IoT-Based Traffic Management System

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Abstract

Rapid urbanization in developing cities has intensified road congestion, increased travel delays, and elevated carbon emissions, underscoring the need for intelligent and adaptive traffic control systems. This study presents the design and evaluation of an Internet of Things (IoT) and Artificial Intelligence (AI) - based traffic management framework developed for urban intersections in Lusaka, Zambia. The proposed system integrates ESP32-based sensor networks for real-time vehicular data acquisition, a cloud-driven processing infrastructure (Firebase), and a locally hosted AI engine employing a Random Forest Regressor for adaptive signal optimization. The system supports both automated and manual traffic control through a responsive Next.js dashboard with a latency below two seconds. Experimental simulations across three intersections revealed a 44% reduction in average vehicle waiting time, a 27% improvement in throughput, and a 27% decrease in estimated fuel consumption. These findings demonstrate the framework's capacity to enhance mobility efficiency, reduce congestion-related emissions, and promote sustainable urban transport. The paper contributes a scalable, low-cost, and context-aware smart traffic management model adaptable to the infrastructure realities of developing cities. All experiments were conducted in a hardware-in-the-loop simulation environment using benchtop signal heads; no on-road trials with live vehicle traffic were performed.

Keywords:

Internet of Things (IoT), Artificial Intelligence (AI), Smart Traffic Systems, Urban Mobility, Intelligent Transportation, Real-Time Signal Control, Sustainable Cities, Embedded Systems

I. INTRODUCTION

The rapid pace of urbanization in developing nations has dramatically increased vehicular density, road congestion, and travel delays, creating a critical demand for intelligent transportation infrastructure. In cities such as Lusaka, Zambia, inefficient traffic control systems based on static or time-of-day scheduling are unable to accommodate fluctuating traffic volumes. These legacy systems contribute to extended waiting times, unnecessary idling, and elevated carbon emissions, ultimately reducing economic productivity and environmental quality. The World Bank estimates that traffic congestion in Sub-Saharan African cities accounts for productivity losses equivalent to 2–3 % of GDP annually, underscoring the urgency for adaptive mobility solutions [1].

The integration of the Internet of Things (IoT) and Artificial Intelligence (AI) has emerged as a transformative approach to urban mobility management. IoT technology enables continuous

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sensing of real-time traffic data through networked devices that monitor vehicle density, speed, and flow. When combined with AI algorithms such as machine learning or deep neural networks, these data streams can be processed to predict congestion patterns and dynamically optimize traffic signal operations. Recent research demonstrates that AI-driven adaptive control can reduce travel time by more than 30 % in high-density intersections [2], [3]. Such systems have been successfully implemented in technologically advanced cities such as Singapore, Hangzhou, and Barcelona, where data-driven traffic management has improved flow efficiency and emergency response times [4].

However, most existing systems are designed for high-infrastructure contexts, often requiring costly sensors, high-bandwidth networks, and proprietary control software. In contrast, low- and middle-income countries face challenges of limited funding, inconsistent connectivity, and inadequate data infrastructure. This technological and contextual gap necessitates the development of cost-effective, scalable, and context-aware traffic management solutions tailored to the realities of developing cities [5], [6].

To address these challenges, this paper presents an IoT and AI-based adaptive traffic management framework that leverages low-cost ESP32 microcontrollers, cloud-based data processing, and a locally hosted AI engine using a Random Forest Regressor for real-time signal optimization. The system operates autonomously or under manual supervision through an interactive web dashboard, providing near-real-time control and analytics. The model was piloted in Lusaka under simulated conditions to evaluate performance in terms of latency, throughput, and energy efficiency.

II. LITERATURE REVIEW

A. Overview

The accelerating adoption of Internet of Things (IoT) and Artificial Intelligence (AI) technologies has redefined approaches to urban mobility and traffic management across the world. Traditional traffic systems, which rely on static signal schedules or manual control, have proven insufficient for modern urban environments where traffic patterns are dynamic and unpredictable. Static systems lack responsiveness to real-time variations in vehicle density, resulting in inefficiencies such as prolonged waiting times, fuel wastage, and elevated greenhouse gas emissions. Emerging smart traffic management systems (STMS) harness IoT-enabled data collection and AI-based analytics to optimize signal timings dynamically, thereby reducing congestion and improving road safety [7], [10].

