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AI-Powered Traffic Management Systems for Kigali's Urban Mobility

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Abstract

Kigali's rapid growth has intensified congestion and degraded air quality along major corridors. This study designed and validated an AI-powered traffic management framework that fused multi-source real-time data—CCTV/YOLO counts, IoT detectors, GPS travel times, and near-road air-quality sensors—to optimize signal control in line with the City Development Strategy (CDS) smart-mobility goals. A Long Short-Term Memory (LSTM) model generated reliable short-term flow forecasts ($R^2 = 0.91$; RMSE = 8.6 vehicles/interval), which were used to train a Deep Q-Network (DQN) controller to adapt phase splits, cycles, and offsets across complex junctions. Over a six-month evaluation on priority corridors (e.g., CBD–Remera, Nyabugogo–Kacyiru), the AI system reduced average control delay by ~29%, increased intersection throughput by ~36%, and lowered corridor travel time by ~30%. Environmental co-benefits were observed, with fuel use declining by ~26% and near-road CO_2 and $PM_{2.5}$ concentrations decreasing by ~25–30% during peak periods. These gains persisted across rainy conditions and demand variability and were confirmed by paired statistical tests and robustness checks. The results demonstrate deployment-ready potential: corridor-level coordination, incident-aware operating playbooks, and deep bus-priority integration (including headway stabilization) can be operationalized within the city's control center. We outline a phased scale-up path to network coordination and propose aligning the controller with electric-bus expansion and charging strategies to maximize mobility and air-quality benefits. While coverage and sensor limitations remain, the evidence indicates that data-driven, adaptive control can materially advance Kigali's goals for a smart, green, and resilient urban transport system.

Keywords: *AI-powered traffic management; LSTM; Deep Q-Network (DQN); reinforcement learning; smart mobility; urban congestion; real-time IoT/CCTV data; $PM_{2.5}$ and CO_2 emissions; transit signal priority (TSP); electric buses (e-bus); SUMO simulation; environmental sustainability; City Development Strategy (CDS) 2024–2029; Kigali*

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1. Introduction

The City of Kigali Development Strategy (CDS 2024–2029) envisions transforming Kigali into a smart, green, and livable city through technology-driven governance, sustainable mobility, and inclusive infrastructure planning (City of Kigali, 2025) [1]. As Rwanda's economic and administrative hub, Kigali continues to expand rapidly—its population rising from 1.86 million in 2024 to a projected 2.5 million by 2029, accompanied by growing motorization and urban densification. The CDS identifies urban mobility and transport efficiency as pivotal enablers of productivity, equity, and environmental resilience. Yet, despite ongoing investments in road expansion and public transport modernization, the city experiences persistent congestion along primary corridors such as Nyabugogo–Remera, CBD–Kacyiru–Gisozi, and Sonatube–Gahanga, particularly during peak hours (Rwanda Utilities Regulatory Authority (RURA), 2023).

These inefficiencies have far-reaching socio-economic and environmental impacts. According to the Rwanda Environment Management Authority (REMA) Air Quality Assessment (2023), vehicular emissions contribute over half of Kigali's $PM_{2.5}$ concentrations, worsening air quality and increasing public health risks (Rwanda Environment Management Authority (REMA), 2023). Prolonged idling and traffic jams not only elevate fuel consumption and CO_2 emissions but also contradict the country's broader commitment to low-carbon, climate-resilient urbanization under Vision 2050 (Republic of Rwanda, 2020).

To address these challenges, this study explores the potential of Artificial Intelligence (AI) to revolutionize Kigali's traffic management system. By integrating real-time traffic data from IoT sensors, CCTV feeds, and GPS devices with predictive algorithms such as Deep Learning and Reinforcement Learning, AI-powered traffic control can optimize signal timing, reduce congestion, and improve the efficiency of public transport operations (Ministry of Infrastructure (MININFRA), 2023), (J. K. Ng, et al., , 2021).This approach directly aligns with the CDS 2024–2029 priority on Smart Mobility and Sustainable Infrastructure, supporting Kigali's transformation into a digitally governed, environmentally friendly, and inclusive metropolis.

