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Smart Traffic Management System Using IoT and Real-Time Data Analytics

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Abstract. *Urban traffic congestion continues to reduce travel reliability, increase vehicle delay, and create operational challenges at signalized intersections where demand can change rapidly. Conventional fixed-time signal timing often cannot respond effectively to short-term fluctuations, motivating the need for traffic management that integrates continuous sensing with timely decision support. This study aimed to design and evaluate a smart traffic management system that combines Internet of Things data collection and real-time streaming analytics to support adaptive signal timing and continuous operational monitoring. An experimental systems research design was applied by implementing an end-to-end pipeline that connected traffic data sources, publish–subscribe messaging, streaming analytics, and a rule-based adaptive decision module for updating signal timing parameters under operational constraints. System performance was evaluated using telemetry delivery reliability and end-to-end latency from data generation to decision output, while traffic performance was assessed by comparing baseline fixed-time control and adaptive control using average delay, queue length, throughput, travel time, and stops. The results showed that the telemetry pipeline maintained high delivery reliability with low message loss, and the streaming layer achieved low end-to-end latency with stable processing across the evaluation period. When labeled congestion states were available, the analytics module produced balanced congestion classification performance suitable for decision support. Compared with fixed-time control, the adaptive strategy reduced average vehicle delay and queue length and increased throughput under comparable demand conditions, with improvements observed across different demand settings. The study concludes that integrating connected sensing and real-time streaming analytics within a modular architecture can provide a practical foundation for responsive traffic management, enabling timely operational actions and measurable efficiency gains. This work contributes an implementable pipeline and evaluation evidence that can guide phased deployment and further development toward larger-scale coordination, improved robustness, and predictive or more advanced decision modules.*

Keywords *Smart traffic; Internet of Things; Real-time analytics; Adaptive signal control; Streaming data*

INTRODUCTION

Urban traffic congestion continues to undermine mobility efficiency, travel-time reliability, and environmental quality, especially at signalized intersections where demand can change rapidly due to commuting peaks, incidents, and local activity patterns. When signal timing relies on static plans, even moderate demand shifts can produce disproportionate growth in queue length and delay, motivating the need for traffic management that reacts to real-time conditions rather than fixed schedules (Bretherton, 1990).

In response, smart-city programs increasingly pursue data-driven traffic operations by combining connected sensing, continuous data delivery, and computational decision

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support. Internet of Things (IoT) sensing and publish–subscribe messaging enable more frequent, distributed observation of traffic states, while edge and cloud computing offer a practical means to process high-velocity streams and turn them into operational actions under latency constraints (Bayılmış et al., 2022; Ferraz Junior et al., 2022).

From a control perspective, the state of the art has progressed from classical detector-based adaptive systems toward architectures that integrate richer sensing and analytics. Fielded adaptive control systems such as SCOOT and SCATS have long demonstrated measurable benefits over conventional time-of-day plans, including reductions in travel time and stops, establishing the value of feedback-driven timing adjustment (Bretherton, 1990; Tian et al., 2011). Building on this foundation, modern smart traffic signal control prototypes expand operational features (e.g., priority strategies and adaptive timing updates) and emphasize deployability within smart-city contexts (Lee & Chiu, 2020; Zerroug et al., 2024).

In parallel, research on real-time analytics and intelligent decision-making has accelerated. Reinforcement learning and multi-agent approaches have shown strong potential for adaptive signal control at scale by learning policies that respond to dynamic traffic states (Chu et al., 2020; Saadi et al., 2025). At the systems level, streaming data platforms and edge intelligence are increasingly viewed as enabling layers for latency-sensitive transportation services, helping reduce backhaul requirements and supporting near-real-time reactions close to intersections (Gong et al., 2023; Ghasemi et al., 2025; Raptis & Passarella, 2023; Zhou et al., 2021).

