simulations, artificial intelligence-based forecasting systems, and policy reviews–have worked towards explaining congestion patterns and their impact on infrastructure delivery.

3.1. Traffic Congestion and Infrastructure Risk in African Cities

Figure 2 Traffic congestion along the Dar es Salaam port corridor. [23]

Due to growing motorisation, antiquated road networks, and inadequate urban planning, many African towns are suffering from extreme traffic congestion. According to Kiunsi, a monocentric urban layout, an outdated master plan, and a lack of road infrastructure that covers less than 2.5% of the city area are the main causes of Dar es Salaam's traffic. Inadequate parking facilities and unregulated informal transportation exacerbate the situation. Dar es Salaam is a prime example of how city systems are strained by population growth and inadequate transport infrastructure [15]. The growing number of private vehicles is outpacing the available road space [16]. Project delivery is hindered by congestion, resulting in poor service, delays, and cost overruns [17]. Because it delays deliveries, raises transportation costs, and messes up labour schedules, congestion has a direct effect on infrastructure projects. The risk profile of urban development projects is increased by these disruptions, especially for those that rely on just-in-time logistics. Research from Kenya and Nigeria confirms that reactive traffic planning and inadequate traffic predictions are frequently linked to project delays.

3.2. Classical Flow and Queueing Theory

Macroscopic traffic flow models such as the Lighthill–Whitham–Richards (LWR) model describe the spatiotemporal evolution of traffic density using conservation laws:

$$\frac{\delta_\rho(x,t)}{\delta t} + \frac{\delta_q(\rho)}{\delta x} = 0$$

Here, $\delta_\rho(x,t)$ represents vehicle density, and q(ρ) is the flow function, typically non-linear. A commonly used form of the flow function is:

$$q(\rho) = \nu_{fp}\left(1 - \frac{\rho}{\rho_{max}}\right)$$

where ρmax is the jam density, and vf is the free-flow speed. Although these models require calibration using local traffic flow and speed data, they perform well for arterial routes. Another traditional method that is particularly helpful for evaluating traffic at crossings is queuing theory. Little's Law is an often-used formula:

$$L = \lambda W$$

Where L is the average queue length, λ is the vehicle arrival rate, and W is the average waiting time. According to empirical research conducted in Ghana and Nigeria, queueing models can be used to accurately model signalised intersections to forecast wait times and intersection delays. [18, 19].

3.3. Compartmental Epidemic Models for Urban Congestion

Dynamics Drawing a comparison between the transmission of disease and traffic breakdowns, Saberi et al. [20] suggested using an epidemic-style SIR model to explain the proliferation of congestion.

Susceptible (S): free-flow road segments.

Infected (I): congested links.

Recovered (R): links that have returned to free flow.

The system of differential equations [20] governing the model is given as:

$$\frac{dc(t)}{dt} \& = -\mu c(t) + \beta \bar{k} c(t)\big(1 - r(t) - c(t)\big)$$

$$\frac{dr(t)}{dt} \& = \mu c(t)$$

$$\frac{df(t)}{dt} \& = -\beta \bar{k} c(t)\big(1 - r(t) - f(t)\big)$$

Where the basic reproduction number, defined as:

$$R^0 = \beta \bar{k}/\mu$$

serves as a threshold indicator for congestion propagation:

1. If $R^0 < 1$, congestion decays over time.

2. If $R^0 > 1$, congestion spreads and may destabilise the network.

Google traffic data has been used to validate this approach in developed cities such as Melbourne and London. The model's low data requirement makes it especially appropriate for African cities, particularly when combined with mobile interventions [21]. In conclusion, the SIR model has shown itself to be an effective instrument for comprehending and forecasting how traffic congestion will develop within urban transport systems. It is particularly useful for proactive congestion management because of its flexibility in responding to several influencing factors, including intermodal interactions, infrastructure capacity, and passenger behaviour. The SIR framework has great potential to support effective urban transit planning and rapid-response traffic control strategies as real-time data collection and modelling capabilities advance [22]. The SIR model's adaptability in capturing dynamic transport behaviours in diverse urban contexts has been demonstrated by the numerous extensions and modifications that have been suggested and used to study urban traffic congestion across multiple continents [23, 24, 25, 26, 27].

