

Integrating Traffic Density Analysis with Automated Violation Detection Through IoT Sensor Fusion

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Abstract— Urban traffic congestion imposes heavy economic and safety burdens on cities, especially in developing countries where fixed-time signal systems are used. Conventional methods are static and exacerbating delays and infractions. This study designs and implements a low-cost intelligent traffic control system that uses density-based signal processing and dual infrared sensors to adapt green-phase durations dynamically. It integrates real-time IoT-enabled offender detection and capture to link control and enforcement. The system uses a PIC16F877A microcontroller with optical dual-sensor arrays to measure traffic density and a Wi-Fi camera to capture images of violators. The Dynamic Time Allocation Technology (DTAT) system uses rules to figure out how much "green time," or 4 to 90 seconds, should be assigned to four different density states. MPLAB IDE is used for firmware development in C++, along with Proteus for simulation and real-world testing of prototypes. The prototype correctly identifies traffic state using a spatial sensor separation of 6 car lengths. It also adjusts the timing proportionally, reducing the number of wasted phases when conditions are uneven. Interrupt-driven enforcement reliably captures and transmits red-phase violations without disrupting control, demonstrating integrated feasibility on resource-limited hardware. This is a flexible, cost-effective approach to managing traffic in resource-poor areas.

Keywords: *Dynamic, Traffic Management, IoT, Transportation, Sensor Fusion*

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1. Introduction

As cities grow quickly and more people drive, the transportation systems we have are under more stress, making old ways of managing traffic less effective [1], [2]. The World Health Organization says that traffic jams and the violations that cause them are detrimental to the economy and public safety. For example, in many poor countries, traffic jams in cities can cost up to 3-5% of GDP [3]. Traditional traffic signal systems rely on fixed or pre-planned times to determine the sequence of red (stop), yellow (ready), and green (move) lights. These systems are based on the idea that traffic flow patterns are consistent and can be predicted. This idea doesn't often hold in the real world when demand is random, conditions change over time, and lane use isn't symmetrical [4], [5]. Because of this, fixed-cycle signaling often worsens traffic, increases the time vehicles spend stationary, and weakens enforcement, especially in high-density corridors [4].

Advances in intelligent transportation systems (ITS) have shifted research attention toward data-driven and adaptive traffic management frameworks that leverage sensing, computation, and communication technologies [6], [7]. Density-based traffic control is a better option than time-based signaling because it matches signal phase allocation with actual traffic demand instead of fixed

schedules [8], [9]. Empirical studies demonstrate that density-responsive systems can reduce average vehicle delay by over 30% and improve intersection throughput under fluctuating traffic loads [10]. But a lot of density-based implementations use either overly simple threshold logic or machine learning models that are hard to use in settings with limited resources. Pattern-detection methods based on signal processing can help fill this gap. These methods can identify useful traffic states in sensor data at a lower computational cost while remaining stable and easy to understand.

Signal processing provides a robust framework for modeling traffic flow as a time-varying signal. This enables the detection of trends in congestion and queue formation, as well as unusual behaviors, through temporal analysis and feature extraction. Methods such as adaptive filtering, pattern recognition, and spectral analysis have been widely used in biomedical engineering, radio communications, and other areas. It has been found that they are beneficial in traffic systems [11], [12]. Kim & Coifman (2013) [13] showed that time-domain signal features derived from vehicle occupancy data could distinguish between free-flow and congested states with relatively little training data. Signal-processing-based systems provide essential characteristics for real-time urban deployments, such as responsiveness, scalability, and resilience to noise, by treating traffic density as a measurable signal instead of a static count [14].

Many cities have started using automated traffic enforcement to improve compliance and lower accident rates by leveraging objective monitoring technology, just as they optimize traffic flow. Vision-based systems for detecting traffic offenders use cameras and image-processing algorithms and have been successful at spotting violations such as running red lights and using lanes illegally [15]. Nevertheless, enforcement modules are frequently designed as standalone systems, disconnected from traffic control logic. Since signal timing decisions are made without knowledge of errors that affect safety or flow, this separation reduces system-level efficiency. By adding real-time offender detection to the traffic control system, it becomes a feedback-driven system that allows for police and control to work together to meet their goals. The literature doesn't cover this kind of interaction very much yet, especially in systems that prioritize simplicity, affordability, and real-time operation [16], [17], [18].

