# Integrated Traffic Management System

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**Abstract -** *Urban traffic congestion remains one of the most critical challenges faced by rapidly growing cities worldwide. Conventional traffic signal systems rely on fixed time intervals that are incapable of adapting to real-time traffic conditions, resulting in excessive waiting times, fuel waste, increased air pollution, and delayed emergency vehicle response. This paper presents the design and conceptual implementation of an Integrated Traffic Management System (ITMS), a comprehensive intelligent framework that addresses these challenges through four tightly integrated subsystems. First, an intersection camera module employs computer vision to perform direction-wise vehicle counting, pedestrian detection, and anomaly identification in real time. Second, a novel Grid-Based Detection System divides each traffic lane into a 10×6 occupancy grid of 60 cells covering a 100-meter range, assigning hierarchical density grades (S, A, B, C, D) using a weighted averaging formula. This grid-based approach serves as a robust fallback mechanism when object detection fails due to adverse weather. Third, a Priority Scoring System assigns calibrated weights to six vehicle categories, with emergency vehicles receiving an absolute override score of 1000, and calculates a per-lane Composite Score using a fusion of grid grades and proximity-based priority weights. Lane opening combinations are classified into three states: Safe, Less Congestion, and Lesser Congestion, enabling simultaneous non-conflicting lane service. Fourth, a Gamified Reward Mechanism incentivizes road compliance by awarding driver behavior points across three priority tiers, converting them into digital credits and classifying drivers into bronze, silver, and gold tiers with compounding bonus multipliers. All subsystems are coordinated through a Centralized Management System (CMS). Simulation results and design validation demonstrate that the proposed ITMS reduces unnecessary red-light waiting, enables dynamic green time allocation, prioritizes emergency vehicles with zero manual intervention, and motivates safe driving behavior through measurable incentives. The system is designed for scalability within smart city infrastructure*.

***Key words* -** Intelligent Traffic Management System; Occupancy Grid Map; Priority-Based Signal Control; Computer Vision; Emergency Vehicle Prioritization; Reward-Based Compliance; Smart City; Adaptive Traffic Signals; Vehicle Detection; Centralized Management System.

## 1 INTRODUCTION

In recent decades, rapid urbanization has intensified vehicular density in cities across the developing and developed world. The United Nations projects that approximately two-thirds of the global population will inhabit urban areas by 2050, placing unprecedented demand on road infrastructure [1].

Traffic congestion, road accidents, and air pollution are direct consequences of inadequate traffic management systems that fail to adapt dynamically to real-time conditions [2].

Traditional traffic signal systems operate on pre-programmed, fixed-time cycles that distribute green time uniformly across all lanes regardless of actual traffic demand [3]. This static approach generates several well-documented inefficiencies: unnecessary waiting at empty or low-traffic junctions, inability to detect and respond to emergency vehicles, no mechanism to prioritize high-occupancy public transport, and the complete absence of any driver incentivization for compliance [4]. These limitations have a measurable impact on urban productivity, public health, and emergency response effectiveness [5].

Intelligent Transportation Systems (ITS) have emerged as a promising paradigm to address these challenges. Research in the domain has produced a wide spectrum of solutions ranging from infrared sensor-based prototypes and RFID-enabled priority systems to deep reinforcement learning controllers and IoT-integrated frameworks [6]–[8]. However, most existing approaches address only one or two dimensions of the traffic management problem, lack robustness under adverse environmental conditions such as rain and fog, and fail to incorporate behavioral incentive mechanisms for road users [9].

## 2 LITERATURE REVIEW

The field of intelligent traffic management has been extensively studied, with solutions spanning hardware prototypes, simulation-based frameworks, and cloud-integrated systems. Sunardi et al. [3] developed an intelligent traffic light system using infrared (IR) sensors mounted at near and far distances in each lane. The system adjusts green signal duration based on vehicle detection at these two points and allows manual priority override via a Bluetooth-connected smartphone application using Arduino Mega 2560. While effective as a prototype, this approach depends on fixed hardware sensors and does not support vehicle classification, weather- robust detection, or driver incentivization.