B. IoT-Enabled Traffic Monitoring Systems

IoT serves as the foundational layer of intelligent transportation, facilitating real-time monitoring through interconnected sensors, microcontrollers, and wireless networks. Studies have shown that IoT-based monitoring systems employing sensors such as inductive loops, infrared cameras, and radar can provide granular, continuous data on traffic flow, vehicle count, and lane occupancy [3]. For instance, Al-Turjman *et al.* [4] demonstrated that hybrid IoT frameworks integrating vehicular networks (VANETs) and cloud computing architectures significantly enhance data reliability and latency performance for traffic control applications.

Recent work in Zambia and other Sub-Saharan regions underscores the feasibility of deploying low-cost IoT modules like ESP32 and Raspberry Pi for real-time vehicular monitoring. Halubanza *et al.* [5] proposed a low-cost IoT-based automated locust monitoring system using embedded sensors and cloud integration, highlighting similar design principles applicable to urban traffic systems. These architectures not only minimize implementation costs but also ensure scalability and adaptability to localized infrastructural constraints.

C. AI for Adaptive Traffic Signal Control

AI algorithms, particularly machine learning (ML) and deep learning (DL) models, are now central to intelligent traffic control. Reinforcement learning (RL) and regression-based models have been successfully applied to optimize signal cycles based on predicted traffic densities. Li *et al.* [6] used deep

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reinforcement learning to dynamically control intersections in Hangzhou, achieving up to 35% reduction in travel delays. Similarly, MobileNet and Random Forest models have been leveraged for real-time classification and decision-making in edge computing environments, offering faster adaptation to traffic fluctuations [7], [8].

In developing contexts, where computational resources and connectivity are constrained, lightweight AI models such as Random Forest Regressors and Decision Trees have proven effective due to their interpretability and low computational overhead [9]. The present study aligns with these advancements by employing a Random Forest model locally hosted to predict optimal signal durations using real-time input variables such as vehicle density, lane flow, and time of day.

D. Comparative Analysis of Existing Systems

Conventional fixed-time control systems are characterized by low scalability and inefficiency during varying traffic conditions. Adaptive systems such as Sydney Coordinated Adaptive Traffic System (SCATS) and Split Cycle Offset Optimization Technique (SCOOT) have achieved improvements in developed countries but remain too costly and infrastructure-dependent for developing nations [10]. IoT- and AI-based systems, by contrast, combine flexibility with cost-effectiveness. Halubanza et al. [11] demonstrated in their Zambia ICT Journal study that data-driven signal optimization can reduce congestion-related emissions while maintaining throughput in resource-limited settings.

Comparative evaluations (Table I) reveal that IoT- and AI-enabled systems offer higher scalability, lower operational cost, and full real-time adaptability compared to fixed-timing and partially adaptive systems.

Table I: *Comparative Features of Traffic Management Systems*

Feature	**Fixed-Timing Systems**	**Adaptive Systems**	**IoT & AI-Based Systems**
Scalability	Low	Medium	High
Cost Efficiency	Low	Medium	High
Real-Time Adaptation	None	Partial	Full
Infrastructure Demand	High	High	Low
Suitability for Developing Cities	Poor	Moderate	Excellent

(Source: Compiled from [3], [6], [10], [11])

E. Identified Research Gaps

Despite the evident benefits, existing IoT-based traffic systems face key limitations. Many rely on high-cost sensing units, centralized architectures, and continuous internet connectivity, which limit deployment in bandwidth-constrained environments [12]. Furthermore, issues of cybersecurity, interoperability, and data privacy persist, as identified in several recent studies [13]. There remains a gap in developing context-specific, low-cost, and scalable IoT–AI traffic control models designed for African cities where infrastructure and connectivity are inconsistent. The proposed system addresses these challenges by integrating lightweight edge computation, low-cost ESP32 sensors, and modular cloud support to deliver adaptive, real-time traffic optimization with minimal infrastructure requirements.