Even though there is increasing research on intelligent traffic systems, some issues remain in existing studies [19], [20], [21]. Many suggested solutions are tested only in simulations under perfect conditions. This doesn't give us a good idea of whether the tools will work or what problems they will encounter in real life. Some people depend on complex tools and coding settings that are hard to get in areas with low to middle income. Visual Basic implementations are often considered outdated. However, they are still helpful for quickly prototyping, connecting hardware, and conducting educational deployments because they are stable and easy to use with simulation tools like Proteus [20], [22]. In [23] it was shown that control logic written in Visual Basic could successfully interface with traffic systems powered by microcontrollers. Nevertheless, their design lacked adaptive density awareness and real-time enforcement capability. This finding reveals a methodological gap that the present study addresses by coupling signal processing intelligence with a practical implementation framework.

This research specifically focuses on the design and implementation of an intelligent traffic control system that utilizes density-based signal processing for pattern detection and integrates real-time capture of traffic offenders. The scope of the study is confined to the complete electronic and algorithmic design of the proposed intelligent traffic control system, moving beyond the limitations of the current fixed-time control paradigm, which simply assigns STOP, READY, and MOVE signals based on elapsed time. This design will be implemented through two primary goals. The first goal is to plan and build the structure of an intelligent traffic control system. This means setting up communication and control logic between sensors and traffic lights so they can adjust their operation based on traffic levels. The second, and more technical, aim is to develop a smart traffic algorithm that translates density-based pattern detection into effective signal timing changes and, concurrently, uses the processed data to identify and log traffic offenses in real time. Finally, the study will demonstrate the feasibility of this integrated design by developing a simulation model of the smart traffic control system in Visual Basic on a platform such as Proteus, serving as a robust proof-of-concept for future physical deployment. This study adds both theoretical and practical knowledge to the ITS literature and shows that intelligent traffic

control is a systems-level problem that needs coordination between sensing, analysis, control, and enforcement, not just separate technological fixes.

2. Method

This study used a systems-engineering approach to plan, build, and test a traffic management system that can sense traffic density in real time, automatically adjust traffic lights, and catch people who break traffic laws. The method was based on the theory of intelligent transportation systems, which views traffic flow as a signal that changes over time and is random, rather than a reliable process that always works the same way [10]. This point of view led to closed-loop feedback in the system design, with real-time traffic-state estimates directly affecting signal changes. The study focused on practical deployability, control logic interpretability, and responsiveness to changing traffic conditions by designing the system around this feedback paradigm. Recent experiments have shown that adaptive signal control systems perform better than fixed-time systems in situations with traffic that can change over time. This concept is especially true at urban crossings where not all lanes are used equally [24]. Because of this, the research methods used had to focus on finding the density of traffic with minimal sensing overhead, turning sensor data into practical control decisions, and ensuring compliance through automated mechanisms that only react to events.

2.1 Hardware Implementation and Component Integration

As shown in Figure 1, the hardware architecture comprised five functional submodules that worked together. These submodules include the microcontroller, power supply unit, optical sensing unit, seven-segment display, and Wi-Fi-enabled camera. These components were physically and logically unified to implement the Dynamic Time Allocation Technology (DTAT) protocol [25].

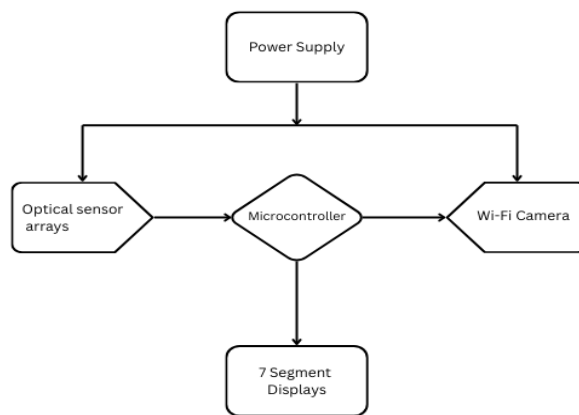


Figure 1. The system block diagram of functional sub-modules and their interaction

The PIC16F877A microcontroller handled all sensing, control, and enforcement coordination tasks. It was selected because its FLASH memory architecture supports repeated write-erase cycles, its instruction set allows straightforward programming, and its configurable input/output structure enables flexible peripheral interfacing [26], [27], [28]. The device has 33 programmable I/O pins, each controlled by a TRIS register. Clearing a TRIS register configures the corresponding port as an output, while setting it configures the port as an input, allowing precise control over data exchange with sensors, displays, and communication modules. This configuration is shown in Figure 2. In addition, the integrated Universal Synchronous/Asynchronous Receiver Transmitter (USART) module supports serial communication, system monitoring, and future scalability.