2. Problem Statement

The City of Kigali is experiencing rapid demographic and infrastructural growth, with its population projected to increase from 1.86 million in 2024 to approximately 2.5 million by 2029, according to the City Development Strategy (CDS 2024–2029). This rapid expansion—equivalent to an annual growth rate of about 4.1 percent—is driving increased motorization and urban density. The Rwanda Utilities Regulatory Authority (RURA) reports that vehicle registrations have been growing by 9–12 percent annually over the past decade, placing mounting pressure on Kigali's existing transport network. Consequently, recurrent congestion now characterizes key corridors such as CBD–Remera, Nyabugogo–Kacyiru, Kimironko–Kanombe, and Sonatube–Gahanga, particularly during morning and evening peaks, as also highlighted in the CDS.

These mobility challenges are accompanied by growing environmental and public-health concerns. The Rwanda Environment Management Authority (REMA) Air Quality Assessment Report (2023) shows that vehicular emissions account for more than 50 percent of fine particulate matter ($PM_{2.5}$) and nearly 40 percent of carbon monoxide (CO) emissions in Kigali [3]. Prolonged idling, low average speeds, and poor signal coordination exacerbate air-pollution levels, increasing respiratory health risks and undermining the CDS goal of building a smart, green, and livable city. This situation also contradicts Rwanda's long-term aspirations for low-carbon, climate-resilient urbanization as articulated in Vision 2050.

Despite visible progress in road expansion and modernization of public transport, Kigali's traffic-management systems remain predominantly static and reactive. Most intersections rely on fixed-time signal plans that cannot adapt to fluctuations in traffic, weather, or unexpected incidents. Institutional fragmentation among the City of Kigali Traffic Control Centre, RURA, and RTDA further limits the use of integrated data and real-time monitoring. This technological and organizational gap contributes to inefficiency, energy loss, and rising emissions, all of which contradict the CDS and National Transport Policy (2023) objectives for smart mobility.

To address these challenges, this research proposes developing an AI-powered, real-time traffic-management framework capable of predicting congestion, optimizing signal timing, and reducing emission hotspots. Integrating Artificial Intelligence with data from IoT sensors, CCTV feeds, and GPS-enabled vehicles can enable adaptive, data-driven control systems that improve efficiency and sustainability. This approach directly supports the CDS 2024–2029 priority on Smart Mobility and Environmental Sustainability and aligns with Rwanda's national development agendas under Vision 2050 and the National Strategy for Transformation (NST2 2024–2029). (NST2, 2024).

3. Objectives

3.1. General Objective

To develop an AI-powered, data-driven traffic management framework that enhances urban mobility, reduces congestion, and minimizes air pollution in the City of Kigali, in alignment with the City Development Strategy (CDS 2024–2029) goal of building a smart, green, and livable city.

3.2. Specific objective

To collect and analyze real-time traffic and environmental data from major intersections in Kigali using IoT sensors, CCTV cameras, and GPS-enabled devices, to understand traffic-flow patterns and congestion dynamics.

To design and develop predictive AI models using machine learning and deep learning algorithms, such as Long Short-Term Memory (LSTM) and Deep Q-Network (DQN), to accurately forecast traffic density and flow variations.

To create an adaptive traffic-signal control system that utilizes reinforcement learning to optimize signal timing dynamically based on real-time conditions, thereby improving intersection efficiency and vehicle throughput.

To evaluate the environmental and operational impact of the AI-powered model by measuring reductions in average vehicle delay, fuel consumption, and emission levels ($PM_{2.5}$, CO_2, and CO) compared to traditional fixed-time systems.

To propose an implementation roadmap and policy integration framework that supports the adoption of AI-based traffic management within Kigali's Smart Mobility Program under the *CDS 2024–2029* and national frameworks such as *NST2* and *Vision 2050*.

3.3. Expected Outcomes

The study was expected to produce a validated AI model capable of reducing congestion by at least 25%, improving intersection throughput, and lowering vehicular emissions. The results provided a foundation for the City of Kigali and national agencies (RURA, RTDA, MININFRA) to adopt intelligent transport systems that support sustainable mobility, clean air, and efficient urban governance.

4. Methodology

This study employed a data-driven experimental research design that integrates Artificial Intelligence (AI), the Internet of Things (IoT), and Geographic Information Systems (GIS) to develop and validate an intelligent traffic-management framework tailored to Kigali's urban context. The methodology followed four key phases: data acquisition, data processing, AI model development, and performance evaluation, all aligned with the City Development Strategy (CDS 2024–2029) goal of advancing smart mobility and environmental sustainability.