3.3.1. Stability Analysis for Epidemic-Inspired Traffic Models

Stability analysis assesses how resistant equilibrium states are to minor perturbations in a dynamical system. This entails determining whether a congested state will gradually subside or worsen throughout the network in the context of SIR-based traffic models. The basic reproduction number, R^0 is the primary indicator of stability in these models:

1. If $R^0 < 1$, The system will return to the free-flow equilibrium.

2. If $R^0 > 1$, Traffic congestion will propagate and potentially become systemic.

Stability analysis is crucial for several urban mobility management tasks:

Identifying Tipping Points: The model parameters β (spread rate), $\bar{k}$ (contact rate), and μ (dissipation rate) are used to identify crucial values that indicate changes from stable to unstable traffic circumstances.

Optimising Interventions: Urban planners can prioritise control measures that increase μ (e.g., rapid incident clearance) or decrease β (e.g., traffic segregation, regulated intersections) by analysing sensitivity to parameter changes.

Predictive Management: Dynamic policies like entry restrictions, signal timing adjustments, or rerouting strategies can be activated to prevent network failure when real-time estimation indicates that $R^0 \approx 1$.

Low-Data Planning: The model is extremely suitable in resource-constrained African cities with poor sensing infrastructure since it uses aggregated flow dynamics rather than specific vehicle-level data.

Risk Management for Infrastructure Projects: Time windows where anticipated congestion is most likely to be unstable can be found using stability analysis. This makes it possible to change delivery schedules or infrastructure projects without increasing systemic risks.

Intelligent systems, like emergency transport systems to save lives and stabilise the scene, can greatly improve the dynamical stability of traffic networks and the estimation of congestion states, according to studies like Qureshi et al. These developments provide more prediction capacity for intelligent urban planning projects and are in line with epidemic-model thresholds such as R^0

3.4. Data-Driven and Hybrid Models (Expanded)

High forecasting accuracy and low training data requirements are characteristics of hybrid and AI-enhanced models, making them especially useful in data-constrained settings, such as those found in African cities. Typical methods include:

- Extreme Learning Machines (ELM) [12].
- Graph Convolutional Networks (GCN) [28].

SIR-ABM Hybrids: using mobile phone data for real-time traffic state updates [11, 12,13, 15, 16, 19, 20, 23-32].

Genetic and Clustering Algorithms: Applied to traffic signal optimisation in CBD and tourist-heavy zones, reducing waiting times without costly road expansion.

ANFIS-PSO (Adaptive Neuro-Fuzzy Systems with Particle Swarm Optimisation): High accuracy in freeway flow prediction, capturing peak vs. off-peak differences [33].

GCN-GRU Hybrid Modelling Recent advances in forecasting combine recurrent architectures such as Gated Recurrent Units (GRUs) or LSTMs for temporal sequence modelling with Graph Neural Networks (GNNs), particularly Graph Convolutional Networks (GCNs) for spatial dependency learning.

This hybrid model integrates:

GCNs to learn spatial dependencies–e.g., how congestion at one road segment influences adjacent segments.

GRUs to capture temporal patterns in traffic flow. Mathematical Structure: Given a traffic network G = (V, E) with N nodes and F input features, let $X_t \in R^{N \times F}$ represent the traffic state at time t, A is the adjacency matrix representing road connections. The graph convolution operation is:

$$H(l+1) = \sigma\left(\underline{D}^{-1/2} A \underline{D}^{-1/2} H^l W^l\right)$$

Where: A = A+I adds self-loops to the graph, D is the degree matrix of A, W(l) is the learnable weight matrix for layer l, σ(.) is a nonlinear activation function (e.g., ReLU).

The output of the GCN is passed into a GRU to model temporal dependencies:

$$h_t = GRU(X_t, h_{t-1})$$

It has been demonstrated that this hybrid GCN-GRU framework outperforms conventional baselines, such as LSTM and Temporal Convolutional Networks (TCNs), and scales well to large networks with spatial heterogeneity, which is particularly advantageous in African cities that are rapidly becoming more urbanised.

3.4.1. Integration with Epidemic-Inspired Models

In epidemic-inspired SIR traffic models, the contact rate $\bar{k}$ can also be dynamically estimated using GCNs. This enables the fundamental reproduction number to be adjusted in real time. To improve the model's responsiveness to abrupt changes and increase the accuracy of tipping point prediction ($R^0 > 1$), $\bar{k}$ can be adjusted via GCNs using live traffic density data. By bridging the gap between AI-enhanced forecasting and low-data epidemic modelling, this integration provides adaptive congestion control appropriate for dynamic locations such as Kigali, Lagos, and Dar es Salaam.

