Smart Adaptive Traffic Signal Management System

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Abstract - *The conventional traffic management system, which relies heavily on fixed signal timers and manual control by traffic police, often results in significant inefficiencies, prolonged waiting times, and increased fuel consumption. As urban areas continue to grow and vehicle numbers rise, these issues become more pronounced, leading to heightened congestion and reduced transportation efficiency. This research paper proposes a novel approach to traffic management that dynamically adjusts signal timings based on real-time vehicle counts at intersections. By accurately measuring the number of vehicles and using this data to determine the optimal duration of green and red lights, the system aims to streamline traffic flow, minimize delays, and decrease overall congestion. This method not only enhances the efficiency of traffic movement but also contributes to environmental sustainability by reducing idle times and subsequent emissions. Our study includes a comprehensive analysis of current traffic problems, the design of the proposed system, and a discussion on the potential benefits and challenges of implementation. The proposed solution offers a practical and immediate improvement over traditional traffic control methods, presenting a viable path towards smarter and more efficient urban mobility.*

Key Words: Intelligent Traffic Control, Real-time Vehicle Counting, Signal Timer Optimization, Traffic Congestion, Urban Mobility, Traffic Management System, Transportation Efficiency, Environmental Sustainability.

1.INTRODUCTION

Urbanization and the exponential growth of vehicle ownership have led to significant challenges in managing traffic flow efficiently. Traditional traffic management systems, which rely on fixed signal timings and manual oversight by traffic police, often fall short in addressing the dynamic nature of modern urban traffic. These conventional systems are inherently rigid, unable to adapt to fluctuating traffic volumes throughout the day. Consequently, this rigidity leads to several inefficiencies: prolonged waiting times for drivers, increased fuel consumption, heightened levels of air pollution due to idling vehicles, and a general decrease in the quality of urban life.

Traffic congestion is not merely an inconvenience; it has far-reaching economic, environmental, and social impacts. Economically, it results in substantial losses due to wasted time and reduced productivity. Environmentally, the continuous idling of vehicles at congested intersections contributes significantly to greenhouse gas emissions, exacerbating climate change and deteriorating urban air quality. Socially, the frustration and stress associated with daily commuting in congested areas can lead to adverse health effects and decreased overall well-being

Recognizing these issues, there is a pressing need to innovate beyond traditional traffic management approaches. This paper explores an intelligent traffic control system designed to address the limitations of current methods by dynamically adjusting signal timings based on real-time vehicle counts. The proposed system aims to optimize traffic flow through intersections by accurately counting vehicles and adjusting signal timings accordingly. This real-time adjustment allows for more efficient traffic movement, reducing wait times and minimizing congestion.

The core of this intelligent system is its ability to collect and process real-time data on vehicle numbers at intersections. By employing straightforward counting mechanisms, the system can determine the optimal duration for green and red lights, ensuring that traffic is managed more effectively. This method stands in contrast to traditional fixed-timer systems, which often operate on outdated assumptions about traffic volumes and patterns. The dynamic nature of the proposed system allows it to respond swiftly to changes in traffic density, leading to smoother traffic flow and reduced overall delays.

Furthermore, the implementation of an intelligent traffic control system can significantly contribute to environmental sustainability. By minimizing idle times at intersections, the system reduces fuel consumption and lowers emissions of pollutants, contributing to cleaner air and a reduction in the urban carbon footprint. This environmental benefit is a critical consideration in the context of global efforts to combat climate change and promote sustainable urban development.

In this paper, we will provide a detailed analysis of the current problems associated with traditional traffic management systems, outline the design and operational principles of the proposed intelligent traffic control system, and discuss the potential benefits and challenges associated with its implementation. Our research aims to demonstrate that with the integration of real-time vehicle counting and adaptive signal timing, cities can achieve a more efficient, sustainable, and driver-friendly traffic management system. Through this innovation, we envision a future where urban mobility is significantly enhanced, making daily commutes faster, safer, and more environmentally friendly.

