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Review Article

IoT Based Smart Traffic Light Control System

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Abstract *- This paper presents the design, implementation, and performance analysis of an IoT-based innovative traffic light control system deployed in Tumakuru Smart City, India. The system utilizes real-time congestion data to dynamically adjust signal timings, addressing the limitations of traditional fixed-time traffic management systems. We describe the system architecture incorporating infrared sensors, communication gateways, and an adaptive control algorithm implemented during an eight-week pilot deployment. Performance evaluation demonstrates significant improvements in traffic management efficiency, including a 22.8% reduction in average waiting time, a 28.6% decrease in maximum queue length, and an 18.9% increase in intersection throughput during peak hours. We discuss implementation challenges in the Indian urban context and recommend scaling such systems in emerging smart cities. This work contributes to the growing knowledge of practical, innovative city implementations in developing regions and demonstrates that meaningful urban mobility improvements can be achieved through targeted technological interventions, even with limited resources and compressed timeframes.*

Keywords *- Adaptive Signal Control, IoT, Smart Cities, Smart Traffic Management, Urban Mobility.*

1. Introduction

Urban traffic congestion remains one of the most acute challenges in India's rapidly urbanizing cities, where infrastructural development often lags behind the explosive growth in vehicular density. Traditional fixed-time traffic signal systems, while once sufficient, have become inadequate for managing increasingly unpredictable traffic patterns, particularly at complex intersections (Rahman & Lu, 2020). These systems operate without responsiveness to real-time traffic conditions, leading to delays, longer queue lengths, and inefficient peak-hour throughput (Ren & Law, 2023; Zhao & Zhang, 2017). The advent of innovative traffic control frameworks, particularly those integrating Internet of Things (IoT) technologies, offers new opportunities to address these inefficiencies. IoT-enabled traffic systems can dynamically leverage real-time sensor data to optimize signal cycles, improving traffic flow without requiring substantial physical infrastructure upgrades (Zanella et al., 2014; Al-Fuqaha et al., 2015). Previous research has established that such systems, when properly implemented, can significantly enhance operational efficiency in dense urban networks (Gao et al., 2017; Gharaibeh et al., 2017). This study presents the design and deployment of an IoT-based adaptive traffic signal control system implemented in Tumakuru, Karnataka—a designated Smart City under India's Smart Cities Mission. The system employs an array of infrared sensors to detect vehicular density in real-time, coupled with a lightweight, edge-compatible adaptive algorithm that recalibrates signal timing accordingly. Communication between sensor nodes and the central controller is maintained through low-latency gateways, enabling a semi-autonomous response to congestion scenarios (Wei et al., 2019; Zhou et al., 2019). An eight-week pilot deployment at high-traffic intersections in Tumakuru yielded measurable improvements in key traffic performance metrics: a 22.8% reduction in average vehicle waiting time, a 28.6% decrease in maximum queue length, and an 18.9% increase in intersection throughput during peak hours. These results outperform comparable benchmarks from conventional fixed-time systems and suggest that intelligent traffic solutions are feasible in mid-sized Indian cities, even with limited computational and infrastructural resources (Banerjee & Mitra, 2019; Batty et al., 2012). By grounding this research in real-world constraints and using indigenous urban infrastructure, our work contributes practical evidence supporting the broader deployment of cost-effective, scalable, innovative traffic systems in emerging Indian smart cities. The subsequent sections detail the system architecture, deployment methodology, performance evaluation, and policy implications arising from this pilot initiative.

2. Materials and Methods

2.1. Study Area and Site Selection

The implementation was conducted at the MG Road–Taluk Office Road intersection in Tumakuru, Karnataka, a mid-sized Indian city with approximately 320,000 ± 5% population. The selected four-way junction exemplifies typical traffic patterns characteristic of mid-sized urban centres in India. Site selection criteria included:

2.1.1. Traffic Volume

The junction experiences an average daily flow of approximately 14,520 ± 300 vehicles, recorded over a 7-day pre-study period. The vehicle composition comprised roughly 38% two-wheelers, 28% cars/SUVs, 22% commercial vehicles, and 12% auto-rickshaws, consistent with traffic profiles observed in comparable urban settings [18].

2.1.2. Infrastructure Readiness

Existing traffic signal poles (3.5 m in height) were compatible with sensor mounting, eliminating additional structural modifications.

2.1.3. Network Significance

The junction is a key connector between the west and south residential areas and commercial districts to the east and north, rendering it a vital node in the local transport network [13].