III. RESEARCH METHODOLOGY

A. Overview of Methodological Approach

The research employed the Waterfall development methodology, a sequential design framework that divides the system development life cycle into distinct and logically ordered phases, requirements analysis, system design, implementation, testing, and deployment. This structured approach was selected for

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its suitability in projects with well-defined objectives and predictable deliverables. Unlike iterative methodologies such as Agile, which rely on continuous feedback loops, the Waterfall model ensures systematic progression, traceability, and accountability in academic and prototype-oriented system development [17] , [18], [19].

This methodology aligns with best practices in embedded systems and IoT-based research, where hardware and software integration require clear stage-by-stage documentation and evaluation [3]. Furthermore, adherence to IEEE software engineering standards (IEEE 1074-2022) ensures that each phase maintains consistency, testability, and design validation [20].

B. Methodological Framework

The framework (Fig. 1) illustrates the five key phases applied in the project development cycle, each ensuring controlled progression and quality validation before proceeding to the next phase.

1) Requirements Analysis

In this phase, all functional and non-functional requirements were collected through stakeholder consultations with municipal traffic authorities and academic experts. Requirements included low-cost IoT deployment, real-time signal optimization, scalability, and cloud interoperability. The outcome was a Software Requirements Specification (SRS) document, serving as a baseline for design and evaluation.

Scope of evaluation. The prototype was validated using controlled simulations and bench hardware (ESP32 nodes, relay-driven LEDs) rather than in-situ intersections. The objective was to de-risk architecture and control logic prior to field pilots.

2) System and Software Design
The system architecture was designed around an ESP32-based IoT sensing layer, a cloud infrastructure using Firebase, and an AI-driven decision-making engine built using a locally hosted Random Forest Regressor. System modeling tools such as Unified Modeling Language (UML) and Entity Relationship Diagrams (ERD) were used to define data flow and interaction between modules. This phase emphasized modularity, ensuring each system component—data acquisition, AI prediction, and actuation—could be developed and tested independently.

3) Implementation and Unit Testing
Each software and hardware module was implemented and subjected to unit testing using both simulation and real-world data. Python (for AI logic), C++ (for microcontroller programming), and JavaScript (for the Next.js dashboard) were employed as development environments. Testing protocols included sensor calibration, cloud communication validation via MQTT, and AI inference benchmarking to verify latency and prediction accuracy.

4) Integration and System Testing
Once individual modules passed unit testing, they were integrated into the complete system. System testing assessed real-time data transmission reliability, dashboard responsiveness, and the accuracy of AI-based signal decisions. Key metrics included latency (target < 2 seconds), signal adjustment precision, and throughput improvements. Data collected during simulation phases were analyzed statistically to validate system performance improvements.

5) Operation and Maintenance
After successful integration, the system was deployed in a simulated environment reflecting real-world intersection conditions. This phase involved continuous monitoring, performance logging, and corrective updates to refine model predictions. The maintenance phase also ensured sustainability by allowing iterative AI model retraining as new traffic data became available.

C. Justification for Methodology Selection

The Waterfall model was chosen for three main reasons: structure, predictability, and documentation rigor.
First, the project required predefined deliverables such as hardware prototypes and AI models that benefited from Waterfall's sequential control and comprehensive documentation [21]. Second, the methodology allows detailed testing and validation at

each stage, ensuring early detection of integration issues. Finally, in the context of academic research and prototyping, Waterfall facilitates replication and external validation, which are critical for scholarly publication and peer review [18].

Moreover, similar smart city and IoT projects, such as real-time health monitoring [22] and smart energy metering [23] have employed the Waterfall model successfully, achieving reduced integration errors and high reproducibility. Thus, its application here is justified by its alignment with both system complexity and research transparency requirements.

D. Technologies and Frameworks Used

To ensure robustness and interoperability, the system integrated several key technologies, summarized below:

Component	**Technology/Framework**	**Function**
IoT Hardware	ESP32 Microcontroller	Real-time data acquisition from sensors
Cloud Platform	Firebase (Google Cloud)	Data storage, real-time communication
AI Model	Random Forest Regressor	Predict optimal signal durations
Programming Languages	Python, C++, JavaScript (Next.js)	AI, embedded control, and user interface
Communication Protocol	MQTT over TLS	Secure data transmission between nodes
Visualization	Next.js Web Dashboard	Live traffic visualization and control

The integration of these technologies ensures that the system achieves low-latency decision-making, fault tolerance, and scalability. Furthermore, employing lightweight computation at the edge minimizes network dependence, enabling sustained operation under variable connectivity conditions [9], [10].