3.5. Agent-Based, Network and Markov Models

A thorough grasp of how individual actions add up to create systemic traffic patterns is made possible by Agent-Based Models (ABMs), which model the decisions and behaviours of individual road users, including private drivers, public vehicles, and informal transport operators (such as boda-bodas in Nairobi or dala-dalas in Dar es Salaam). In African cities with sizeable informal transport sectors that defy conventional rule-based modelling, these models work particularly well.

ABMs are especially well-suited to evaluating the results of infrastructure or policy changes in a controlled setting. Planners can, for example, model how system-wide congestion would change in response to bridge closures, BRT expansions, or new traffic laws [34, 35]. ABMs are effective tools for adaptive urban planning when paired with geographical data (such as GIS layers) and mobility data from mobile phones, especially in situations where real-time sensing equipment is scarce.

Simultaneously, network-based models use graph theory to depict transportation systems, treating crossings as nodes and road lengths as edges. To find bottlenecks or crucial connections whose failure could paralyse the network, these models concentrate on metrics like betweenness centrality. Furthermore, traffic phase transitions, where isolated delays develop into system-wide congestion, are modelled using ideas from symbolic dynamic entropy and percolation theory [1, 12, 13, 15, 16, 19, 20, 23, 24, 25, 26, 28, 29, 31, 32]. This is consistent with views influenced by epidemics, in which changes resemble the spread of an infection.

3.5.1. Applying Markov Chain Theory

Another complementary viewpoint, especially for freight and cargo logistics systems, is offered by Markov chain models. The system is envisioned in this context as passing through distinct states, including Delivered, Delayed, In Transit, and Waiting at Port. System-level inefficiencies are revealed by analysing these transitions under steady-state settings; for instance, in Dar es Salaam, barely 25% of cargo is successfully delivered under current conditions. Markov models are therefore helpful when state-based decisions rule cargo operations because they provide an organised method of analysing sequential bottlenecks, downtime, and the likelihood of moving forward towards delivery [14].

By capturing cascading delays that mimic transmission dynamics– where each delay raises the chance of congestion at downstream nodes– these discrete-state models might complement frameworks inspired by epidemics. The way that disturbances at one node (such as a flooded junction) probabilistically affect delays in later segments can also be modelled using Markov processes.

3.5.2. Combining Cellular Automata with Max-Flow

Max-flow algorithms have been utilised to identify unmet transport demand along key regional corridors, such as those connecting Dar es Salaam with inland destinations like Lusaka or Lubumbashi, to capture infrastructure-level constraints [14]. Given capacity limits at each node or edge, these algorithms calculate the maximum flow that may pass through a network.

A potent two-layer strategy is created when combined with cellular automata (CA) models, which mimic the behaviour of individual cars on discrete road grids. Max-flow analysis provides a macroscopic perspective of network throughput, whereas CA models incorporate micro-level congestion impacts (e.g., lane-blocking due to potholes or car breakdowns). This integrated knowledge is particularly important when developing infrastructure for large-scale freight transit or assessing the durability of important logistical corridors [36].

Furthermore, incorporating these methods into traffic models inspired by epidemics improves their capacity to forecast localised tipping points, which is comparable to epidemiology's basic reproduction number (R^0). For example, if interventions are not carried out promptly, a particular junction may surpass its threshold capacity and cause network-wide congestion. These node-specific R^0 counterparts can be used as proactive indicators of traffic or logistics control early warning.

3.6. Economic Implications and Empirical African Studies

Urban traffic congestion has serious economic repercussions, particularly in African cities that are expanding quickly. Traffic inefficiencies are strongly correlated with delays in infrastructure projects, a loss of economic productivity, and disruptions in the delivery of public services, according to empirical research conducted throughout the continent.

Transit-Phase Bottlenecks: According to studies by Kunambi et al. [14], the transit phase accounts for almost half of the time spent transporting freight (50%), presenting a significant opportunity for optimisation. Significant efficiency benefits can be achieved by creating alternative bypass routes, implementing real-time route adjustments, and utilising predictive congestion monitoring. Transitions from Susceptible to Infected (i.e., free-flow to congested) mimic transit nodes approaching or surpassing capacity thresholds, and these delays reflect the dynamics represented in epidemic-inspired traffic models. Therefore, proactive urban logistics planning requires real-time congestion modelling.