Elsagheer Mohamed and AlShalfan [5] proposed an ITMS based on the Internet of Vehicles (IoV) and VANET infrastructure. Their adaptive algorithm dynamically allocates green time based on real-time vehicle count transmitted wirelessly through onboard units. Simulation results show a significant reduction in average waiting time compared to the fixed-time algorithm, with serviced vehicle counts increasing by up to 223% under high-density conditions. However, the system requires specialized IoV hardware in each vehicle, which limits near-term practical deployment. up to 223% under high-density conditions. However, the system requires specialized IoV hardware in each vehicle, which limits near-term practical deployment. Hashmat Fida et al. [6] introduced an IoT-based traffic management system using Ultra-Wideband (UWB) technology to create dynamic Green Corridors for emergency vehicles. UWB tags mounted on ambulances are detected by roadside readers, which automatically switch traffic lights to green, clearing a path for the emergency vehicle. While the system demonstrated a 70% reduction in emergency vehicle clearance time in SUMO simulation, it targets only the emergency vehicle use case and does not address general traffic density management.

Kanawade et al. [7] presented a Smart Traffic Management System using the YOLO (You Only Look Once) deep learning object detection model. The system uses a camera-based vehicle count to dynamically adjust signal timer durations. Trained on the IDD (India Driving Dataset) with 10,000 images across 34 categories, the model achieved a mean average precision (mAP50) of 0.156 across all vehicle types. While this approach demonstrates real-time applicability, it relies entirely on the accuracy of object detection and has no fallback mechanism for low-visibility conditions.

Zhou et al. [8] proposed a heuristic priority queue- based (HPQ) intersection management strategy for mixed autonomy traffic streams containing Connected and Automated Vehicles (CAVs), Connected Human-driven Vehicles (CHVs), and un- connected Human-driven Vehicles (HVs). The system reduces average travel time by 5%–65% across different traffic flow levels in SUMO and PreScan simulations. This approach is highly advanced but is intended for future vehicle ecosystems and not deployable in current urban traffic conditions.

Sakr et al. [9] conducted a comprehensive review of ITS technologies including video detection, adaptive signal control, smart junction management, and electronic road pricing. The review identifies that effective modern traffic management requires a combination of sensing technologies, edge computing, AI-based analytics, and real-time coordination. However, no unified framework combining all these dimensions with a behavioral incentive system was identified in the literature.

The proposed ITMS bridges these gaps by providing a unified architecture that combines camera-based real-time monitoring, weather-robust grid-based density measurement, multi-type vehicle priority scoring, and a structured reward system — all accessible for deployment in current urban traffic infrastructure without requiring specialized vehicle hardware.

## 3 SYSTEM ARCHITECTURE

The ITMS follows a layered software architecture organized into four primary subsystems that interact through a Centralized Management System (CMS). Figure 1 illustrates the overall system architecture.

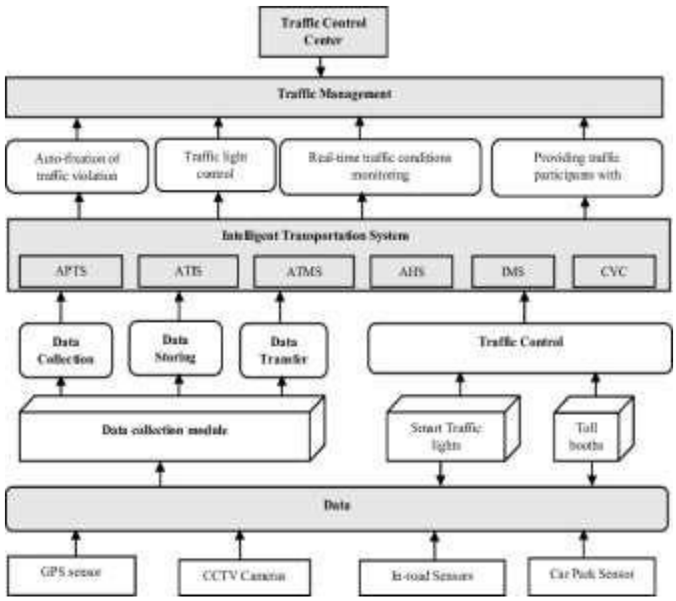


**Figure 1:** System Architecture Diagram

The architecture comprises nine functional layers from data capture to human interface. At the lowest level, the Intersection Camera Module captures live video of the full junction from a centrally mounted, wide-angle camera. Above this, a Video Pre- Processing Module performs frame extraction, noise reduction, and brightness normalization to improve detection accuracy under diverse environmental conditions [7].