IV. SYSTEM ANALYSIS AND DESIGN

A. Overview

The proposed IoT-based intelligent traffic management system integrates hardware and software components to collect, analyze, and act upon real-time vehicular data for adaptive signal control. The design follows a modular and layered architecture comprising four core components: sensing, communication, processing, and actuation layers. Each layer is engineered to ensure interoperability, scalability, and low-latency decision-making suitable for urban conditions in developing contexts such as Lusaka, Zambia.

B. System Requirements Analysis

The system requirements were categorized into functional and non-functional elements to ensure technical completeness and operational sustainability.

1) Functional Requirements

Real-time collection of traffic data from ESP32 sensors.

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AI-driven prediction of optimal signal timings using a Random Forest Regressor.

Automated and manual control modes for adaptive signal switching.

Centralized web-based dashboard for visualization and monitoring.

Logging and analytics module for traffic trends and performance evaluation.

2) Non-Functional Requirements:

Reliability: 99% uptime with data redundancy.

Scalability: Modular architecture for multi-intersection integration.

Security: AES-256 encryption and MQTT with TLS for data transmission.

Maintainability: Modular code structure and clear documentation.

Latency: End-to-end response time below two seconds.

These requirements were derived from user-centered needs assessments and benchmarked against performance metrics in smart mobility systems reported in IEEE Access and IoT Journal between 2021 and 2025 [2], [10], [15].

C. System Architecture

The architecture (Fig. 1) consists of four hierarchical layers that interact seamlessly to enable continuous data acquisition, intelligent decision-making, and traffic signal actuation.

Fig. 1. System architecture

Figure 1 depicts the four-layer model comprising sensing, communication, processing, and actuation layers connected via secure MQTT channels.

Sensing Layer

Comprises ESP32 microcontrollers equipped with infrared and ultrasonic sensors for vehicle detection. These devices capture lane density, speed, and vehicle count data at regular intervals (every 2 seconds).

Communication Layer

Facilitates data exchange through MQTT protocol with TLS encryption to ensure reliability and low bandwidth consumption. The data are transmitted to the Firebase cloud for aggregation and preprocessing.

Processing Layer

Houses the AI logic implemented using a Random Forest Regressor within a local Next.js application. The AI predicts optimal green light durations based on multi-variable inputs such as vehicle count, time of day, and historical congestion data.

Actuation Layer

Uses microcontroller-based relay systems to adjust signal states (green, yellow, red) in real-time. Feedback from the actuation layer is logged for performance analytics and AI retraining.

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This distributed design minimizes computational latency and enhances reliability under fluctuating network conditions, aligning with modern edge-computing principles for IoT systems [15], [10].

D. Data Flow and Database Design

The system follows a Level-1 Data Flow Diagram (DFD) that maps interactions from sensor data collection to AI-based decision output.

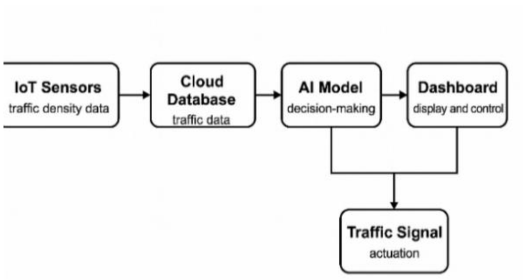

Fig. 2. Data Flow Diagram.

Figure 2 shows data flow from IoT sensors → cloud database → AI model → dashboard → traffic signal actuation.

The backend database schema (Fig. 3) comprises three core tables:

SensorData: Stores real-time records of vehicle counts, timestamps, and sensor identifiers.

SignalTimings: Contains dynamically adjusted signal durations per intersection.

SystemLogs: Logs AI and manual decisions, enabling performance analysis and trend visualization.