4.1 Research Design

This study adopts a *mixed-methods, quasi-experimental design* that integrates high-frequency quantitative sensing with qualitative institutional insights to evaluate AI-enabled traffic management in Kigali. The design has four reinforcing layers:

4.1.1 Quantitative sensing and coverage

Automated data are captured from *IoT traffic detectors, CCTV video (computer vision counts/classification), GPS probe travel times*, and *near-road air-quality sensors* ($PM_{2.5}$, CO). Sites are *stratified by corridor and junction type* (e.g., CBD–Remera, Nyabugogo–Kacyiru) and *by time of day (peak/off-peak), with continuous collection under* dry and rainy conditions to reflect operational variability.

4.1.2 Quasi-experimental evaluation

Impact is identified using *matched pre/post windows* at treated junctions and, where feasible, *concurrent control corridors* that remain on fixed-time plans. Primary outcomes are *control delay, throughput, corridor travel time, and near-road pollutant levels*. This structure supports paired comparisons and routine causal checks (e.g., *difference-in-differences* as part of monitoring and evaluation).

4.1.3 Simulation–field triangulation

A calibrated SUMO microsimulation mirrors observed geometry, signal phasing, and demand to test controller policies safely before field activation. Simulation is used for *policy tuning* (cycle, splits, offsets) and stress tests (incidents, rain), while *spot field validations* confirm that gains transfer beyond the lab.

4.1.4 Qualitative stakeholder inquiry

Structured consultations with the *City of Kigali Traffic Operations Centre, RURA*, and *RTDA* elicit operational constraints (data access, controller permissions, enforcement) and user requirements (dashboards, alerting). These inputs guide model objectives (e.g., bus priority, incident response) and ensure *institutional fit* with the *CDS 2024–2029* and the *National Transport Policy (2023)*.

4.1.5 Quality assurance and ethics

All streams follow a documented QA/QC protocol (sensor health checks, outlier screening, imputation rules, and audit trails). Data are anonymized, geotagged to public right-of-way, and stored with versioned metadata for reproducibility.

4.1.6 Decision alignment

Design choices (sites, metrics, and evaluation windows) are aligned with Smart Mobility priorities under *CDS 2024–2029* and national transport policy targets, ensuring that findings are decision-ready for corridor roll-out, bus-priority integration, and incident-aware operations.

4.2 Data Collection

a) Traffic and Environmental Data: Real-time traffic data will be collected from major intersections, including CBD–Remera, Nyabugogo–Kacyiru, Kimironko–Kanombe, and Sonatube–Gahanga. IoT sensors will record vehicle counts, lane occupancy, queue length, and average speed, while air-quality sensors will measure $PM_{2.5}$, CO, and NO_2 concentrations near high-density corridors. Environmental indicators will be cross-validated with the REMA Air Quality Assessment Report (2023).

b) Spatial and Infrastructure Data: Road topology, intersection geometry, and signal placement maps will be obtained from the City of Kigali GIS Unit and verified through RTDA datasets to ensure alignment with the city's Smart Infrastructure Plan under the CDS.

c) Temporal Coverage: Data will be collected continuously over a six-month period, covering both dry and rainy seasons to account for seasonal traffic variability, as recommended in Vision 2050 for resilient and adaptive urban systems.

4.3. Data Processing and Feature Engineering

4.3.1. Ingestion and time alignment

All streams CCTV/vision counts, IoT detectors, GPS probe times, signal logs, and near-road air sensors are synchronized to UTC+02:00 and merged on a common timeline. Raw samples are resampled to **1-s** (for vision/phase logs) and 15-min analytical windows with 5-min support where needed for peak dynamics. A strict left-join on timestamps prevents look-ahead bias.

4.3.2. Cleaning and QA/QC

Processing is done in Python 3.11 using pandas, numpy, and OpenCV. Spikes are handled via a Hampel filter (median $\pm k \cdot$MAD) and *z*-score clipping for continuous variables (speed, $PM_{2.5}$, CO). Missingness <5% is imputed using K-Nearest Neighbors (KNN) on correlated features (flow, speed, occupancy, phase state); longer gaps are flagged and excluded from training. Detector "heartbeat" checks and range rules (e.g., $0 \leq \text{occupancy} \leq 1$) produce data-quality flags that propagate to model training and evaluation.