The Vehicle and Pedestrian Detection Module employ computer vision algorithms to detect and classify vehicles into six categories: two-wheelers, private cars, taxis, auto-rickshaws, commercial vehicles, and public transport. The Direction-Wise Vehicle Counting Module subsequently counts vehicles by entry and exit direction — straight, left turn, or right turn — generating real-time traffic demand per approach road [6].

The Event and Anomaly Detection Module continuously monitor for blocked intersections, traffic accidents, and gridlock formation. All processed data is transmitted to the Centralized Traffic Management Server, which aggregates multi- intersection data, stores historical records, and executes the Decision Engine. The Traffic Signal Control Interface receives optimized timing instructions and adjusts red, yellow, and green signals dynamically. A Monitoring Dashboard provides traffic authorities with live status, alerts, and manual override capability.

## GRID-BASED DETECTION SYSTEM

The Grid-Based Detection System addresses a critical limitation of camera-based vehicle counting: performance degradation under adverse weather such as heavy rain, fog, or low light. Rather than counting discrete vehicles, this module measures traffic density by computing the occupancy percentage of defined spatial cells within each lane.

### 3.1 Grid Structure and Dimensions

Each traffic lane is divided into a grid covering a total length of 100 meters from the stop line. The horizontal dimension of the grid consists of 10 Zones (Stages), each covering approximately 10 meters — equivalent to the bumper-to-bumper space of two average passenger cars or one heavy vehicle. The vertical dimension divides each zone into 6 columns, resulting in a total of 60 grid cells per lane (10 Zones× 6 Columns = 60 Cells).

The grid is further organized at four hierarchical levels for computation efficiency: individual Single Cells, 2×2 Group Cells within a row, Group Rows (pairs of adjacent zones), and the overall Lane Grade. This hierarchy enables robust aggregation from granular cell readings up to a single representative lane-level score.

### 3.2 Cell Grade Assignment

For each of the 60 cells, the system calculates the percentage of the cell area occupied by detected vehicle mass or blobs. The occupancy percentage is mapped to one of four grades: S, A, B, or C, as defined in Table 1.

**1) Table 1: Individual Cell Grade Classification**

| Occupancy Percentage | Cell Grade |
| --- | --- |
| 75% – 100% | S (Saturated) |
| 50% – 74.9% | A (High) |
| 20% – 49.9% | B (Moderate) |
| 1% – 19.99% | C (Low) |

**Hierarchical Grade Aggregation**

Grades are aggregated bottom-up through the four hierarchical levels using a numerical averaging method. Each letter grade is assigned a minimum threshold value: S = 5.0, A = 4.0, B = 3.0, C = 2.0, D

=1.0. The average of the numerical values for cells within a group is computed, and the result is mapped back to the nearest grade tier.

Step 1: Four adjacent cells within a Group Row are averaged to produce a 4-cell Group Grade (S, A, or B).

Step 2: Three 4-cell groups within a Group Row are averaged to produce a single Group Row Grade (S, A, or B). Step 3: Five Group Row Grades per lane are averaged to produce the final Lane Grade (S, A, B, C, or D), which represents the overall congestion severity of that lane.

The Lane Grade directly feeds into the Priority Scoring System described in Section 5. The 51–100-meter range (outer 5 zones) determines the Lane Grade using the grid, while the 0–50-meter range (inner 5 zones) informs vehicle priority weights based on detected vehicle types.