2. LITERATURE SURVEY

The evaluation presented in [1] examines the SCATS Master Isolated (SMI) control for non-coordinated signalized intersections, comparing its performance to traditional vehicle-actuated (VA) control methods through both simulations and field surveys. To assess effectiveness, various SCATS-like adaptive control algorithms were developed and tested. Results indicate that SMI control typically achieved lower delays and reduced queue lengths compared to VA control. While field surveys revealed only slight improvements due to well-optimized VA settings, SMI control demonstrated a marked advantage in scenarios involving detector malfunctions. The findings underscore SMI control's potential for more efficient traffic management at isolated intersections.

The study in [2] analyzes the SCOOT traffic network optimization system, which has been implemented globally and was specifically evaluated in Nijmegen, Netherlands, to compare its effectiveness with the existing system. Initiated in July 1991, the project faced delays, completing calibration by September 1993, with data analysis finalized in January 1995. Key metrics, including journey times, stops, and queue lengths across various transport modes, were assessed. SCOOT delivered mixed results, showing improvements during morning periods but poorer performance in the evenings compared to the previous system, with no significant overall difference. The study also delves into implementation challenges, such as calibration complexities and specific intersection issues, providing insights into the intricate dynamics of urban traffic management.

The paper in [3] discusses Intelligent Transportation Systems (ITS) designed to alleviate urban congestion from rising travel demand and limited roadway capacity. It highlights adaptive traffic control systems like SCATS (Sydney Coordinated Adaptive Traffic System), which optimize signal timings in real time to enhance traffic flow and minimize delays. Although certain studies report benefits in travel time, fuel consumption, and emissions reduction, evaluations like the one conducted in Troy, Michigan, find no significant differences compared to pre-timed control systems. These mixed findings suggest the necessity for further research to optimize adaptive traffic control systems and ensure their efficacy across diverse urban settings.

The study in [4] utilizes data from Los Angeles' Automated Traffic Surveillance and Control (ATSAC) system, covering 75 detectors across nine intersections on Olympic Boulevard, for simulating the Santa Monica Freeway Corridor using the INTEGRATION model. The research focuses on efficient data extraction and integrity verification. Three data processing programs were developed: ATSAC.CPP for data formatting, SLICE.CPP for half-hourly aggregation, and COMBINE.CPP for detector data merging. The analysis confirmed high data reliability, with only one detector malfunctioning among 45 assessed, validating the data for use in traffic simulation models and future performance evaluations.

In [5], adaptive traffic control systems (ATCS), such as SCOOT (Split Cycle Offset Optimization Technique) and SCATS (Sydney Coordinated Adaptive Traffic System), are examined for their ability to reduce delays, stops, and journey times. Comparative studies indicate that both systems generally outperform traditional methods, with SCATS often achieving fewer stops. SCOOT employs online optimization, while SCATS relies on heuristic adjustments using feedback. Recent evaluations via VISSIM simulation highlight SCATS' efficient implementation of offsets and splits under heavy traffic loads. The research identifies the need for improved calibration and performance assessment in oversaturated conditions to enhance the systems' overall efficiency.

The paper in [6] introduces SURTRAC (Scalable Urban Traffic Control), a decentralized, real-time adaptive traffic signal control system aimed at reducing urban congestion. SURTRAC integrates traffic control theory with multi-agent planning, allowing intersections to allocate green time independently based on real-time traffic, communicate with neighboring signals, and adjust dynamically every few seconds. A pilot deployment in Pittsburgh, Pennsylvania, demonstrated significant reductions in travel times and emissions compared to traditional control systems. The system's architecture, featuring a decentralized model,

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schedule-driven adjustments, and robust communication, shows promise for scalable urban traffic management.