Weather and Accident Sensitivity: The crucial influence of weather and traffic accidents on congestion dynamics has been demonstrated by simulation-based sensitivity analysis. For example, while it's raining in Dar es Salaam:

- The journey time for heavy trucks increased by 20%, from 45 to 54 minutes.
- From 0.3 to 0.5, the likelihood of random slowdowns rose.
- Potholes and flooded roadways caused congestion to spread much more quickly.

These results highlight the usefulness of non-linear models, such as cellular automata and Markov chains, for capturing environment-driven volatility, particularly in cities impacted by infrastructure fragility and seasonal floods.

3.6.1. Empirical Case Studies:

According to a study by Marafa et al. [37] on traffic in Kebbi, Nigeria, delays caused by traffic drastically lower corporate productivity, especially for companies that rely heavily on logistics. The authors promoted infrastructure decentralisation and data-driven signal timing.

Traffic in Kigali was examined, and it was discovered that optimising signal timing reduced congestion by 15%. Their research confirmed the usefulness of simplified flow models in situations with limited data and underlined the significance of integrating road user behaviour into modelling frameworks [36, 38, 39, 40].

Increased traffic density is a significant cause of construction schedule delays, according to Musa et al. [4], who studied sustainable traffic management in smart cities. According to their research, traffic congestion models should be incorporated, especially throughout the project design and procurement stages.

According to statistical analysis conducted by Onyeneke et al. [38] there is a significant positive link between the number of registered automobiles and road deaths over a multi-decade period. The results highlight how unchecked car expansion is a major cause of traffic jams, collisions, and persistent delays. Even though the setting is high-income, the implications are relevant in African cities like Lagos and Dar es Salaam, where rapid motorisation without corresponding investments in infrastructure or public transport exacerbates traffic and causes financial losses.

In Ghana, although projects often suffer delays and overruns, “crisis-driven acceleration” occasionally restores schedules, demonstrating how congestion pressures compel governments to make costly last-minute resource injections [41]. In South Africa, weak road design and unchecked vehicle growth contribute to escalating accident rates, while delays in project delivery frequently led to litigation. Real-time adaptive traffic control through AI mitigates downstream disruption risks to construction projects [42, 43, 44]. These cases highlight congestion not only as a mobility issue but also as a systemic economic risk that undermines infrastructure financing and delivery.

All things considered, these African studies show how combining empirical fieldwork, simulation tools, and mathematical models, including frameworks inspired by epidemics and queuing, offers workable, affordable solutions for infrastructure resilience and congestion reduction.

3.7. Micro-Level Congestion Analysis and Remedies

In their study of Dhaka, Bangladesh, Mahmud et al. proposed low-cost solutions for addressing local traffic jams caused by encroachments, illegal parking, and manual signal control. Cities like Kampala, Accra, and Lagos may immediately benefit from these solutions, which include dedicated lanes and signal automation. The study backs hybrid modelling that combines ABMs and local audits [46].

Rank	Country	Traffic Index
1	Nigeria	334.8
2	Kenya	240.1
3	Egypt	226.7
4	South Africa	186.1
5	Tunisia	133.9

Figure 3 Comparative data on traffic congestion levels across the top five African cities in mid-2025.[45]

The Bahir Dar case illustrates the direct economic costs of congestion at the segment level. With more than half of traffic composed of Bajaj three-wheelers, average travel speeds of only 9–20 km/h, and service levels deteriorating to LOS D, the city experiences prolonged delays and reduced road efficiency [47]. These inefficiencies result in lost productive time, higher operating costs for vehicles, and increased fuel consumption, with pedestrian congestion and on-street parking further reducing network capacity. The study suggestions– such as pedestrian overpass provision, bottleneck removal, and Bajaj taxi passenger car unit (PCU) value revaluation– indicate the imperative of targeted infrastructure and regulatory adjustments to reduce economic losses incurred due to congestion.

In Accra (Ghana), queueing models reveal intersections with queues of over 65 vehicles and waiting times of over four minutes [41], while system dynamics reveal the correlation between congestion, urban population growth, and rising emissions [48]. SUMO simulations in Bamako integrate chemical transport models to quantify hotspots of pollution, providing a high-resolution understanding of the implications of congestion's two-way traffic environment. Micro-level models, such as these, are especially valuable for planning projects, where bottlenecks at specific choke points can accumulate across entire building schedules.