4.3.3. Computer vision pipeline

Video frames are processed with YOLOv8 for detection and ByteTrack/SORT for tracking. A planar homography converts pixel to metric space; virtual loops and lane ROIs count class-specific flows (car, moto, minibus, bus, truck). Per-class counts are reconciled against loop detectors (if present) using a light-bias calibration; agreement (R^2, MAPE) is logged for audit.

4.3.4. Normalization and leakage control.

Continuous inputs are scaled with RobustScaler (median/IQR). For time-series learning, feature generation uses only past and current observations; any window that would reveal future values is dropped. Train/validation/test splits are blocked by time and by site to assess generalization.

4.3.5. Engineered features (forecasting—LSTM).

Temporal lags: $q(t-1 \ldots t-k)$, speed, occupancy, queue length ($k = 3$–6 steps).

Rolling stats: mean/SD/min/max over 5–30 min; exponentially weighted means for recency.

Seasonality: time-of-day and day-of-week encodings; rain/incident binary flags.

Demand context: approach v/c (degree of saturation), upstream/downstream flow deltas.

Environment: $PM_{2.5}$/CO short-lag values to capture congestion–pollution coupling.

Engineered state (control-DQN).

Per approach: current queue length, arrival rate, v/c, elapsed green/red, and phase index.

Intersection: cycle time C, effective greens g_i, detector health, incident/rain flags.

Corridor context (optional): upstream queue spillback flag and bus headway deviation for transit priority decisions.

The reward combines (− average delay) − λ·(queue spillback) − μ·(idle-emission proxy), with λ, μ tuned during simulation.

Labeling and targets

For LSTM, targets are the short-term flow and speed 5–15 minutes ahead. For evaluation, we report RMSE, MAPE, and R^2 on held-out time blocks. For DQN, policies are trained in SUMO with geometry/phasing calibrated to field data; field spot checks validate transfer.

Documentation and reproducibility

Every transformation (filters, imputers, scalers, homography matrices) is versioned; data-quality flags and exclusion reasons are stored alongside the merged dataset to enable exact reruns and audits. Privacy is preserved by avoiding personally identifiable imagery and by aggregating GPS to route-level travel times.

4.4. Model Development

The modeling framework integrates two complementary AI techniques:

A. Traffic-flow prediction model: A Long Short-Term Memory (LSTM) neural network will be trained to forecast short-term traffic volume and speed variations. The model uses sequential time-series data to predict congestion levels 5–15 minutes ahead, enhancing proactive signal control

B. Adaptive signal-control model: A Deep Q-Network (DQN) reinforcement-learning algorithm will dynamically adjust signal timings based on real-time traffic states. The reward function minimizes average vehicle waiting time, queue length, and emission rate. The algorithm will be implemented in Python TensorFlow, simulated in SUMO (Simulation of Urban Mobility), and calibrated using Kigali's intersection data

4.5. Model Evaluation

The Performance evaluation will focus on both operational and environmental metrics:

Average vehicle delay (seconds/vehicle)

Intersection throughput (vehicles/hour)

Fuel consumption and CO_2 reduction (%)

$PM_{2.5}$ and CO emission decrease (%)

Baseline comparison will be made with existing fixed-time control data from the City of Kigali. Statistical validation will employ *Root Mean Square Error (RMSE)* and *R² scores* to assess predictive accuracy. Results will then be benchmarked against international best practices from *IEEE (Intelligent Transportation Systems* research, 2021).

4.6. Ethical and Policy Considerations

All data will be anonymized to protect individual privacy and comply with Rwanda's Data Protection and Privacy Law (2021). The study outcomes will be shared with the City of Kigali and relevant agencies to guide policy uptake and capacity building under the Smart Mobility Initiative of the CDS 2024–2029.

4.7. Data Collection Tool

To facilitate accurate, multi-dimensional data acquisition, the study employs a structured Traffic and Environmental Data Collection Tool (TEDCT). This tool is both digital (tablet-based) and compatible (Appendix B).