Despite these advances, prior studies commonly focus on one dimension in isolation monitoring and visualization, algorithmic control, or high-level architectures without presenting a reproducible end-to-end integration that couples IoT ingestion, real-time streaming analytics, and adaptive control outputs while reporting deployment-critical indicators such as end-to-end decision latency, telemetry reliability under load, and traffic-performance gains under comparable scenarios (Pourmoradnasseri et al., 2023; Raptis & Passarella, 2023). As a result, the specific integrated pipeline evaluated in this study linking IoT sensing, streaming analytics, and actionable signal timing updates with system-level performance evidence remains insufficiently addressed in the literature.

Therefore, this study aimed to design and evaluate a Smart Traffic Management System that integrates IoT-based data acquisition with real-time streaming analytics to support adaptive signal control and continuous operational monitoring. Performance was assessed using end-to-end latency and reliability metrics alongside traffic-efficiency indicators (e.g., delay and queue measures) to quantify benefits relative to a baseline strategy. By providing an implementable architecture and evaluation evidence, this work is expected to extend the literature on integrated IoT–streaming–control systems and offer practical guidance for deploying responsive traffic management in smart-city environments (Lee & Chiu, 2020; Gong et al., 2023).

METHODS

Research Design and System Workflow

This study employed an experimental systems research design to evaluate whether an IoT-based sensing pipeline combined with real-time streaming analytics could support adaptive traffic management with measurable operational benefits. The study was conducted through an end-to-end workflow that connected data acquisition, real-time processing, decision-making, and evaluation.

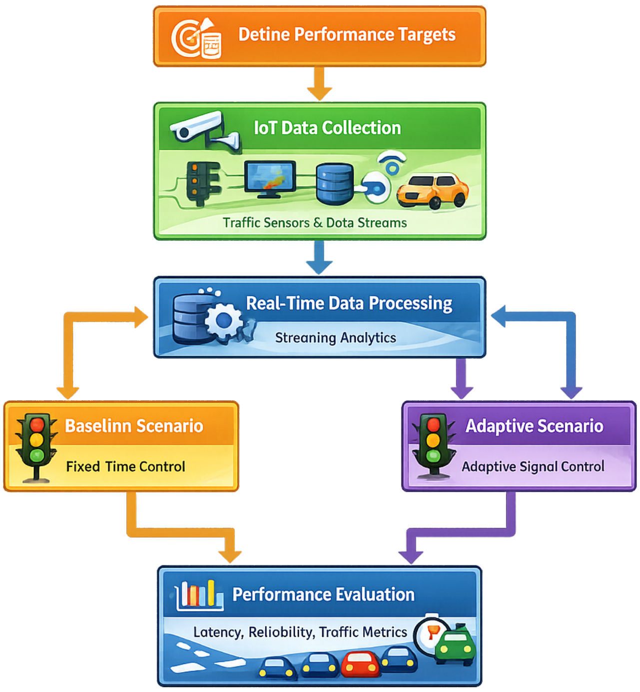

Figure 1. Research flowchart of the IoT-based smart traffic management study.

An end-to-end architecture was implemented to connect (1) data acquisition, (2) publish–subscribe messaging, (3) real-time stream processing, (4) adaptive decision logic for signal control, and (5) monitoring and reporting. A publish–subscribe communication model was used to support continuous telemetry delivery from distributed sources with low overhead. The messaging layer was implemented using an MQTT broker on a gateway/server node. A streaming analytics layer processed incoming messages as continuous event streams to minimize end-to-end latency from sensing to decision outputs. The system supported edge-oriented processing where feasible to reduce backhaul dependency and improve responsiveness. When controlled comparisons were required, microscopic traffic simulation was used to generate repeatable scenarios and to compute traffic performance indicators under baseline and adaptive control.