3.8. Empirical Traffic Congestion Pattern

Recent studies have discovered that unplanned growth, enforcement, and inadequate infrastructure are the primary causes of congestion [49]. They suggest decentralised planning, public education, institutional reforms, and BRT investment.

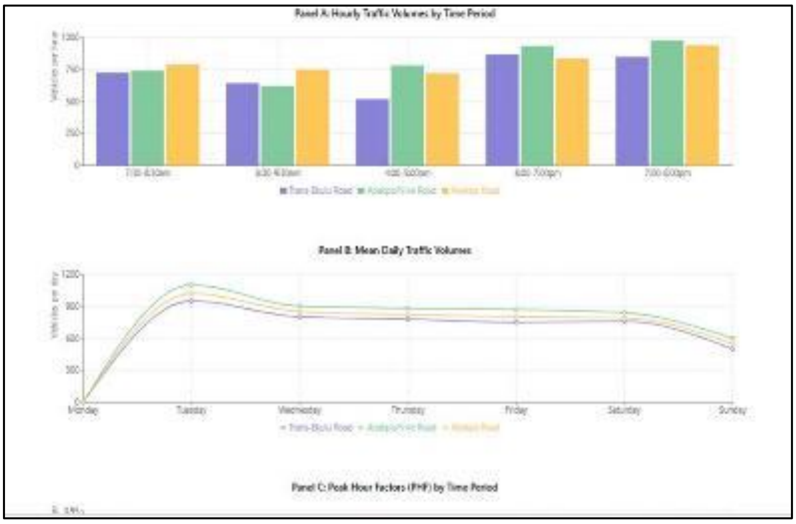

Figure 4 Analytical results of traffic congestion patterns based on urban survey data, showing peak-hour intensity and variation. [50]

Their results support the use of data-light models in conjunction with governance tools and validate the hybrid approach of technical and policy considerations. During morning and evening peak hours, urban traffic congestion is primarily concentrated at major intersections and central business districts, exhibiting consistent spatial and temporal patterns across African cities [51][52]. Modern data-driven techniques, including floating car data (FCD), real-time vehicle speeds, and in-vehicle navigation systems, have been used to map these congestion hotspots. These techniques offer comprehensive insights on speed variation indices and trip delays[52, 53]. Underdeveloped infrastructure, growing urban populations, inadequate public transportation capacity, and lax traffic regulation are common contributory factors.

In Egypt, a non-homogeneous traffic without lane discipline analysis made comparisons between speed–density relations and values derived from both parametric and non-parametric models. Field data (video and automatic counters, 30-sec interval) showed the best fit to be the normal case of the exponential model (R^2 = 0.91). Capacity estimates were lower than for the Highway Capacity Manual (HCM), and therefore, a recommended adjustment factor of 0.8–0.85 has been proposed for applying HCM to developing country conditions [54]. Also, Kinshasa (DRC) shows how informal operators—matatus, boda-bodas, and pirated minibuses—form the backbone of urban transit. Such diversity means that congestion models must account for local modal dependence rather than positing homogenous vehicle flows.

Furthermore, to identify high-delay corridors and create targeted responses such as optimised signal timing or route diversion, studies now use methods such as clustering speed profiles, simulation modelling, and benchmarking of traffic performance metrics [51, 52]. These empirical studies demonstrate the importance of customised solutions based on real-time urban mobility data in addition to confirming that congestion patterns are quantifiable and predictable. Please, leave two blank lines between successive sections as here.

4. Discussion

According to a summary of the examined research, a complex interaction between infrastructure, behaviour, governance, and urban form is the cause of traffic congestion in African cities. Although classical flow models are accurate, their applicability in many African environments is limited by their dependence on precise data and infrastructure calibration. Rather, scalable and interpretable tools for anticipating congestion are provided by models such as the compartmental epidemic model [20], especially in situations where GPS or mobile data is available. Similarly, informal transport behaviours such as those of dala-dalas and okadas can be reflected in agent-based models [39].