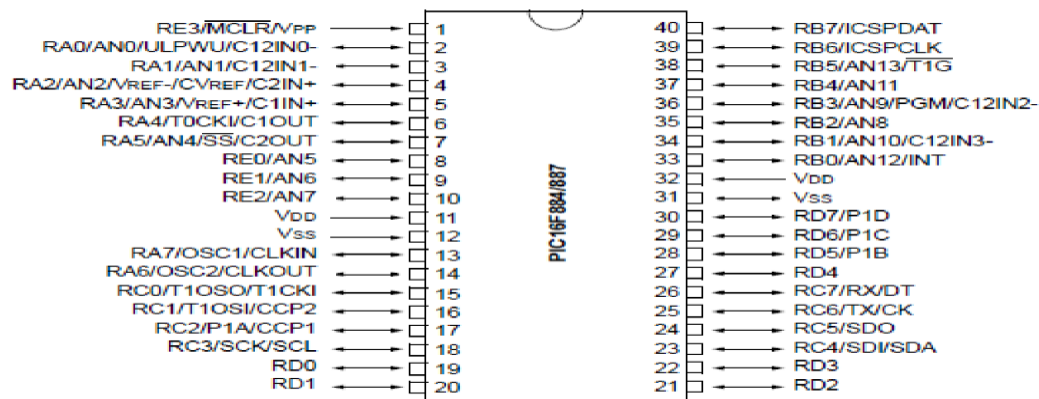


Figure 2. Pin configuration of the PIC16F877A microcontroller

The power source sub-unit was built to ensure that all digital components would work smoothly and without noise. The system gets 220 VRMS AC as its primary input. A transformer lowers this to 12 volts, and a diode-based full-wave rectifier converts it to DC. Then a filter removes the ripple components. A 7805 linear voltage regulator then changes the filtered DC voltage to a steady 5 V output. This stage of regulation keeps the system safe from changes in input voltage and load. This way, as shown in Figure 3, the microcontroller, sensors, and communication units all work consistently. Real-time sensing and timed logic are very sensitive to unstable voltage. Because of this, stable power delivery was seen as a necessary part of the process.

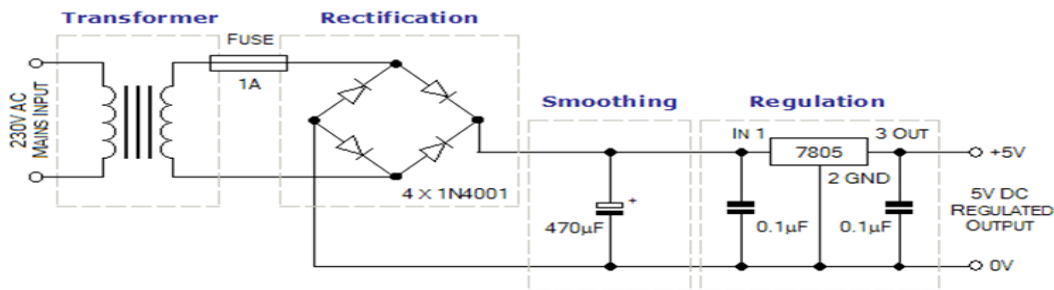


Figure 3. power supply circuit

Traffic density sensing was implemented using an optical sensor subunit composed of co-directional infrared transmitters and receivers. This configuration was adopted because reflective infrared sensing has been shown to offer reliable vehicle detection under variable lighting conditions and moderate environmental noise. The emitter sends a 950 nm infrared signal that has been modified to reduce the risk of interference from other light sources. The receiver is filtered both visually and electronically, so it can only spot reflections at this wavelength. When a metal vehicle enters the sensing zone, it generates a digital pulse by sending a signal back to the receiver. The system uses these pulses to detect both stationary and moving vehicles. Multiple sensor modules were installed per lane to improve spatial coverage and robustness, producing the raw traffic data required for DTAT-based categorization.