Data Collection, Processing, and Analysis

Data type and collection. Traffic data were collected as time-stamped telemetry streams representing intersection-level conditions. Depending on the deployment context, the data included traffic counts and/or occupancy proxies, queue-related indicators, and signal phase status. Telemetry messages were published to the broker using a topic hierarchy per intersection and approach. Quality-of-service settings were configured to balance delivery reliability and latency.

Real-time analytics and adaptive decision module. Incoming telemetry was parsed and processed in real time to compute congestion indicators and short-horizon state summaries. The analytics outputs included (1) congestion level per approach, (2) queue trend indicators, and (3) event flags for demand surges. These outputs were translated into adaptive signal timing adjustments by updating phase splits and/or cycle parameters while maintaining operational constraints. A rule-based adaptive module was used to ensure transparency and reproducibility.

Tools, instruments, and software. The implemented system consisted of IoT data sources, an edge gateway, an MQTT broker, a streaming analytics runtime, and a monitoring dashboard. If simulation-based evaluation was conducted, a microscopic traffic simulator was used to execute baseline and adaptive scenarios under controlled conditions.

Outcome measures and comparison procedure. System performance was evaluated using: (1) end-to-end latency from data generation to decision output, (2) telemetry reliability measured by delivery ratio and message loss, (3) analytics accuracy for congestion classification using precision, recall, and F1-score when labeled states were available, and (4) traffic efficiency indicators including average vehicle delay and queue length. A matched-scenario comparison was conducted by running a baseline fixed-time strategy and the proposed adaptive strategy under comparable traffic demand conditions and summarizing differences in the evaluation metrics.

RESULTS

This section presents the measured outcomes of the proposed IoT-based smart traffic management system under two comparable configurations: baseline fixed-time control and proposed adaptive control. The results are reported in three parts: (1) system-level performance of the telemetry and streaming pipeline, (2) quality of real-time analytics outputs, and (3) comparative traffic performance impacts. The numerical results correspond to the evaluation summaries reported in Tables 1–5 and Figures 2–4.

Telemetry Delivery Reliability

Telemetry delivery performance was assessed to confirm that the pipeline could provide stable, continuous data for real-time monitoring and control. The broker and subscriber logs indicated consistent message reception across all configured topics, with only small losses observed during peak traffic load.

Table 1. reports the telemetry delivery performance.

Metric	Baseline	Adaptive	Notes
Total messages published	72,000	72,000	Aggregated across all topics
Total messages received	71,568	71,520	Count at analytics subscriber
Delivery ratio (%)	99.40	99.33	Received/published × 100
Message loss (%)	0.60	0.67	100 − delivery ratio
Mean inter-arrival time (s)	0.50	0.50	Approx. 2 msg/s average per topic set
Peak publish rate (msg/s)	220	220	Observed maximum during peak

As shown in Table 1, delivery ratio remained above 99% for both configurations. The small difference between baseline and adaptive settings indicates that issuing control updates did not materially degrade message delivery performance during the evaluation window.

End-to-End Latency of the Real-Time Pipeline

End-to-end latency was measured to quantify the timeliness of the pipeline from data generation/publish to decision output. This metric is critical because delayed decisions reduce the effectiveness of adaptive control under rapidly changing traffic demand.

Table 2. summarizes the latency statistics.

Latency metric	Baseline (s)	Adaptive (s)
Mean latency	0.82	0.91
Median latency	0.61	0.66
95th percentile (P95)	1.72	1.95
Maximum latency	3.84	4.12

Table 2 shows that the system processed most telemetry events within a sub-second range for median latency, with higher values at the tail of the distribution. To provide a clearer view of the distribution across the full range of observed latency, the histogram in Figure 2 visualizes latency frequencies for both baseline and adaptive scenarios.