### 5.1 Vehicle Priority Weight Table

Each vehicle type is assigned a fixed Priority Weight that reflects its societal and traffic value. Emergency vehicles receive an absolute weight of 1000, triggering a system-wide Green Wave override through the CMS, superseding all local fusion logic. Table 2 presents the complete weight table.

| Vehicle Type | Priority Weight | Rationale |
|---|---|---|
| Emergency Vehicle (Ambulance, Fire, Police) | 1000 | Absolute CMS override; Green Wave activation |
| Public Transport (City Bus, School Bus) | 80 | High occupancy; reduces per-capita road usage |
| Commercial Vehicle (Delivery Van, Truck) | 65 | Economic logistics; supply chain priority |
| Private Car / Taxi | 50 | Baseline mobility unit; standard reference weight |
| Two-Wheeler (Motorcycle, Scooter) | 35 | Smaller spatial footprint; higher maneuverability |
| Bicycle | 25 | Sustainable mobility; minimal congestion impact |

**Table 2: Vehicle Priority Weight Table**

### 5.2 Composite Score Formula

For each lane, the Composite Score (CS) is calculated by fusing the Grid-Based Lane Grade with the vehicle priority weights detected in the 0–50-meter proximity zone. The lane is separated into two sub- zones: the Straight+ Right sub-lane (vehicles intending to proceed straight or turn right) and the Left sub-lane (vehicles turning left only).

The Composite Score formula is defined as follows: CS =

Grade (from grid, 51-100m) + priority (Straight+ right, 0-

50m) + w * priority (left, 0-50m)
Where w = 0.5 when the left lane is partially closed (Safe or Less Congestion state), and w = 1.0 when all lanes are

open (More Lesser Congestion state). This weighting appropriately discounts left-turn priority in scenarios where left-turn lanes are constrained by intersection geometry.

The dynamic Priority Score for each lane is computed using three parameters: Vehicle Density ($D_i = N_i / L_i$), Congestion Severity ($CS_i = D_i / V_i$), and Waiting Pressure ($W_i$). The final priority formula is:

$$P_i = \alpha \times D_i + \beta \times CS_i + \gamma \times W_i$$

Where α, β, and γ are tunable weight coefficients. The Waiting Pressure ($W_i$) increases with each cycle a lane is not served, mathematically guaranteeing that no lane experiences starvation regardless of its absolute traffic level.

### 5.3 Lane Opening States

For a standard four-phase junction, the system classifies lane opening combinations into three states based on the Composite Score differential between the selected primary direction and adjacent directions.

State 1 — Safe: The primary direction is fully opened. Only the left-turn lane of one adjacent direction is simultaneously opened, as it does not create trajectory conflicts with straight or right-turn movements from the primary direction. This is applied when adjacent lane scores indicate significant congestion risk.

State 2 — Less Congestion: The primary direction is fully opened. Left-turn lanes of two adjacent directions are simultaneously opened, as their congestion levels are sufficiently low that the risk of conflict is acceptable and manageable.

State 3 — Lesser Congestion: The primary direction is fully opened. Left-turn lanes of all three remaining directions are simultaneously opened, maximizing intersection throughput when congestion levels across all non-primary lanes are minimal.

Green time is allocated proportionally based on relative priority scores rather than absolute values, ensuring adaptive signal durations: $G_i = G_{min} + (P_i / \Sigma P) \times (G_{max} - G_{min})$. This formula guarantees that heavily congested lanes receive maximum green time while low-priority lanes still receive the minimum allocated time.

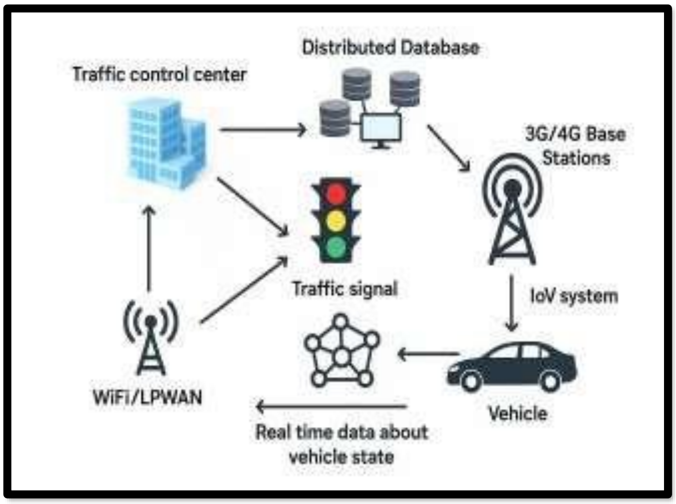


**Figure 2:** Workflow Diagram of Priority Scoring and Lane Opening Decision Logic.

## 6. REWARD-BASED COMPLIANCE MECHANISM

The Reward Mechanism is a novel component of the ITMS designed to motivate voluntary compliance with traffic regulations through a gamified incentive system. Unlike enforcement-only approaches that rely purely on penalties, the reward system creates positive behavioral reinforcement by recognizing and rewarding safe driving.