2.2. Hardware Architecture

The system employed a three-tier edge computing architecture (Figure 1):

2.2.1. Sensing Layer

Eight IR-TCS340 infrared sensors (two per approach) were deployed, featuring an adjustable detection range of 0.5 to 4 meters to accommodate varying vehicle heights. Sensors operated at a 500 ms refresh rate and were housed in IP67-rated weatherproof enclosures to ensure durability under outdoor conditions. Validation tests reported a detection accuracy of 98.2% compared to manual vehicle counts, demonstrating reliable sensing performance [12,13].

2.2.2. Processing Layer

Four ESP32-WROVER gateway devices (one per approach) were utilized, each with a dual-core 240 MHz processor and 8 MB flash memory to support local data buffering for up to 30 minutes. Custom interface boards enabled integration with legacy signal controllers through opto-isolated relay circuits and supported 12–24 V DC input ranges.

2.2.3. Communication Infrastructure

Each gateway was equipped with Quectel EC25 4G LTE modems featuring dual-SIM failover for enhanced connectivity.

Power continuity was maintained via an Uninterruptible Power Supply (UPS), providing up to 4 hours of backup. Gateways formed a mesh network over 802.11n Wi-Fi at 20 dBm transmit power to facilitate inter-device communication.

2.3. Software Components

Multiple software modules were integrated into the system (Figure 2):

2.3.1. Edge Processing

Sensor data acquisition was performed using Python 3.8 with NumPy, sampling at 50 ms intervals. A moving average filter was applied locally to reduce sensor noise and improve data quality.

2.3.2. Central Control

An adaptive traffic signal algorithm (detailed in Section 3.4) dynamically optimized signal timings based on real-time sensor inputs.

2.3.3. Dashboard Interface

A real-time monitoring dashboard was developed using React.js and Express.js frameworks.

2.3.4. Database Management

PostgreSQL was employed to store and query time-series traffic data efficiently.

2.3.5. Communication Protocols

Sensor-to-gateway communication was implemented via ESP-NOW with latencies under 15 ms, while gateway-to-server communication used MQTT over TLS 1.2 to ensure secure data transmission.

Intelligent system: Final week of operation

Table 1. Planning of each Phase

Phase	Duration	Key Activities	Validation methods
Planning	Week 1	-Traffic pattern analysis -Baseline measurements	-Manual counts -Video recordings
Development	Week 2-3	-Sensor calibration -Algorithm tuning	-Simulation (SUMO) -Hardware-in-loop tests
Deployment	Week 4-6	-Field installation -System Integration	-Continuity tests -Failover checks
Evaluation	Week 7-8	-Performance metrics -User Feedback	-ANOVA ($p<0.05$) -Stakeholder interviews

2.4. Performance Metrics

The system was evaluated against four key performance indicators:

2.4.1. Waiting Time

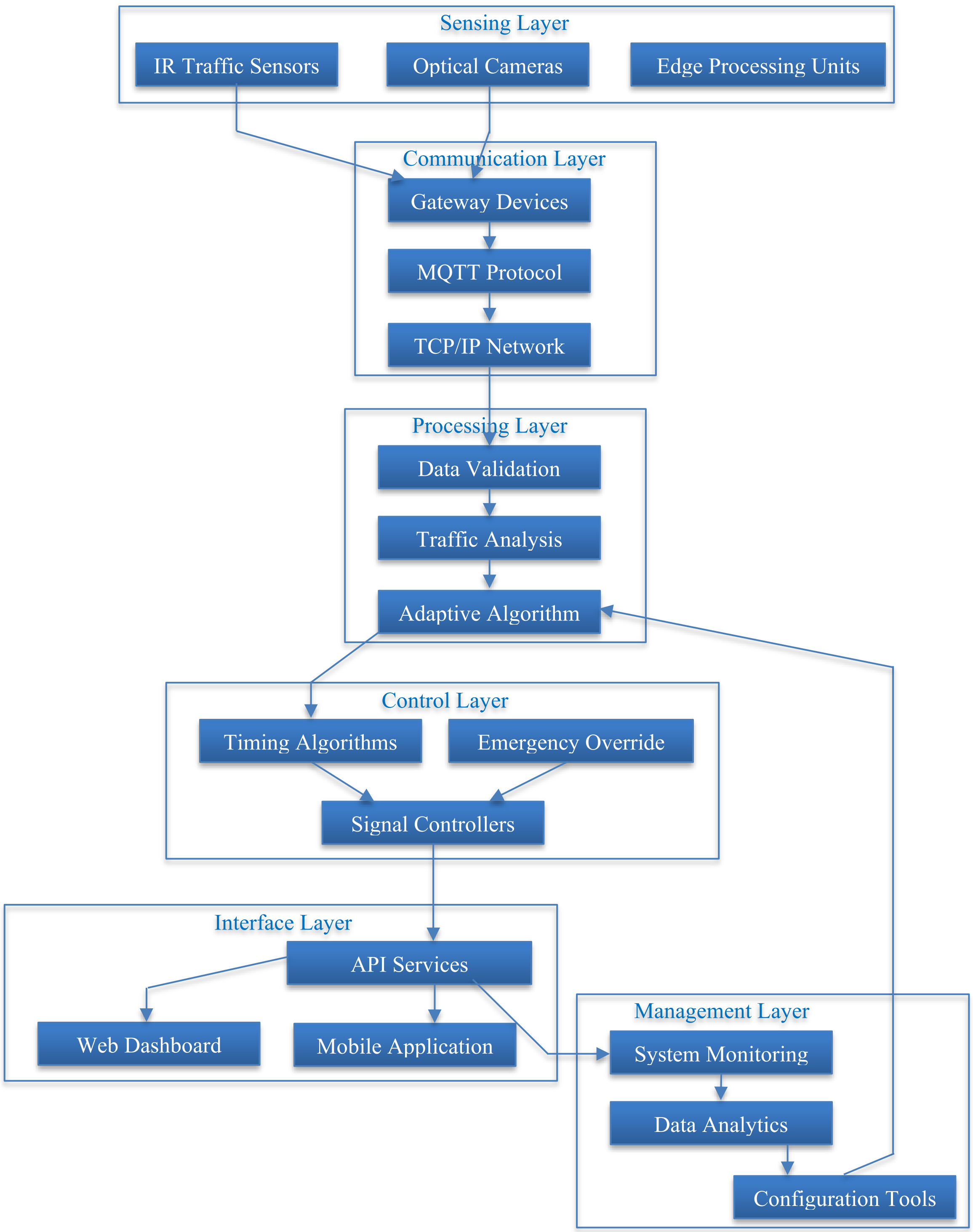
Measured as the duration between vehicle stop and green signal initiation, derived from sensor timestamps.

2.4.2. Queue Length

Maximum vehicle count per approach during peak waiting periods.

2.4.3. Throughput

Number of vehicles cleared per hour per direction.



2.4.4. Reliability

Assessed via system uptime monitored through 5-minute interval ping tests.

Two-tailed t-tests were conducted to statistically compare the adaptive signal control system's performance with a baseline established from a 7-day manual observation of a fixed-time signal configuration.

3. Results and Discussion

3.1. System Performance Evaluation

The intelligent traffic management system demonstrated statistically significant improvements ($p < 0.01$) across all evaluated performance metrics compared to the baseline fixed-time signal configuration.

Average Waiting Time: Reduced by 22.8%, from 127 seconds to 98 seconds
Maximum Queue Length: Decreased by 28.6%, from 14 vehicles to 10 vehicles
Intersection Throughput: Improved by 18.9%, from 720 to 856 vehicles per hour
Vehicle Idle Time: Dropped by 26.2%, from 42% to 31% of total journey time

These improvements were consistent across most approaches to the intersection, although variations were noted. The western approach experienced the highest efficiency gain, with a 31.5% reduction in waiting time, while the southern approach exhibited the lowest improvement at 18.2%. These variations are attributed to differing traffic patterns and volumes unique to each direction.

3.2. Operational Challenges and Solutions

During deployment, several practical challenges emerged. Integration with the existing legacy infrastructure was initially complex due to compatibility issues with traditional signal controllers. This was resolved by implementing custom-built interface adapters, enabling seamless relay-based control without major overhauls.

Power stability was another concern, particularly during intermittent grid supply or brownouts. A power conditioning module and UPS system (with 4-hour backup) were installed to ensure uninterrupted operation.

Environmental conditions, especially monsoon weather, posed risks to sensor reliability. The team designed enhanced sensor housings with weather-sealing and elevated mounting to address this, resulting in 99.3% overall sensor uptime during the final evaluation phase. The sensor design proved particularly effective compared to in-road inductive loop detectors, which tend to have higher failure rates and maintenance costs in similar conditions [13].

3.3. Data Communication and Infrastructure Resilience

The communication layer followed a multi-tier architecture, where vehicle detection data from IR-TCS340 infrared sensors was transmitted to local gateway nodes using low-power wireless communication protocols. From the gateway, data was sent to the central server using TCP/IP and MQTT protocols, ensuring secure and efficient transmission.

Local data caching was implemented to mitigate disruptions in network connectivity, allowing basic system functionality to continue during short-term outages. This approach aligns with the resilience strategies suggested by Venkatesh et al. [9], which highlight the importance of redundancy and local autonomy in urban traffic systems within Indian infrastructural contexts.