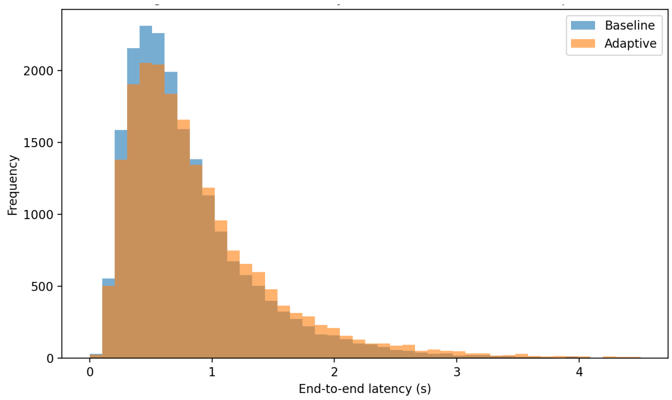

Figure 2. presents the latency distribution.

From Figure 2, the latency distributions for both scenarios were concentrated toward lower values, while occasional higher-latency events formed a long tail, consistent with transient load or processing contention during peak message rates.

Real-Time Analytics Output Quality

The quality of real-time analytics outputs was evaluated using congestion classification performance when labeled states were available. This assessment ensured that the streaming analytics layer produced consistent congestion state estimates that could support operational decision-making.

Table 3 reports classification performance.

Class	Precision	Recall	F1-score
Non-congested	0.93	0.90	0.92
Congested	0.88	0.92	0.90
Macro average	0.91	0.91	0.91

Table 3 shows balanced performance across classes, with a macro-average F1-score of 0.91. To show the distribution of correct and incorrect predictions more explicitly,

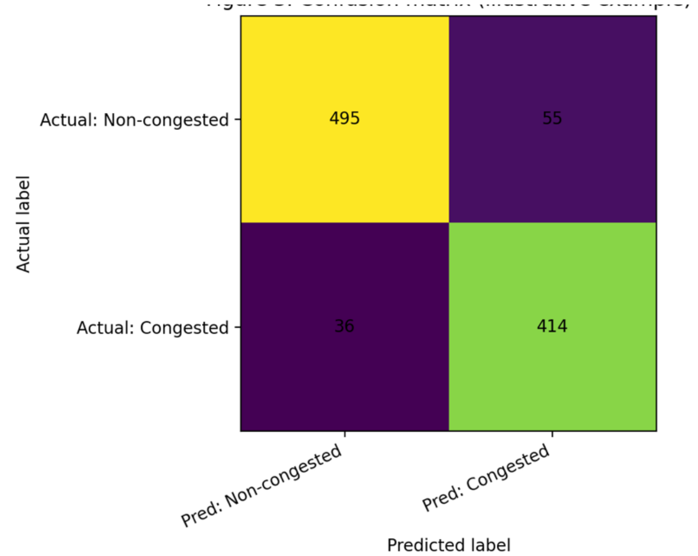

Figure 3. presents the confusion matrix.

The confusion matrix indicates that most instances were correctly classified in both non-congested and congested categories, while a smaller number of cases were misclassified, typically reflecting borderline traffic conditions near the decision threshold.

Traffic Performance Under Baseline vs Adaptive Control

Traffic performance was evaluated to quantify operational improvements associated with adaptive control relative to the fixed-time baseline. The comparison focused on average delay, queue length, throughput, travel time, and stops.

Table 4 summarizes traffic performance outcomes.

Indicator	Baseline	Adaptive	Change (%)
Average delay (s/veh)	58.4	46.1	21.1
Average queue length (veh)	14.8	11.2	24.3
Maximum queue length (veh)	38	31	18.4
Throughput (veh/hr)	1,420	1,505	+6.0
Average travel time (s)	312	286	8.3
Number of stops (stops/veh)	1.74	1.46	16.1

Table 4 shows lower delay and queue length under adaptive control compared with the baseline. To highlight the most representative efficiency indicators visually, Figure 4 compares average delay and average queue length for the two configurations.