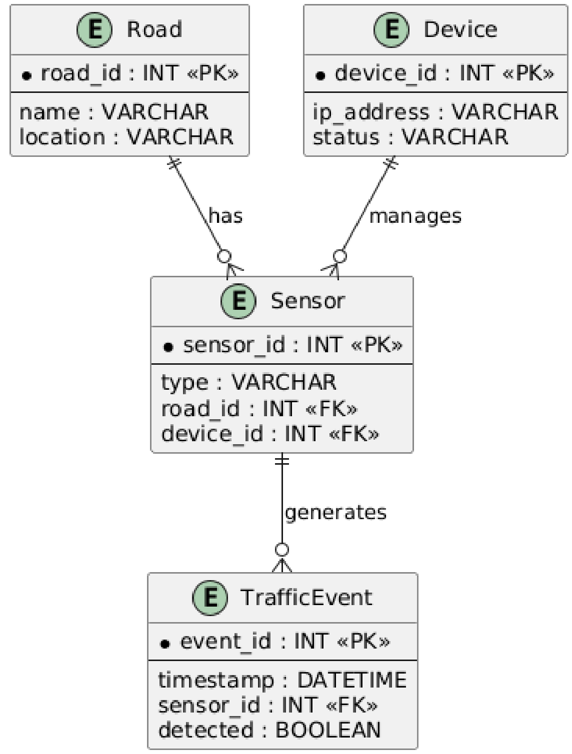

Fig. 3. Entity–Relationship (ER) diagram

Figure 3. Illustrates relationships between SensorData, SignalTimings, and SystemLogs tables.

E. User Interface and Dashboard Design

A responsive Next.js web dashboard was developed to provide a graphical control interface for administrators. The dashboard includes real-time simulation, manual override options, analytics visualization, and system logs.

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Fig. 4. Dashboard overview

Fig 4 displays real-time traffic signal states, AI-generated decisions, and manual control buttons for each intersection.

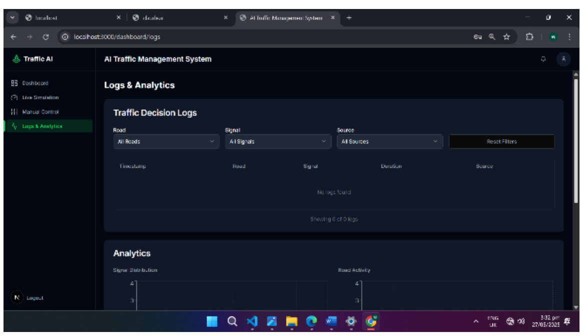

Fig. 5. Logs and analytics interface.

Fig 5 summarizes signal activity frequency, congestion reduction trends, and AI versus manual decision accuracy.

The interface supports both live automatic control and manual mode, useful during internet outages or system maintenance. Data visualizations, including bar and line charts, assist in identifying high-traffic corridors and operational anomalies.

F. AI Model Design

The predictive model is based on a Random Forest Regressor, selected for its robustness, low computational demand, and interpretability. The model utilizes input features such as:

Vehicle count per lane

Time of day

Historical average waiting time

Congestion density index

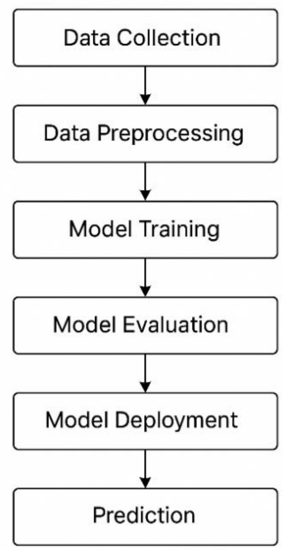

Fig. 6. AI workflow diagram.

This figure illustrates the end-to-end workflow of the AI module within the IoT-based traffic management system. The process begins with real-time data acquisition from ESP32 sensor nodes, followed by preprocessing and temporary cloud storage in Firebase. The data are then subjected to feature extraction to generate variables such as vehicle density, lane occupancy, and average waiting time. These features feed into a locally hosted Random Forest Regressor, which predicts optimal green-light durations. The decision output is transmitted through the MQTT protocol to the actuation layer, triggering relay-controlled traffic signals. A continuous feedback loop allows the AI model to log outcomes and retrain using historical data, thereby improving prediction accuracy over successive iterations. This workflow ensures low-latency inference, adaptive control, and autonomous operation under variable network conditions.