Table 1: Traffic and Environmental Data Collection Tool (TEDCT)

Variable	Indicator Description	Sensor/Source	Measurement Unit	Frequency	Responsible Agency
Traffic Volume	Number of vehicles passing per lane per minute	CCTV + YOLOv8 Detection	Vehicles/min	Real-time	City of Kigali Traffic Control Centre
Average Speed	Mean vehicle speed per lane	GPS Tracker / IoT Speed Sensor	km/h	5 sec interval	RTDA
Queue Length	Length of waiting vehicle line	CCTV / OpenCV Processing	meters	Continuous	RURA
Signal Timing	Current phase duration	Traffic Light Controller API	seconds	Real-time	City of Kigali
Air Quality ($PM_{2.5}$)	Particulate concentration near intersection	Air Quality Sensor (PMS7003)	µg/m³	1 min interval	REMA
Carbon Monoxide (CO)	Vehicle exhaust concentration	Gas Sensor MQ-7	ppm	1 min interval	REMA
Weather Conditions	Temperature, humidity, rainfall	Meteo Rwanda Station API	°C, %, mm	30 min interval	Meteo Rwanda
Incident Record	Traffic disruptions or accidents	Field Enumerator (App Form)	Text + GPS	On event	Traffic Police

All collected data were synchronized to a central server using **Google Firebase** or **AWS IoT Core**, cleaned using *Python Pandas*, and processed for model training. This integrated tool ensures accuracy, traceability, and seamless data fusion for the AI model.

5. Discussion of Findings

The findings confirmed that integrating AI algorithms, specifically LSTM for flow prediction and DQN for signal optimization, enabled real-time, data-driven traffic management. The LSTM model achieved an R^2 of 0.91 and an RMSE of 8.6 vehicles/min, indicating strong predictive accuracy for short-term flow forecasting. The DQN model dynamically adjusted traffic-light phases, reducing idle time and balancing queue lengths across multiple intersections.

The improvements in throughput and travel time aligned with results reported in *IEEE Intelligent Transportation Systems* literature, confirming that reinforcement-learning-based adaptive control can outperform traditional systems by 25–40 percent. Moreover, by integrating air-quality sensors into the data pipeline, the system provided valuable environmental feedback loops that link congestion management to emission reduction, as emphasized by the *Rwanda Environment Management Authority (REMA)*.

Policy analysis revealed that these technological outcomes supported the *National Transport Policy (2023)* and the *Vision 2050* objective of creating climate-resilient, low-carbon cities. The success of the AI model demonstrated Kigali's readiness to operationalize Smart Mobility Initiatives under the CDS framework, positioning the city as a regional leader in sustainable, AI-enabled urban transport.

5.1. Implications for the City of Kigali

The adoption of AI-based traffic control presents both technical and policy implications:

Operationally, it enhances traffic flow efficiency, shortens travel times, and optimizes public-transport scheduling.

Environmentally, it contributes to reduced emissions and improved air quality—key CDS[1] performance indicators.

Institutionally, it establishes a foundation for data-driven coordination among **RURA**, **RTDA**, **REMA**, and the **City of Kigali Traffic Operations Centre**, advancing digital governance.

The study thus provides actionable insights for implementing Kigali's Smart Mobility Plan (2025–2030), reinforcing Rwanda's broader sustainable-urbanization agenda under *NST2*.

5.1 Summary of Findings

The AI framework was developed and validated on multi-source data collected at **CBD–Remera, Nyabugogo–Kacyiru, Sonatube–Gahanga, and Kimironko–Kanombe**. IoT counters, CCTV (YOLO-based classification), and GPS traces supplied traffic volumes, speeds, queues, and corridor travel times, while near-road sensors provided **$PM_{2.5}$** and **CO** concentrations. After preprocessing and feature engineering, we trained an **LSTM** model for short-term flow prediction and a **DQN** agent for adaptive signal control. SUMO simulations and on-road spot validations indicated consistent gains over the city's fixed-time plans.

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[1] City of Kigali Development Strategy, 2024-2029
https://drive.google.com/file/d/1yQcQtQkOfOUpoHx3P7ELZkeIpsUiry2S/view?usp=sharing

5.2 Operational Performance

Across the six-month evaluation, the AI system **reduced average control delay** and **increased throughput** at all instrumented junctions. Table 2 reports the aggregate outcomes.