The studies conducted in Kigali [1] and Dhaka [39] highlight that reducing traffic involves more than just building new infrastructure; it also entails lane management, signal optimisation, and street usage enforcement. Long-term change requires decentralised planning and institutional coordination, as the Nigerian study [49] further demonstrates. The necessity of hybrid modelling frameworks is highlighted by these findings:

- Using epidemic models to track the points at which traffic jams occur.
- Cellular or agent-based automata for behaviour simulation.
- Economic models to evaluate monetary losses.
- Using network theory to evaluate the security of key junctions.
- Street-level facts are captured by micro-level audits.

Even cities with limited or no data can enhance infrastructure resilience and develop predictive capabilities by combining these methods.

4.1. Challenges and Research Gap

Despite methodological diversity, critical gaps remain. Many cities, especially in Central and smaller Southern African contexts, lack robust modelling, relying instead on descriptive reports or outdated data. Informal transport, though dominant in most African cities, is rarely incorporated into mathematical or simulation models, leaving major blind spots. Even advanced modelling in South Africa and North Africa often overlooks links between congestion and infrastructure project risks, with Ghana being a rare exception. Data scarcity, particularly traffic counts, modal shares, and reliable speed–volume–density measures, remains the single largest barrier to developing transferable and predictive congestion models across Africa. Additionally, there is ineffective institutional cooperation between modelers and planners, as models are barely modified to reflect informal transportation behaviour.

4.2. Prospects for Future Research

Future research should prioritise:

- Creation of streamlined, agent-based, or hybrid models appropriate for unofficial transportation.
- Using data from mobile phones to estimate congestion in real time or updated data collection strategies that account for informal mobility systems.
- Tools for forecasting project delays caused by congestion.
- Comparative calibration: Cross-city modelling (e.g., Lagos–Johannesburg–Cairo) transferable insights.
- Climate sensitivity: for embedding rainfall and environmental factors into African traffic models.

Recommendation

To support resilient urban mobility and reduce infrastructure risk, the following are recommended:

- Use SIR-style models to track and forecast the spread of congestion based on the data that is currently available.
- Use telecom mobility data and ride-hailing GPS data to gain real-time insights.
- Use agent-based models (ABMs) to incorporate informal transportation frameworks.
- Increase the ability of local transportation authorities (like LATRA, Road Transport and Safety Agency (RTSA), Road traffic management (RTM), and Road Traffic Management Corporation (RTMC)) to implement these approaches
- Make use of the reproduction number as a planning indicator for the resilience and stress of infrastructure.

5. Conclusion

Urban traffic congestion can serve as a diagnostic tool for identifying institutional and infrastructural weaknesses in African cities, in addition to being a serious issue. As this review has shown, epidemic and agent-based modelling approaches are becoming increasingly beneficial, especially due to their adaptability and low data requirements, even though classical models such as queuing theory and macroscopic flow equations remain useful.

Models inspired by epidemics, such as the SIR framework, make it possible to simulate congestion dynamics in a straightforward yet effective way. They assist in determining crucial thresholds (e.g., $R^0 > 1$) beyond which traffic conditions may degenerate into chronic gridlock when combined with stability analysis. They are particularly well-suited to the data-poor but mobile-rich environments of Sub-Saharan Africa due to their interpretability and low data requirements.

Additionally, agent-based models (ABMs) provide a versatile tool for simulating human-driven traffic behaviours by successfully incorporating the complexity and heterogeneity of informal transport systems like dala-dalas and boda-bodas. Planners' capacity to predict and alleviate congestion is further enhanced by network science, hybrid models, and machine learning techniques.

These results highlight the need for adaptive traffic control systems and prompt actions to stop the growth of congestion, especially when it comes to controlling delayed feedback (such as rain-triggered chokepoints) and reducing systemic interruptions to the delivery of infrastructure.

Extending the SIR model with queueing dynamics, time delays, and cost functions would allow congestion thresholds to be directly linked to project delays and cost overruns. Such hybrid models, calibrated with African traffic data and adapted to informal transport realities, offer a pathway toward predictive, risk-sensitive planning tools for urban infrastructure delivery.

Overall, mathematical models inspired by epidemics, particularly when combined with stability analysis, provide African cities with a competitive edge in predicting, comprehending, and controlling urban traffic congestion. Their minimal data requirements and interpretability make them ideal for resource-constrained environments. This approach bridges theoretical modelling with applied urban challenges, laying the foundation for a pan-African modelling agenda that strengthens infrastructure resilience in the face of accelerating urbanisation.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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