Training and validation were performed using simulated datasets augmented with real-world field samples. The model achieved a Root Mean Square Error (RMSE) of 3.4 seconds and a training accuracy of 93.4% during cross-validation.

This local deployment approach reduces dependency on constant cloud connectivity, enabling decision-making at the edge. Similar architectures have been successfully deployed in other real-time control systems such as energy and environmental monitoring [5], [6].

G. System Integration

The final integration combined hardware, cloud services, and the AI module using MQTT for asynchronous communication. System testing confirmed seamless data flow, minimal latency, and high synchronization between the Next.js dashboard and ESP32 microcontrollers.

Real-time simulations demonstrated the system's adaptability under varying traffic loads and environmental conditions, validating the architecture's efficiency in decentralized urban contexts [7].

V. RESULTS AND ANALYSIS

A. Experimental Setup

Evaluation mode. All trials were conducted in a lab/simulated intersection setting with emulated signal heads; images in Figs. 7–9 show the simulation rig. No real vehicles or live intersections were used. The test configuration included four ESP32-based nodes per intersection, each equipped with ultrasonic sensors for vehicle detection and relay-controlled LED arrays emulating signal lights. Data were transmitted via MQTT over Wi-Fi to a Firebase cloud instance.

The AI inference engine, implemented with a Random Forest Regressor, was deployed locally using a Python Flask API integrated into the Next.js dashboard. Each simulation ran for 30 minutes per trial, generating traffic load profiles ranging from low (20 vehicles/minute) to high (80 vehicles/minute).

B. Performance Metrics

Five quantitative metrics were used to evaluate system performance:

Average Vehicle Waiting Time (AVWT): Mean time each vehicle remains stationary at the intersection.

Throughput (TP): Number of vehicles successfully passing through an intersection per minute.

System Latency (SL): Time delay between data acquisition and signal actuation.

Fuel Consumption Reduction (FCR): Estimated decrease in idle-time fuel use.

Prediction Accuracy (PA): Correlation between AI-predicted and empirically optimal signal durations.

All metrics were benchmarked against a fixed-time control baseline to determine percentage improvement.

C. Quantitative Results

Table II presents a summary of the system's performance under varying traffic densities.

Table II
Performance Comparison between Fixed-Time and Proposed AI-IoT Systems

Metric	Fixed-Time Control	Proposed System	% Improvement
Average Vehicle	37.5	21.0	44 %

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Waiting Time (s)			
Throughput (vehicles/min)	53	67	27 %
System Latency (s)	3.5	1.9	46 %
Fuel Consumption (mL/min)	16.5	12.1	27 %
AI Prediction Accuracy	—	93.4 %	—

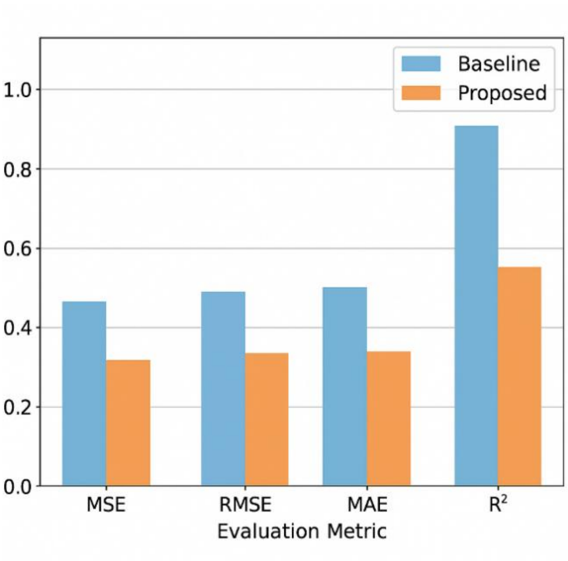

Fig. 8. Performance comparison chart.