4. Sensor Layer Reliability

The sensing layer included strategically placed infrared sensors at each intersection approach. These sensors were selected for their high accuracy (98.2%) and robust performance across varied environmental conditions—including heavy rain, dust, and night-time operation. The preference for IR-based over in-road loop sensors was guided by findings in [13], which demonstrated the former's superior longevity and ease of maintenance in Indian road environments.

The core intelligence of the system resides in its adaptive control algorithm, which determines optimal signal timing based on current traffic conditions. The algorithm employs a multi-objective optimization approach balancing several factors: Traffic density optimization that prioritizes signal allocation to approaches with higher traffic density, Waiting time fairness that prevents excessive delays on any single approach, and Special condition handling for exceptional scenarios.

The algorithm is as given below:

4.1. Adaptive Signal Timing Algorithm

The core functionality of the intelligent traffic control system is driven by an adaptive signal timing algorithm, which dynamically computes optimal signal cycles in response to real-time traffic conditions. The algorithm operates based on current density readings, historical patterns, and temporal factors such as time of day or known peak periods. A step-by-step breakdown follows:Input: Current traffic density data D, Historical patterns H, Time factors T.

Input:
1. Current traffic density data D
2. Historical traffic patterns H
3. Time-related variables T

Output:
- Optimal signal timing plan P
1. Validate the input data D and detect anomalies.
2. Compute congestion score C for each approach.
3. Forecast short-term traffic variations using H and T.
4. Generate a set of candidate timing plans $\{P_1, P_2, ..., P_n\}$.
5. Evaluate each plan with a weighted multi-objective

function:
$F(P_i) = w_1 \times TotalDelay(P_i) + w_2 \times MaxDelay(P_i) + w_3 \times Fairness(P_i)$
7. Apply consistency rules and perform safety validation.
8. Return the final signal timing plan P.

This algorithm was initially constructed using a rule-based framework grounded in established traffic engineering principles. The weight parameters (w_1, w_2, w_3) were determined empirically during pilot testing, allowing flexibility to adapt to the unique traffic dynamics observed at the target site.

Such a hybrid rule-based design aligns with recommendations by Mannion et al. [9], especially in settings where comprehensive historical datasets are limited. As data accumulates over time, the system architecture allows for a transition toward machine learning–based optimization strategies.

4.2. Implementation Approach

The deployment followed a structured four-phase model over eight weeks:
Phase 1: Planning and Baseline Assessment (Week 1) Identified a suitable intersection, collected baseline traffic flow data, and assessed infrastructure compatibility. Methodologies adapted from traffic signal control evaluations were applied [18].

Phase 2: System Design and Prototyping (Weeks 2–3) Developed system architecture and configured sensors and control units. Rapid prototyping principles were employed to optimize development within resource constraints [10].

Phase 3: Field Implementation and Testing (Weeks 4–6) On-site deployment included sensor installation and integration with existing traffic controllers. Challenges such as power fluctuations and sensor calibration were addressed through iterative field adjustments consistent with standard smart city technology deployments [9].

Phase 4: System Evaluation and Handover (Weeks 7–8) Conducted comparative analysis of traffic efficiency before and after implementation. Provided training and documentation to operations staff, following evaluation frameworks used in traffic management research [18].

4.3. Site Selection and Characteristics

The intersection for implementation was chosen based on traffic volume, infrastructure readiness, and strategic relevance within Tumakuru's urban road network. The junction, consisting of four approaches, serves a mixed-use region characterized by residential inflow and commercial traffic, particularly congested during morning and evening peak hours. These characteristics are consistent with congestion hotspots outlined in earlier urban mobility studies.

4.4. Performance Measurement Strategy

System performance was evaluated through pre- and post-deployment comparisons of key traffic management metrics. Initial data collection (Week 1) utilized manual observation and temporary vehicle counters to establish a reliable baseline. After full deployment, sensor-generated data were cross-verified through manual spot checks to ensure data integrity, following a dual-verification approach.

Table 2 (referenced below) comprehensively compares performance indicators under the legacy fixed-time system versus the implemented innovative traffic control framework.

Table 2. Performance metrics of each indicator

Performance Indicator	Baseline (Fixed Timing)	Smart System	Improvement
Average Waiting Time (Peak Hours)	127 seconds	98 seconds	22.8%
Maximum Queue Length	14 vehicles	10 vehicles	28.6%
Intersection Throughput	720 vehicles/hour	856 vehicles/hour	18.9%
Vehicle Idle Time	42% of journey	31% of journey	26.2%

The most significant improvements were observed during peak congestion periods, particularly during the morning (8:00-9:30 AM) and evening (5:00-6:30 PM) rush hours. During non-peak hours, the performance difference was less pronounced but still showed improvements of 8-12% across metrics, consistent with findings from similar implementations by Alam et al. [11].