The seven-segment display served as the primary human-machine interface by visually communicating the dynamically allocated signal time to road users [6]. Figure 4 shows that the display consists of seven light-emitting diode segments, labeled A through G, and their connections. The microcontroller directly controls the display by writing binary values to the connected output port: a logical '1' activates a segment and a '0' deactivates it. The system increases transparency during operation and testing by displaying numerical countdown values corresponding to the active traffic phase via selective illumination of segment combinations.

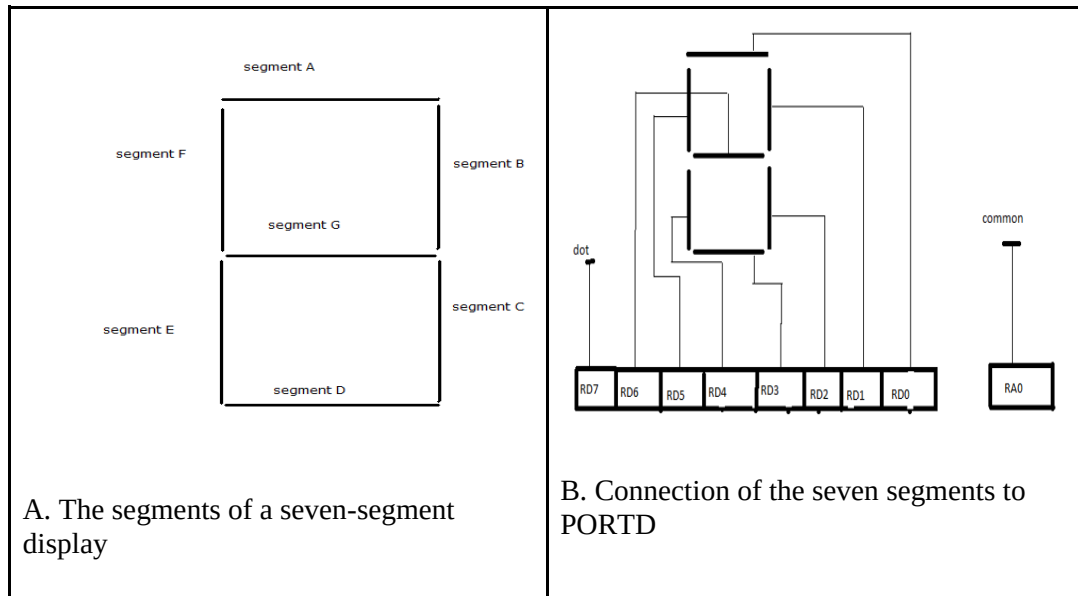


Figure 4. Seven-segment display and connections

The Wi-Fi camera constituted the enforcement and Internet of Things (IoT) component of the system [29]. This camera was equipped with a wireless communication interface and configured to operate under direct command from the microcontroller. The microcontroller sends a trigger signal to the camera when its optical sensors detect a traffic violation, such as a vehicle moving while the signal is red. The camera takes a clear picture of the car and sends it to a remote computer or server without a cable. This process establishes an IoT communication link that enables automatic gathering, storage, and retrieval of evidence. A visible signage as intersection approaches stating that image capture is active for traffic enforcement, enabling informed consent by presence is installed. The system encrypt all image data during Wi-Fi transmission (using TLS) and store files on the remote server with role-based access controls and audit logs to prevent unauthorized viewing. The captured images are stored only for a legally defined period of 30 days, after which they are automatically and irreversibly deleted unless required for active dispute resolution.

2.2 Software Architecture and Algorithmic Design

A closed-loop finite-state machine (FSM) is used to model predictable control logic that powers the system's intelligence. Unlike linear controllers that execute fixed-duration cycles, this architecture uses a parametric evaluation function to calculate phase durations in real time. The software logic is physically mapped to the hardware interface as illustrated in Figure 5, where sensor inputs act as state-transition variables.