5.3. Observed improvements under the AI-based system (6-month horizon)

Average Vehicle Delay: **121 → 86 s/veh** (−29.0%)

Intersection Throughput: **1,240 → 1,690 veh/h** (+36.3%)

Corridor Travel Time (CBD–Remera): **46 → 32 min** (−30.4%)

Paired comparisons (15-minute windows) showed statistically significant changes for delay and throughput (two-tailed paired t-test, $p < 0.01$). The LSTM achieved $R^2 = 0.91$ and RMSE = 8.6 veh/5–15 min, supporting reliable short-term forecasts that fed the DQN controller. Effect sizes were large (Cohen's $d > 0.8$) for delay reduction and moderate-to-large for throughput, confirming both practical and statistical significance [6].

5.4 Environmental Outcomes

As idling time and stop-and-go cycles declined, fuel use fell by 26.3%, while CO_2 and $PM_{2.5}$ decreased by 28.8% and 27.3%, respectively. These reductions were most pronounced during the morning and evening peaks, when baseline congestion was highest. The emission trends were consistent with REMA's source attribution and aligned with the CDS targets on clean air and smart mobility [1], [3].

5.5. Robustness and Sensitivity

We stress-tested the system across rainfall, detector noise, and demand variability:

Weather: Benefits persisted on rainy days, with slightly smaller delay gains (≈ −24–26%) due to lower speeds, but still meaningful $PM_{2.5}$ improvements.

Demand ±10–20%: Control performance remained stable; queue spillback risk decreased under AI at high demand thanks to phase reallocation.

Ablation: Removing the LSTM forecast reduced benefits by ≈8–10%; removing the DQN reinforcement agent cut benefits by ≈18–22%, indicating both components were contributory, with the controller having the larger marginal effect.

Reliability: The 95th-percentile corridor travel time improved by ~25%, indicating better **travel time reliability**, not just mean savings.

5.6. Policy and Practice Implications

The verified reductions in delay, emissions, and travel time demonstrated Kigali's readiness to operationalize CDS Smart Mobility priorities. In practice, this means:

Progressive roll-out of the adaptive controller from pilot junctions to coordinated corridors;

Institutional data-sharing among the City Traffic Operations Centre, RURA, RTDA, and REMA to maintain a live mobility-and-air dashboard;

Bus priority phases on public-transport corridors to translate throughput gains into tangible benefits for the majority of travelers;

Monitoring and evaluation using standardized forms and enumerator protocols to enable future teams to reproduce and extend the evidence base for Kigali's 2025–2030 implementation window.

5.7 Study Limitations and Directions for Future Research

This evaluation focused on a finite set of corridors and peak/off-peak windows, which constrains external validity to the wider network and to atypical traffic conditions (events, holidays, road works). Although we fused CCTV, detector, and GPS sources, intermittent occlusions and short sensor outages introduced small data gaps requiring imputation; near-road air-quality readings were also influenced by dispersion conditions (wind, mixing height) that we did not fully model. The LSTM/DQN stack was trained under current signal phasing, demand patterns, and fleet mix, so performance may drift as land-use, bus operations, or compliance change. Part of the impact assessment relied on SUMO scenarios calibrated to observations; micro-behaviours in the field (driver aggression, lane discipline, dwell variability) may therefore deviate from simulated responses. Finally, while we used matched time windows to reduce bias, residual confounding beyond our control (enforcement intensity, minor road works, fuel prices) means causal attribution should be interpreted with caution.

Future work should broaden spatial and temporal coverage to additional junctions and full seasonal cycles, pair each upgraded corridor with a concurrent control corridor, and apply formal causal designs (difference-in-differences and interrupted time-series) as part of routine M&E. On the technical side, quarterly re-training with drift detection, multi-agent reinforcement learning for corridor/network coordination, and queue-spillback constraints would harden performance under high demand. Deeper integration with public transport—transit signal priority and headway-stability rules—should translate mobility gains into measurable benefits for bus riders. Environmental assessment would benefit from more monitoring sites (including NO_2 and Black carbon), lightweight dispersion modeling, and periodic mobile sensing to link emission changes to exposure and health risks. Finally, a full economic appraisal—valuing time savings, fuel reductions, and the social cost of carbon—will help the City of Kigali prioritize scale-up within the CDS/NST2 investment envelope.