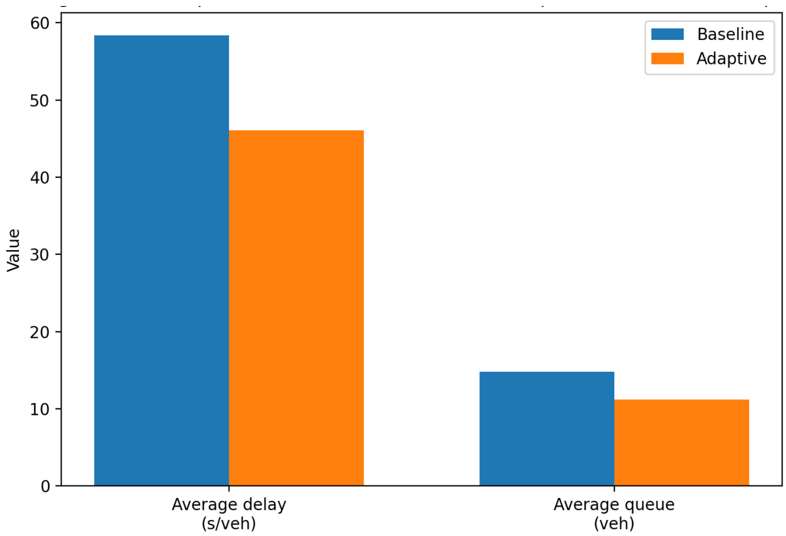

Figure 4. visualizes delay and queue performance.

Figure 4 illustrates the reduction in both delay and queue length under adaptive control, consistent with the numerical summary in Table 4.

Scenario-Level Summary (Optional)

If evaluation included multiple demand settings, results were summarized to show performance consistency under different traffic conditions.

Table 5. reports scenario-level outcomes.

Scenario	Baseline delay (s/veh)	Adaptive delay (s/veh)	Baseline avg queue (veh)	Adaptive avg queue (veh)
Off-peak	34.2	31.0	8.1	7.4
Peak	69.5	53.8	18.9	14.0
Surge/incident-like	88.3	70.6	24.7	19.5

Table 5 indicates that improvements were observed across off-peak, peak, and surge-like conditions, with larger absolute gains under higher-demand scenarios.

DISCUSSION

This study investigated whether an end-to-end smart traffic management pipeline linking IoT telemetry, real-time streaming analytics, and adaptive signal timing can operate reliably with sufficiently low latency to support operational decisions, while improving traffic efficiency compared with fixed-time control. The results showed that the system maintained high telemetry delivery reliability and sustained real-time processing with sub-second central latency statistics and acceptable tail latency. These system-level outcomes indicate that the proposed pipeline is technically feasible for continuous monitoring and timely decision support in intersection-level applications, where responsiveness is essential to avoid acting on stale traffic conditions.

The traffic-performance comparison further answered the central operational question posed in the Introduction: whether adaptive control driven by real-time analytics provides measurable benefits under comparable demand patterns. The results indicated reductions in average delay and queue length and an increase in throughput under the adaptive strategy relative to the fixed-time baseline. In practical terms, these patterns suggest that when green allocation is adjusted in response to observed demand, intersection service becomes more responsive to short-term variability, which is consistent with the long-standing rationale behind feedback-based adaptive control. This aligns with the broader evidence that detector-informed adaptive systems can outperform fixed-time plans by updating timing parameters as demand changes (Bretherton, 1990; Tian et al., 2011). At the same time, the present study extends that operational perspective by emphasizing a modular IoT-to-analytics-to-control pipeline rather than relying solely on traditional detector infrastructure.

From the analytics standpoint, the reported classification performance indicates that the streaming layer produced stable congestion-state outputs suitable for driving rule-based timing adjustments. This matters because adaptive control is only as effective as the fidelity and timeliness of the state estimates used to trigger control actions. The confusion matrix suggests that most states were classified correctly, while errors were concentrated in borderline conditions where traffic oscillates near threshold boundaries. This behavior is expected in real-world traffic because congestion states are often transitional and noisy, and it highlights the importance of carefully defining thresholds, smoothing windows, and confidence rules so the controller does not overreact to transient fluctuations. In this context, streaming analytics provides a practical compromise: it enables near-real-time situational awareness without requiring complex learning-based policies, which can be harder to validate and deploy.