The system flowchart (Figure 6) formalizes the core algorithmic operational sequence. The control loop uses a Round-Robin scheduling protocol across the three intersecting roads (Road A, Road B, and Road C). For each active lane, the algorithm samples the Boolean states of the dual-sensor array (S_{front} and S_{rear}). These inputs are processed by a conditional logic block that maps the sensed density to a specific time weight. This ensures that the system dynamically scales the green-light window (T_g) proportional to the instantaneous queue length. At the same time, the system employs an asynchronous event listener for traffic enforcement. An interrupt-driven routine monitors the enforcement devices while the main loop controls traffic. The system instantly activates the Wi-Fi camera module to record and send proof when a violation is detected (movement during a red phase), regardless of the traffic light state. Algorithm 1 shows the high-level decision process for this Dynamic Time Allocation Technology (DTAT).

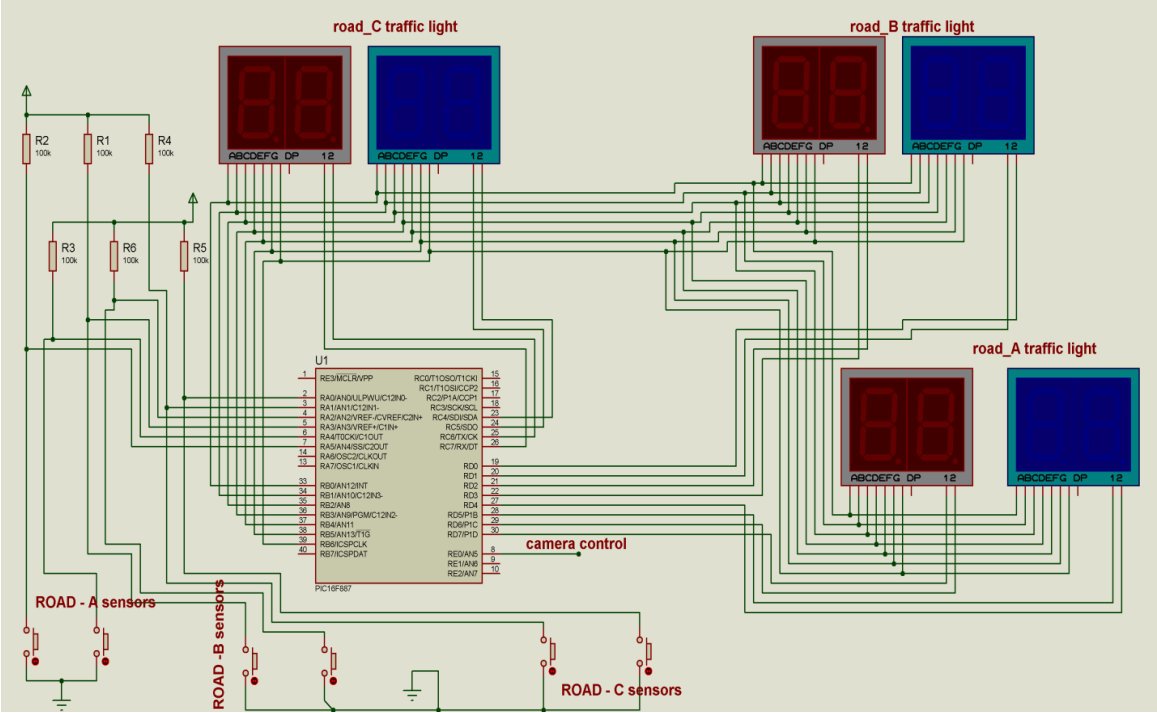


Figure 5. The system circuit diagram

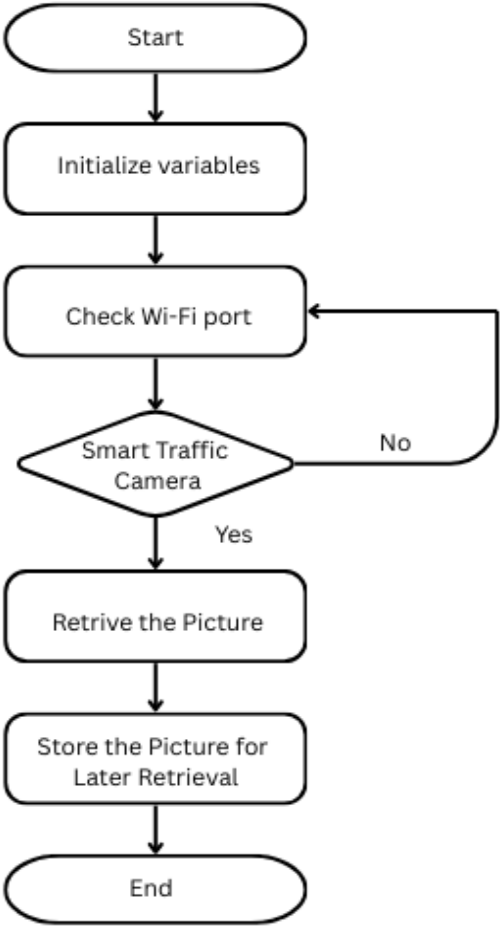


Figure 6. System Flowchart

Algorithm 1: Dynamic Time Allocation and Enforcement Protocol

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\caption{DTAT Traffic Control Logic} \begin{algorithmic} \REQUIRE Sensor Arrays  $S_{front}$ ,  $S_{rear}$ 
Enforcement Sensor  $S_{offense}$  \ENSURE Dynamic Green Duration  $T_g$ , Violation Capture

\STATE \textbf{Initialize} Ports, Timers, and Interrupts \WHILE{System is Active} \FOR{each Lane
L in  $\{Road_A, Road_B, Road_C\}}$  \STATE \textbf{Read}  $S_{front}$  and  $S_{rear}$  status
    \IF{ $SS_{front} == 1 \text{ AND } SS_{rear} == 1$ }
        \STATE  $T_g \leftarrow 90s$  \COMMENT{Heavy Traffic Regime}
    \ELSIF{ $SS_{front} == 1 \text{ AND } SS_{rear} == 0$ }
        \STATE  $T_g \leftarrow 45s$  \COMMENT{Normal Traffic Regime}
    \ELSIF{ $SS_{front} == 0 \text{ AND } SS_{rear} == 1$ }
        \STATE  $T_g \leftarrow 30s$  \COMMENT{Light Traffic Regime}
    \ELSE \STATE  $T_g \leftarrow 4s$  \COMMENT{Idling/Keep-Alive Regime}
    \ENDIF