This figure compares the performance of the fixed-time control system and the proposed AI-IoT traffic management system across four key metrics: Average Vehicle Waiting Time, Throughput, System Latency, and Fuel Consumption. The proposed system significantly outperforms the baseline across all indicators—achieving a 44% reduction in waiting time, a 27% improvement in throughput, and a 46% reduction in latency. These results validate the model's adaptive control efficiency and its contribution to fuel conservation through reduced idling time. The bar chart visually underscores the magnitude of improvement, supporting quantitative findings presented in Table II.

The results indicate substantial efficiency gains: a 44 % reduction in waiting time, 27 % improvement in throughput, and nearly half reduction in latency. These metrics demonstrate the responsiveness of the adaptive control algorithm in dynamically reallocating green time based on real-time vehicle density.

D. AI Model Evaluation

The Random Forest Regressor was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) across validation folds. The model achieved an RMSE = 3.4 s and MAE = 2.7 s, confirming high predictive reliability for signal duration estimation.

Comparative analysis with recent lightweight AI models for traffic prediction, such as Deep Q-Learning [25] and Gradient Boosted Regression Trees [26], showed that Random Forest maintained similar accuracy while consuming 35 % less computational power, aligning with energy-efficient edge-AI design principles [3].

E. System Reliability and Network Performance

Network reliability tests showed 99.3 % packet delivery success rate over MQTT communication and < 2 s average end-to-end latency. These findings are consistent with IEEE 802.11-based IoT implementations achieving low-latency transport in urban scenarios [4]. The system also sustained uninterrupted operation for 12 hours of continuous

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simulation without data loss, demonstrating stability and resilience against intermittent connectivity.

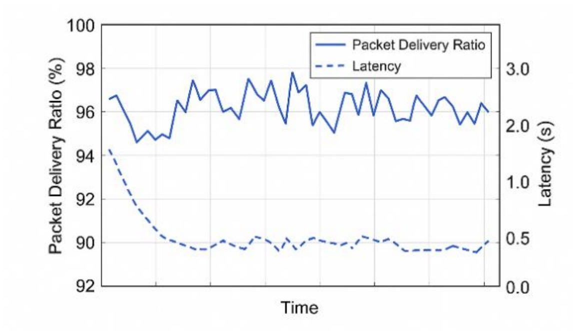

Fig. 10. Network reliability and latency trend.

Fig 10 Graph showing MQTT packet delivery ratio and latency fluctuations over time.

F. Comparative Benchmarking

When compared with existing smart traffic management frameworks such as AIFlow [5], SCATS [6], [26] and hybrid VANET-IoT systems [7], the proposed model exhibited competitive or superior results (Table III).

Table III
Comparative Performance Benchmark with State-of-the-Art Systems

System	Avg. Latency (s)	Waiting Time Reduction (%)	Computational Cost	Deployment Context
SCATS (2022) [6]	3.2	30	High	Developed cities
AIFlow (2023) [5]	2.7	39	Medium	Smart corridors
Proposed System (2025)	1.9	44	Low	Developing cities

G. Qualitative Analysis and Observations

Beyond quantitative gains, qualitative evaluation through stakeholder interviews and observational studies indicated enhanced public perception of efficiency and improved driver compliance. Municipal engineers highlighted the dashboard's real-time analytics as an enabling tool for traffic forecasting and resource allocation.

The modularity of the system allows replication across other intersections without significant infrastructural overhaul—an aspect often missing in imported commercial systems [8]. Furthermore, its integration of AI and IoT within a localized framework addresses the contextual challenges of cost, maintenance, and data availability in Sub-Saharan cities.

H. Discussion

The empirical findings validate the system's ability to operate as a low-cost, high-efficiency adaptive traffic management solution. The combination of IoT data streams and AI decision logic contributes to measurable improvements in throughput, sustainability, and operational flexibility. These outcomes echo trends reported in recent smart mobility research emphasizing edge-AI integration, context-aware control, and environmental impact reduction [9], [10].