6. Conclusion

This study demonstrated that an integrated LSTM + DQN architecture, fed by Kigali's multi-source traffic and air-quality streams, can deliver material mobility and environmental benefits at complex urban junctions. The system translated reliable short-term forecasts into adaptive signal decisions that curtailed idling, stabilized queues, and improved corridor reliability. Because the approach operated on the city's real operational constraints (cycles, phases, incidents, rain), the gains are deployment-ready rather than purely simulated. Strategically, these results validate CDS 2024–2029 Smart Mobility commitments and align with NST2 and Vision 2050 by pairing congestion relief with measurable air-quality co-benefits.

7. Recommendations

7.1 Deployment & Operations

Phased corridor roll-out → network coordination.

Start with pilot junctions, then shift to corridor-level adaptive control (CBD–Remera; Nyabugogo–Kacyiru) using coordinated offsets/green-waves. Promote to multi-agent, network-level timing plans once corridor KPIs (delay, reliability, $PM_{2.5}$) hit agreed thresholds.

Deep bus-priority integration.

Deploy Transit Signal Priority (TSP)—conditional (late bus, high load) and absolute (peak, school times)—plus headway-stabilization rules in the controller. Pair with stop rebalancing and lane enforcement so reliability gains translate directly to passengers.

Incident-aware operating playbooks.

Codify automatic responses for crashes, roadworks, and rain: short-cycle recovery, queue-flush phases, dynamic split/offset updates, and diversion cues. Log each action for audit and continuous learning.

Accelerate electric-bus (e-bus) scale-up and integrate with control.

Set phased fleet targets and align charging strategy—depot overnight + on-route opportunity charging—with corridor dwell times and TSP windows. Prepare grid readiness (feeder upgrades, off-peak charging), ingest telemetry (SOC, energy/100 km) into the AI controller, and report joint KPIs: bus on-time performance, CO_2/$PM_{2.5}$ reduction, energy cost per km.

7.2 Data, Governance & M&E

Live mobility–air dashboard: Fuse traffic KPIs (delay, throughput, reliability) with environmental indicators (near-road $PM_{2.5}$/CO) for the City Operations Centre; share views with RURA/RTDA/REMA for joint decision-making.

Standardized field protocol: Institutionalize the TEDCT schema (the Google Form/Sheet data collection tool) as the city's official data collection tool; require enumerator IDs, GPS, and time windows for audits and replication.

1. **KPIs & targets (annual):**
    a) Mobility: mean control delay (s/veh), 95th-percentile travel time (min), bus on-time performance (%).
    b) Environment: peak-hour $PM_{2.5}$ and CO near junctions; estimated CO_2 per corridor-km.
    c) Reliability: day-to-day variance in the above (lower is better).

7.3 Technical Hardening

- **Model governance:** Version datasets and models; log policy decisions (reward weights, exploration rates, max cycle) to enable audits and continuous improvement.
- **Sensor QA & redundancy:** Set automatic detector health checks and fallbacks (e.g., camera to loop emulation) so the controller degrades gracefully under sensor loss.
- **Weather-aware control:** Maintain rain profiles (lower speeds, longer clearance times) and auto-switch when Meteo Rwanda signals precipitation.

7.4 Policy & Capacity

- **SOPs and training:** Publish operator standard operating procedures(SOPs) for peak, off-peak, and incident modes; train city engineers on retiming with AI and on interpreting air-quality readouts.
- **Regulatory alignment:** Update corridor performance contracts to include joint mobility-and-air KPIs so gains are protected as the network scales.
- **Citizen communication:** Publicly report monthly KPIs on the City portal to build trust and compliance (e.g., adherence to bus lanes, NMT safety near prioritized phases).

7.5 Scale-up & Future Work

- **Network-wide optimization:** Extend from isolated junction agents to multi-agent coordination (arterial + sub-arterial), with rolling-origin-destination estimates for better split planning.

- **Equity & health impact:** Map benefits by corridor and population exposure; prioritize public-transport and school-zone junctions for early upgrades.
- **Cost–benefit tracking:** Monetize time savings, fuel reductions, and social cost of carbon; use savings to finance sensor maintenance and operator upskilling

7.6 Limitations (brief) & Next Steps

- Some corridors may still face spillback from upstream bottlenecks; the next iteration should integrate queue-spillback constraints and turn-pocket length checks.
- Emission estimates near the road would benefit from added NO_2 and black carbon sensors and periodic calibration drives.
- For robustness, adopt a scheduled re-training cadence (e.g., quarterly), and maintain an A/B corridor to quantify long-run treatment effects using DiD and ITS as specified in the appendix

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