    \STATE \textbf{Execute} Green Phase ( $T_g$ )

    \WHILE{Timer  $< T_g$ }
        \STATE Update 7-Segment Display ( $\$Countdown$ )
        \IF{ $SS_{offense}$  detected on restricted lanes}
            \STATE \textbf{Trigger} Camera\_Snapshot()
            \STATE \textbf{Transmit} Data to Server via Wi-Fi
        \ENDIF
    \ENDWHILE

    \STATE \textbf{Switch} Lane  $L$  to Red
\ENDFOR
\ENDWHILE \end{algorithmic} \end{algorithm}

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2.3 Software Implementation and Development Environment

A dual-environment method was used to build the system's firmware and backend infrastructure to ensure strong embedded control and dependable IoT communication. Control software for the PIC16F877A microcontroller was developed in C++ using the MPLAB Integrated Development Environment (IDE). MPLAB provided a single platform for compiling, editing, and debugging the source code. The embedded C++ code directly changes the TRIS and PORT hardware registers in the microcontroller. This is how the nanosecond-level timing accuracy needed for signal synchronization is achieved. After compilation, the source code was converted into a hexadecimal machine file. It was then loaded onto the microcontroller with a PICKIT2 coder. This straight programming method ensures that the DTAT algorithm is stored in non-volatile memory, allowing the system to return to regular operation immediately after a power loss.

A complementary server-side program was made using the Arduino Integrated Development Environment (IDE) to handle the data stream from the Wi-Fi camera. The Arduino IDE is used mainly for writing microcontroller code, but its extensive library options (especially the Wiring project libraries) make it easier to create a lightweight listener app. This software continuously monitors the selected Wi-Fi port of the host server. When the traffic camera sends a packet header, the application uses Application Programming Interfaces (APIs) to read the incoming binary stream, retrieve the high-resolution JPEG image, and save the file in a folder marked with the time and date so it can be easily found by administrators.