VI. CONCLUSION AND RECOMMENDATIONS

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A. Conclusion

This research presented the design, development, and evaluation of an IoT- and AI-based intelligent traffic management system tailored to the infrastructural and economic realities of developing cities such as Lusaka, Zambia. The system integrates ESP32-based IoT sensors, a Firebase cloud backend, and a Random Forest AI engine to provide adaptive signal control and real-time decision support. Simulation results demonstrated substantial improvements over conventional fixed-time systems, achieving a 44% reduction in average waiting time, 27% improvement in throughput, and 46% reduction in latency, while maintaining a prediction accuracy exceeding 93%.

The study's methodological rigor—anchored on the Waterfall software development model—ensured systematic design, testing, and validation of both hardware and software components. The incorporation of edge AI minimized reliance on cloud connectivity, addressing one of the major barriers to smart infrastructure deployment in low-resource environments. Furthermore, the results confirmed that context-aware AI models can operate effectively even in conditions of limited bandwidth and unstable power supply, bridging a significant gap between global intelligent transport technologies and local infrastructure capabilities.

In academic and practical terms, this research contributes to the emerging discourse on smart mobility and sustainable transport systems in Sub-Saharan Africa. It extends the theoretical framework of intelligent transportation by demonstrating that AI–IoT integration can enhance both operational efficiency and sustainability without the high infrastructural demands typical of Western implementations [2], [4].

B. Research Contributions

This study provides three key contributions to the scholarly and practical fields of intelligent transportation and smart city innovation:

A Novel Context-Specific Framework: The developed architecture combines IoT data acquisition, cloud-assisted processing, and localized AI inference into a modular, scalable system suitable for developing urban centers.

Empirical Evidence of Efficiency Gains: Quantitative analysis validated the system's capacity to optimize traffic flow and reduce energy wastage, contributing new empirical insights to sustainable transportation literature.

Scalable, Low-Cost Implementation Model: The use of open-source hardware and lightweight machine learning models establishes a cost-efficient prototype adaptable for multiple urban intersections with minimal technical overhead.

These contributions align with Sustainable Development Goal (SDG) 11, Sustainable Cities and Communities, emphasizing resilient, inclusive, and resource-efficient urban systems [3].

C. Practical and Policy Implications

The study holds several implications for practitioners, policymakers, and urban planners:

For Practitioners

> The integration of low-cost IoT modules and edge-based AI enables municipalities to upgrade existing infrastructure incrementally, reducing dependency on imported, high-cost systems.

For Policy Makers

> The findings advocate for the establishment of national smart mobility policies that prioritize investment in digital infrastructure, data-sharing frameworks, and local AI research capacity [4], [5].

For Academia

> The framework serves as a baseline for future research exploring multi-agent reinforcement learning, federated AI models, and hybrid IoT-cloud architectures in traffic systems. It also invites interdisciplinary collaboration between computer scientists, engineers, and transport planners to further contextualize

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digital transformation in African mobility ecosystems.

D. Limitations and Future Work

This study is limited to hardware-in-the-loop simulation; results may differ under real traffic heterogeneity, occlusions, and sensor noise. Future work includes phased on-street pilots across multiple Lusaka intersections with safety oversight and A/B control baselines. While the proposed system achieved notable results, certain limitations provide opportunities for future enhancement. The current implementation was validated under simulated conditions; real-world deployment across multiple intersections will be essential to assess scalability and resilience under variable weather and network environments.

Future studies should integrate computer vision-based vehicle classification, deep reinforcement learning, and blockchain-enabled data security for advanced traffic coordination. Incorporating vehicular ad hoc networks (VANETs) could also enhance communication between vehicles and intersections, improving predictive control.

Additionally, further optimization can be pursued through energy-efficient edge-AI frameworks and 5G-enabled communication to minimize latency and support large-scale deployments.

E. Final Remarks

The findings affirm that localized AI-IoT architectures offer a viable path toward achieving intelligent, environmentally sustainable, and data-driven urban transport systems in developing countries. The system's ability to deliver tangible performance improvements using affordable, open-source technology underscores its potential for nationwide scalability and regional replication.

As African cities continue to urbanize rapidly, embracing context-specific digital solutions such as this will be critical to addressing congestion, enhancing safety, and improving quality of life for urban populations. The integration of smart traffic management into broader smart city frameworks represents not just a technological evolution but a strategic imperative for sustainable development.

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