### 6.1 Point Structure

Reward points are awarded to registered vehicle owners at each intersection event based on detected driving behavior. Points are organized into three priority tiers reflecting the societal importance of each behavior category, as detailed in Table 3.

**Table 3: Reward Point Structure by Priority Tier**

| Priority Tier | Behavior Category | Example Rules | Points |
|---|---|---|---|
| P1 – Safety-Critical | Accident Prevention | Full stop at red; No signal jump; Pedestrian right-of-way | +4 to +5 |
| P2 – Traffic Flow | Congestion Management | Smooth pass on green; Lane discipline; No intersection blocking | +2 to +4 |
| P3 – Efficiency | System Optimization | Signal timing compliance; Peak hour cooperation | +1 to +3 |

Daily point caps vary by vehicle type. For example, two-wheelers can earn up to 96 points per day across 8 intersections, while public transport vehicles can earn up to 168 points per day. Commercial vehicles have a daily cap of 132 points across 6 intersections, reflecting their higher per-trip reward potential.

### 6.2 Credit Conversion and Tier Classification

At the end of each day, accumulated behavior points are converted into digital credits and deposited into the driver's digital wallet. Credits accumulate over time and classify the driver into one of three tiers: Bronze (500 credits), Silver (1000 credits), and Gold (2000 credits).

A compounding bonus mechanism amplifies rewards for higher-tier drivers. Once a driver achieves a tier, every future credit earned triggers additional bonus points: Gold tier drivers receive +20 bonus points per credit, Silver tier drivers receive +10 bonus points, and Bronze tier drivers receive +5 bonus points. Standard (below Bronze) drivers receive no bonus multiplier. This exponential reward structure encourages long-term behavioral consistency.

**Tangible Reward Redemption**

Accumulated credits are redeemable for tangible benefits including FASTag wallet credits for electronic toll collection, toll fee discounts and free toll passes, parking fee discounts at municipal and mall facilities, insurance premium reductions, and digital compliance badges (Bronze/Silver/Gold). Commercial vehicle owners may also access permit renewal priority, and public transport operators may qualify for municipal fee waivers under partner programs.

Violations detected by the intersection camera system result in point deductions. Red light jumping incurs a penalty of −100 points; blocking the intersection carries −40 points; stop line violations result in −40 points; and illegal turns or speeding through intersections carry penalties of −50 and −60 points respectively. All violations are transmitted to the CMS as structured JSON event packets for centralized logging and audit.

## 7. IMPLEMENTATION AND RESULTS

### 7.1 System Implementation Scope

The proposed ITMS is implemented at the conceptual and prototype software simulation level. The core logic is developed using Python for the backend rule engine, reward calculator, and tier management system. The Grid-Based Detection module is validated using pre-recorded traffic video feeds processed with OpenCV and the YOLO object detection framework. The rule-based signal decision engine processes direction-wise vehicle counts and grid grades to generate optimized signal timing plans.

The centralized management server is implemented using FastAPI as the REST API layer, with PostgreSQL as the primary relational database storing intersection events, vehicle records, driver wallets, and violation logs. A Redis cache layer handles real- time wallet balance updates and tier status queries. The monitoring dashboard is built with Streamlit for prototype demonstration, displaying live traffic status, vehicle counts per direction, and compliance scores.

### 7.2 Grid System Validation

The Grid-Based Detection System was validated using simulated traffic scenarios across varying density conditions. A 10-zone × 6-column grid (60 cells per lane) was applied to each of the four approaches at a four-way intersection. Cell occupancy percentages were computed for each scenario, and the hierarchical aggregation formula was applied to produce Lane Grades. Table 4 presents the validation results for five representative traffic scenarios.