3. Result and Discussion

It was necessary to test the system at full operational level to confirm that it could sense traffic

density, dynamically allocate signal time, and ensure compliance through automated detection. Once it had power, the system activated all its sensing, control, and communication modules simultaneously. This made it possible to watch all three of the T-junction's approach roads in real time. Optical sensors were installed on each approach to monitor cars and their speeds continuously. They sent digital data to the microcontroller for processing. The system treated each road as a separate control unit that could be serviced one at a time. This way, traffic conditions on one road can be monitored without affecting the roads already being serviced. Figure 7 displays the smart traffic prototype.



Figure 7. The smart traffic after construction

For Road A, the microcontroller first processed sensor inputs to determine the prevailing traffic state. Based on this assessment, the controller set the green phase to the appropriate length and immediately changed the seven-segment display to show the allotted moving time. Road A got a green light and a countdown display, while Roads B and C showed red-phase countdowns for the same amount of time, each assigned to its road based on the current situation. When the countdown ended, the machine relinquished control of Road A and moved to Road B, where the sensing and allocation process repeated. This cyclic operation continued across all approaches, thereby validating the system's ability to implement Dynamic Time Allocation Technology (DTAT) in real time without reliance on preset schedules.

The Proteus Design Suite's simulations looked very similar to the real-life version. This indicated that the signal-timing logic, sensor-based state changes, and display alignment were all right. The match between the simulated and real-life behavior shows that the system design is correct. It demonstrates that the control logic operates deterministically under both virtual and hardware-in-the-loop conditions.

3.1 Performance of Dynamic Time Allocation Technology (DTAT)

The DTAT mechanism was the analytical core of the proposed system. It was tested by checking its ability to change signal timing based on different traffic densities. Unlike conventional systems with fixed time intervals, the controller did not assume that traffic would flow evenly or at regular intervals. It figured out how dense the traffic was by analyzing patterns of sensor activity before it assigned a movement time to any lane. Traffic flow theory holds that real-time occupancy and queue formation are better indicators of congestion than static timing assumptions. This approach is in line with that way of thinking.

The method grouped traffic into four categories based on volume: heavy, normal, light, and no traffic. The controller saw a vehicle when both front and rear lane sensors were triggered. It then thought there was heavy traffic and gave a 90-second green phase. When only the rear sensor detected vehicles, the controller classified the condition as light traffic and allocated 30 seconds. When only the front sensor detected vehicles, the system identified regular traffic and assigned 45 seconds. Since both sensors failed to detect anything, the controller set a 4-second minimum delay to avoid wasting time waiting. The four traffic conditions and sensor detection are summarized in Table 1.

Table 1. Summarization of the four traffic conditions and sensor detection

Front Sensor	Rear Sensor	Interpretation
Detects	Detects	Heavy traffic
No detection	No detection	No traffic
Detects	No detection	Normal traffic
No detection	Detects	Light traffic

The way the system worked showed that these allocations led to signal timing that was both responsive and proportional. Heavily congested lanes received extended green phases that allowed queue dissipation, while underutilized lanes were not overserved. Fixed-time systems often waste green phases on empty or lightly occupied approaches, a problem this behavior directly addresses. The system showed increased throughput and decreased idle waiting by dynamically reallocating time, especially in situations with asymmetric demand.

3.2 Comparative Assessment Against Existing Traffic Control Practices

The proposed system was evaluated conceptually against prevailing traffic control practices, including manual traffic policing and fixed-time signal operation. In many cities, traffic police officers manually adjust signal timing to prevent traffic jams. While this approach introduces human adaptability, it also introduces inconsistency, delayed response, and decision-making bias. Fixed-time traffic signals suffer a different limitation because they assume predictable traffic patterns and therefore fail under fluctuating demand [30], [31].

The DTAT-based system used both methods, but they were later replaced by automated decision-making based on real-time data. Unlike systems controlled by people, the controller reacted to conditions consistently, without getting tired or forming personal opinions. Unlike systems with set times, it adjusts signal lengths in real time based on traffic conditions. The system's ability to run without manual adjustment demonstrated that it can perform tasks that would typically require many people without losing responsiveness. This capability directly affects the cost of running the system and the ability to scale up in developing urban areas.