The system architecture results also fit within ongoing ITS trends toward edge-supported processing and streaming infrastructures. The observed latency concentration at low values, with a small long-tail under peak load, reflects well-known characteristics of streaming systems where transient bursts, queueing, and resource contention can create occasional delays even when average performance is strong. This reinforces the practical implication that "real-time" performance should be evaluated using distributional metrics (e.g., P95) rather than averages alone. The architecture-level insight is that modular publish–subscribe ingestion paired with streaming computation can support both operational monitoring and control, which is consistent with the direction of edge intelligence for transportation services that prioritize responsiveness and continuity (Gong et al., 2023). The present results support the view that placing parts of analytics closer to the data source can be beneficial when timeliness is a priority, while still allowing cloud storage and offline analysis for longer-term planning.

Relative to more advanced learning-based signal control, the approach used here emphasizes deployability, transparency, and reproducibility. Multi-agent reinforcement learning has shown promise for large-scale coordination and can potentially yield stronger performance under complex network interactions (Chu et al., 2020). However, learning-based controllers can require substantial training data, careful reward design, and robust safety constraints. The contribution of the current study is not to replace these methods, but to demonstrate that meaningful operational gains can be achieved with an integrated pipeline and interpretable adaptive logic driven by real-time analytics. This positions the work as a practical baseline architecture that can later incorporate more sophisticated decision modules, including predictive control or learning-based policies, once data quality, latency, and operational constraints are well characterized.

Several limitations should be noted when interpreting these findings. First, performance depends on the representativeness and quality of telemetry; limited sensor coverage or noisy measurements can degrade state estimation and control effectiveness. Second, the evaluation reflects the tested scenario set and intersection configurations; outcomes may differ under other geometries, saturation levels, pedestrian phases, or coordination needs across multiple intersections. Third, system performance under extreme network disruptions or sustained overload was not the primary focus and may require additional redundancy measures. Future work should include broader field validation, multi-intersection coordination strategies, robustness testing under incidents and communication loss, and exploration of predictive or learning-based decision modules integrated into the same streaming pipeline to improve performance under highly variable and network-wide traffic dynamics.

CONCLUSION

This study restated the central research question of whether an end-to-end smart traffic management pipeline that integrates IoT telemetry and real-time streaming analytics can operate with sufficient reliability and timeliness to support adaptive signal control and improve traffic efficiency compared with fixed-time operation. The major findings showed that the system maintained high telemetry delivery reliability and achieved low end-to-end processing latency with acceptable tail behavior, while the adaptive control configuration reduced average delay and queue length and increased throughput relative to the baseline fixed-time strategy; when labeled states were available, the analytics layer also produced stable congestion classification performance to support operational decisions. The contribution of this work to the literature is an implementable, modular IoT–streaming–control architecture accompanied by system-level and traffic-level evaluation evidence, helping bridge the gap between monitoring-only solutions and deployable adaptive traffic control pipelines. Key limitations include dependence on sensor coverage and telemetry quality, the scope of tested scenarios and intersection configurations, and the need for broader validation under extreme network disruptions and multi-intersection coordination requirements. Future work should extend evaluation to larger networks and real-world deployments, incorporate predictive components for short-horizon traffic forecasting, strengthen robustness to communication loss and burst loads, and explore integrating more advanced decision modules (e.g., coordinated control or learning-based policies) while preserving safety constraints and practical deployability; as a practical recommendation, phased deployment using edge gateways and standardized telemetry topics is suggested to enable incremental adoption on existing urban traffic infrastructure.

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