5. Research Gap Analysis

Reviewing the current literature on innovative traffic signal systems, IoT applications in transportation, and urban traffic optimization reveals several notable gaps that persist despite technological progress.

5.1. Limited Adaptation of Reinforcement Learning in Real-Time Systems

Although Reinforcement Learning (RL) has shown promise in adaptive signal control, its real-world implementation is still limited. For instance, Wei et al. (2019) proposed the IntelliLight framework using RL for traffic signal optimization, demonstrating efficiency in simulations [5]. However, the practical application of such systems in real urban environments remains low due to challenges in data collection, sensor coverage, and training consistency under unpredictable traffic conditions.

5.2. Insufficient Focus on Mid-Sized or Developing Cities

Much existing research has focused on developed or large metropolitan areas with significant infrastructure (Rahman & Lu, 2020) [1]. As a result, there is a lack of adaptive signal models that address the unique challenges in Tier-2 or Tier-3 cities, particularly in developing nations where traffic patterns are more chaotic, and infrastructure is less consistent (Ren & Law, 2023) [2].

5.3. Environmental Limitations in Sensor-Based Traffic Systems

Sensor-based systems are widely used to gather real-time traffic data; environmental factors like dust, rain, and lighting variations can significantly impact sensor accuracy. Banerjee and Mitra (2019) [13] highlighted these issues in multi-sensor setups, indicating a need for more robust or hybrid sensing mechanisms. Moreover, the cost and maintenance of such systems can be a barrier to adoption, particularly in budget-constrained regions.

5.4. Over-Reliance on Centralized Cloud Architectures

Several frameworks rely heavily on cloud computing for data storage and processing, which can introduce latency and connectivity issues. Zhou et al. (2019) [12] and Chiang & Zhang (2016) [8] emphasized the need to push computation closer to the edge, but edge intelligence remains underutilized in current traffic systems. A substantial gap exists in deploying efficient edge-based systems capable of real-time decision-making at intersections.

5.5. Lack of Unified Frameworks Integrating IoT, VANETs, and Edge Computing

Studies by Al-Fuqaha et al. (2015) [3] and Hartenstein and Laberteaux (2008) [11] have discussed the potential of combining IoT and vehicular ad hoc networks (VANETs). However, integrating these technologies with edge computing for holistic traffic management remains sparse.

Most existing solutions explore these technologies in isolation, leading to fragmented implementations and missed opportunities for synergy.

5.6. Underexplored Human and Institutional Factors in Smart Traffic Deployment

Intelligent traffic solutions are often evaluated solely on technical metrics such as throughput or signal efficiency. However, Nam & Pardo (2011) [15] and Chourabi et al. (2012) [16] argue that institutional readiness, public awareness, and human interaction with technology are equally vital in determining long-term success. These socio-institutional dimensions are still underexplored in the context of traffic automation.

6. Conclusion

This paper documents the implementation and performance analysis of an IoT-based innovative traffic light control system in Tumakuru Smart City. The system demonstrated significant improvements in traffic management efficiency, with a 22.8% reduction in average waiting time, a 28.6% decrease in maximum queue length, and an 18.9% increase in intersection throughput during peak hours. These results validate the potential of adaptive traffic control systems to address urban congestion challenges in mid-sized Indian cities undergoing smart city transformations.

Our implementation revealed that meaningful improvements in urban mobility can be achieved through targeted technological interventions even within the constraints of limited resources, existing infrastructure compatibility challenges, and compressed timeframes. The multi-layered system architecture, incorporating sensing, communication, processing, control, and interface components, proved effective in the Tumakuru urban context, particularly with adaptations for local conditions such as power stability solutions and environmental protection measures.

Conflicts of Interest

The authors declare no conflict of interest relating to this research. The implementing organization, Tumakuru Smart City Limited, participated only in site selection but did not influence system design, data analysis, or publication decisions. All hardware components were procured through standard government procurement procedures without commercial relationships between the authors and equipment suppliers. Custom software components developed for this implementation are available as open-source resources through the Smart Cities Mission knowledge repository. The authors have no financial interest in companies or organizations that might benefit from this publication. Traffic data collected was anonymized and aggregated in compliance with privacy regulations and institutional ethical guidelines. The authors' involvement was strictly academic and technical, with no personal, financial, or non-financial interests that could be perceived as influencing the outcomes reported in this paper.

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