The study in [7] presents an adaptive traffic management system designed for rapidly urbanizing cities in India. It proposes an IoT-based approach employing camera sensors and machine learning algorithms, such as TensorFlow, to optimize signal timings dynamically based on traffic conditions. The system prioritizes lanes with higher vehicle densities, aiming to minimize wait times and congestion. Techniques like Min Max Fairness, AIMD (Additive Increase Multiplicative Decrease), and PCA (Principal Component Analysis) are integrated to enhance traffic efficiency and pollution control. The approach addresses urban challenges by improving emergency response and leveraging advanced data analysis for dynamic traffic management

Paper [8] outlines an Intelligent Traffic Management System (ITMS) using a Deep-Neuro-Fuzzy model to tackle urban traffic congestion. It incorporates the Dijkstra algorithm for optimal route planning based on road segment weights calculated by the model. The research uses SUMO (Simulation of Urban Mobility) for simulation and demonstrates the system's effectiveness in real-world scenarios. The framework integrates IoT sensors and offers a user-friendly GUI for real-time data analysis and decision-making. Performance comparisons of routing algorithms in SUMO show the Deep-Neuro-Fuzzy model's adaptability and accuracy, suggesting potential enhancements for future ITMS iterations.

The paper in [9] introduces an Intelligent Traffic Management System leveraging the Internet of Vehicles (IoV) and Vehicle Ad-hoc Networks (VANETs) to improve signal efficiency. The system adjusts signal timings dynamically based on real-time vehicle density, offering a cost-effective and scalable solution by utilizing existing infrastructure. It discusses the role of IoV and VANETs in future Intelligent Transportation Systems (ITS), emphasizing GNSS-based vehicle positioning. The proposed system enhances traffic flow, safety, and efficiency, using IoV technology for real-time urban traffic management.

3. METHODOLOGY

3.1 Creating the Simulation

To realistically simulate vehicle behavior and interactions, we employ the Intelligent Driver Model (IDM). The IDM is a car-following model that simulates the acceleration and deceleration of individual vehicles based on the distance to the vehicle in front, the relative speed, and the desired speed of the driver. This model is essential for creating realistic traffic flow in the simulation as it captures the dynamics of real-world driving behavior. The IDM adjusts each vehicle's speed to ensure safe following distances, smooth acceleration and deceleration, and efficient lane changes, contributing to a more accurate representation of traffic patterns. The equations have been shown in the following figure [Figure 1].

$$\dot{x}_\alpha = \frac{\mathrm{d}x_\alpha}{\mathrm{d}t} = v_\alpha$$

$$\dot{v}_\alpha = \frac{\mathrm{d}v_\alpha}{\mathrm{d}t} = a\left(1 - \left(\frac{v_\alpha}{v_0}\right)^\delta - \left(\frac{s^*(v_\alpha, \Delta v_\alpha)}{s_\alpha}\right)^2\right)$$

$$\text{with } s^*(v_\alpha, \Delta v_\alpha) = s_0 + v_\alpha T + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{a\,b}}$$

Figure 1. Equations in IDM

The roads in our adaptive traffic signal control system simulate the physical and behavioral characteristics of road segments, managing vehicle dynamics and interactions with traffic signals. It initializes with start and end coordinates to define the road's structure, and utilizes a deque for efficient vehicle management. Geometric properties such as road length and orientation are calculated to support vehicle movement simulations. Traffic signal integration allows the class to control vehicle behavior in response to signal states, managing transitions between moving, slowing down, and stopping. By continuously updating vehicle positions and responses to traffic signals, the Road class provides a realistic simulation of traffic flow, enabling the evaluation and optimization of adaptive signal control strategies. Figure 2 demonstrates the start of the simulation.