3.3 Traffic Density Interpretation Using Dual-Sensor Configuration

Using two optical cameras per lane was very important to the system's ability to estimate traffic density with very little extra work. The front and back sensors were about 6 car lengths apart. This distance made it easier for the system to tell the difference between lined-up cars, few new arrivals, and quickly growing traffic, so it didn't have to use complicated image processing or vehicle counting methods.

The controller assumed that the queue stretched across the sense area, indicating heavy traffic, even though both sensors spotted cars. The lane was considered empty as long as neither sensor detected a vehicle. The controller could distinguish between regular flow and light traffic using asymmetric detection patterns. The logic based on this reasoning showed consistent, repeated traffic patterns during tests, even when vehicles moved briefly. This method demonstrates that a straightforward sensing setup and clear reading logic can determine traffic density.

3.4 IoT-Enabled Traffic Offense Detection and Enforcement

The system's ability to enforce traffic laws during busy signal phases gave us a way to see it in action. The optical sensors found cars that weren't moving and unpermitted motion during red phases. The front sensor recorded and instantly alerted the microcontroller when a car moved during a forbidden time period. The controller then turned on the Wi-Fi camera assigned to the affected lane.

The camera captured a clear picture of the car and sent it to a server for storage. This process occurred on its own and didn't affect traffic control actions already in place. The fact that violation images could be sent and stored demonstrated that the IoT communication link was reliable and that the system could function as a single platform for control and punishment. By adding enforcement to the traffic control loop, the system turned compliance monitoring from a passive observation job into an active, data-driven process.

3.5 Practical Limitations and Experimental Constraints

Several limitations constrained the spread of system validation. The limited availability of certain parts made it hard to look into other sensing technologies, and budget issues meant that field deployment on a big scale wasn't possible. Power instability during development caused delays, but testing continued with auxiliary power generation. Due to time constraints, the review could only be conducted using optical sensing, so a comparative test with camera-only or inductive-loop methods was not possible. These problems don't hurt the system's overall truth. Instead, they show a clear path for future work. It makes sense for the current study to be followed by additional tests in real urban traffic, merging with centralized traffic management systems, and comparing results with machine-learning-based controllers.

4. Conclusion

Because fixed-cycle signal control doesn't work well in today's cities, we need to start thinking of traffic flow as a changing, measurable signal rather than an unchanging schedule. This study built and tested a density-responsive system that combines real-time control with automated regulation to meet this critical goal. The successful use of the Dynamic Time Allocation Technology (DTAT) protocol demonstrated that intersection performance can be optimized through computationally efficient signal processing, without the delays or resource requirements of complex machine learning models. To address the flaws of preset timers, the system used a dual-sensor setup to filter out transient noise and map random arrival patterns to precise control windows of 4 to 90 seconds. Physical and simulated tests align closely, validating deterministic transitions and countdown synchronization. Asynchronous interrupts handle red-phase movements seamlessly, activating Wi-Fi imaging and transmission to create evidentiary records that reinforce compliance without manual oversight. These results build on earlier density-responsive designs by combining control and enforcement on a single, low-cost platform. This makes them more efficient overall than systems that work on their own. The method needs very little infrastructure. It uses off-the-shelf microcontrollers and optical sensors that work well in changing light conditions, so it can be used where more advanced machine learning or vision-only methods are too expensive. The study contributes practical evidence that adaptive traffic control does not require complex machine learning pipelines to be effective. The system achieves transparency, predictability, and deployment ease by using interrupt-driven event handling, finite-state control, and signal-processing logic. Limitations in computational resources, funding, and technical maintenance capacity make this feature crucial. You can follow every control decision back to sensor states and timing rules. This aspect makes automated decision-making easier to understand and more trustworthy. The public release of firmware, server scripts, and circuit schematics further reinforces this contribution by supporting reproducibility and future extension. The findings point toward several clear research directions. Field-scale deployment under heterogeneous urban traffic conditions would allow quantitative evaluation of delay reduction, throughput improvement, and violation rates over extended periods. Integration with centralized traffic management platforms could enable corridor-level coordination rather than isolated intersection control. Additional sensing modalities, such as camera-based occupancy estimation or vehicle-to-infrastructure communication, could be layered onto the existing framework without altering its core logic. These directions build naturally on the present work because the architecture was deliberately designed to be modular and extensible.

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