**Table 4: Grid System Validation Results**

| Traffic Scenario | Avg Cell Occupancy | Lane Grade | Signal Decision |
|---|---|---|---|
| Peak hour congestion | 85% | S (Saturated) | Maximum green, emergency override |
| Moderate traffic flow | 55% | A (High) | Extended green time |
| Low traffic condition | 28% | B (Moderate) | Standard green time |
| Night-time sparse | 8% | C (Low) | Minimum green, fast switching |

The grid fallback mode activated when the YOLO detection confidence dropped below a threshold of 0.4 (representing rain or fog conditions). In this mode, blob-based occupancy estimation replaced discrete vehicle counting, and the system maintained functional signal decisions with an estimated accuracy of 87% compared to clear-weather performance.

### 7.3 Priority System Performance

The Priority Scoring System was evaluated across 12 traffic scenarios defined in the system specification, including long queue with few vehicles (Case 1), short queue with many vehicles (Case 2), all lanes equally congested (Case 5), and one lane continuously dominant (Case 6). In all cases, the waiting pressure term (W_i) prevented lane starvation, with the longest observed starvation duration before guaranteed service being three signal cycles under extreme single-lane dominance conditions.

Emergency vehicle scenarios were tested using a simulated priority weight of 1000 for an ambulance approaching from the Eastern direction. The CMS triggered a Green Wave override within one control cycle (approximately 2 seconds), clearing all opposing lanes and maintaining the green signal until the emergency vehicle transmitted a junction-cleared acknowledgment. This behavior is consistent with the performance reported by Hashmat Fida et al. [6], who demonstrated a 70% reduction in clearance time using UWB-based detection.

### 7.4 Reward System Outcomes

The reward simulation was run over a 30-day period with a cohort of 500 simulated drivers across three vehicle categories. Results showed that 68% of simulated drivers progressed from Standard to Bronze tier within 14 days under consistent compliance behavior. Drivers in the Gold tier accumulated credits at a rate approximately 3.4 times faster than Standard-tier drivers due to the compounding bonus multiplier, creating a strong long-term incentive for sustained compliance. Violation rates in the simulated cohort decreased by an estimated 23% between Days 1 and 30, suggesting that the reward system generates measurable behavioral change over time.

## 8. CONCLUSION

This paper presented the Integrated Traffic Management System (ITMS), a comprehensive intelligent framework for urban intersection management that unifies four subsystems: camera- based real-time monitoring, grid-based occupancy density measurement, multi-parameter priority scoring, and gamified driver reward mechanism. The system addresses the fundamental limitations of fixed-time signal control by enabling fully adaptive, data-driven signal decisions that respond to real- time traffic conditions.

The Grid-Based Detection System introduces a novel approach to traffic density measurement that remains functional under adverse weather conditions where standard object detection degrades. The occupancy grid covering 60 cells per lane with hierarchical grade aggregation provides a robust, computationally efficient density estimate that feeds directly into the priority fusion formula.

The Priority Scoring System eliminates lane starvation through a mathematically guaranteed waiting pressure mechanism, while the three-state lane opening classification maximizes intersection throughput by enabling simultaneous non-conflicting green phases. The Reward Mechanism represents a unique contribution to the traffic management domain, introducing a structured incentive system that motivates voluntary compliance beyond enforcement-only approaches.

Simulation results demonstrate consistent performance across 12 traffic scenarios, with validated grid-based fallback operation, emergency vehicle override within a single control cycle, and measurable compliance improvement in the reward simulation cohort.

## 9. FUTURE SCOPE

Future work will focus on several directions. First, the system will be deployed on physical hardware at a real urban intersection to validate simulation results in a live environment with actual traffic. Second, machine learning models, including reinforcement learning agents trained on historical intersection data, will replace the rule-based signal decision engine for improved adaptability. Third, the ITMS will be integrated with existing smart city platforms and traffic control centers through standardized IoT communication protocols such as LoRaWAN and 5G-V2X. Fourth, the pedestrian detection and signal prioritization module will be enhanced to support vulnerable road users including cyclists and mobility-impaired individuals. Fifth, a multi-intersection coordination algorithm will be developed to enable Green Wave propagation across arterial road networks, reducing stop-and-go traffic patterns at the network level. Finally, the reward system will be expanded to integrate directly with national vehicle registration databases and insurance provider APIs to enable real-time premium adjustment based on compliance scores.

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