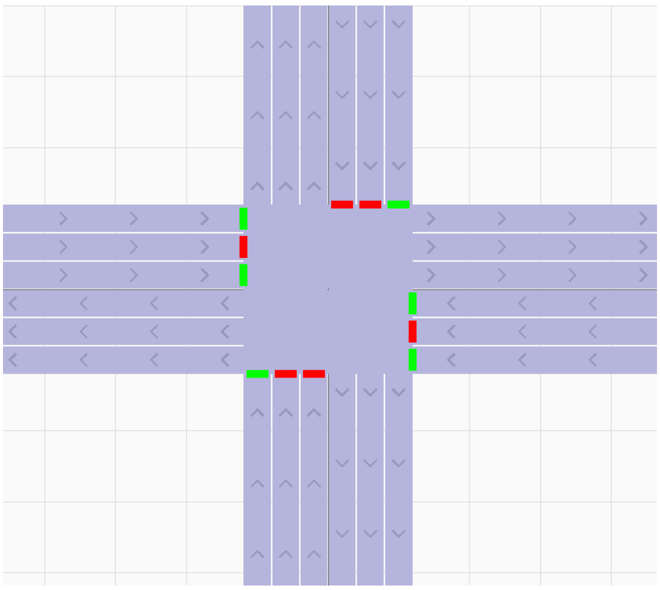

Figure 2. Simulation generation

3.2 The Algorithm

The intersection features four primary directions: East, West, North, and South. Each direction includes three lanes for incoming traffic and three lanes for outgoing traffic. The lanes are designated as direction_in1, direction_in2, direction_in3 for incoming traffic, and similarly, direction_out1, direction_out2, direction_out3 for outgoing traffic. This configuration allows for a structured flow of vehicles through the intersection. Vehicles in the first lane (designated as _in1) are restricted to turning right. Vehicles in the second lane (_in2) proceed straight through the intersection, while vehicles in the third lane (_in3) are designated for left turns. This specific lane designation helps to organize traffic flow and reduce potential conflicts within the intersection.

The traffic lights at the intersection regulate vehicle flow. The control system uses a matrix to decide which lanes should receive green lights, based on current traffic densities. This matrix is an 8x8 grid where each row and column correspond to specific lanes. The values within the matrix indicate whether a particular pair of lanes (designated by the respective row and column) can have green lights simultaneously. The matrix values are binary, where a value of 1 indicates that the corresponding lanes can be green at the same time. For example, if matrix[0][2] equals 1, this means that westin1 and eastin1 lanes can simultaneously have green lights. Multiple 1s in a row suggest several potential green light combinations, but the system will select the pair of lanes with the highest traffic density. The system continuously calculates the traffic density for each lane. Based on these densities, it determines which two lanes, having the highest traffic, should be granted green signals to optimize flow and minimize congestion.

The simulation flow begins by setting up the Pygame environment and creating the display window, which forms the foundation for the graphical simulation. A function is then defined to draw the lanes and intersection layout on the screen, using lines or rectangles. Each direction includes three lanes for both incoming and outgoing traffic, accurately depicting the traffic setup. Vehicle classes and their behavior are defined according to lane directions (right turn, straight, left turn), and vehicle positions are updated based on the status of traffic lights, ensuring realistic vehicle movement within the simulation. Traffic signal logic utilizes the provided matrix to determine possible green light pairs, calculates the number of vehicles in each lane to assess traffic density, and then determines the two lanes with the maximum traffic to grant green signals, effectively managing congestion.

The 8x8 matrix represents allowable green light combinations for the lanes, with rows and columns corresponding to specific lanes: Row 0 = Col 0 = westin1 lane, Row 1 = Col 1 = southin1 lane, Row 2 = Col 2 = eastin1 lane, Row 3 = Col 3 = northin1 lane, Row 4 = Col 4 = westin2 lane, Row 5 = Col 5 = southin2 lane, Row 6 = Col 6 = eastin2 lane, and Row 7 = Col 7 = northin2 lane. The matrix indicates which pairs of lanes can be green simultaneously. For example, matrix[0][2] = 1 signifies that westin1 and eastin1 can both have green lights at the same time. Although multiple 1s in a row suggest several potential green light combinations, the system prioritizes the pair with the most traffic. The next steps involve implementing the Pygame setup, initializing Pygame, and creating the display window to begin the simulation. A function is defined to accurately draw the lanes and intersection layout on the screen. A vehicle class is created to manage the properties and movement of vehicles, implementing movement logic that adheres to lane directions. The traffic light control is implemented using the matrix, calculating traffic densities and determining which lanes receive green lights. Finally, a main loop is created that continuously updates vehicle positions, adjusts traffic lights based on real-time traffic densities, and renders the updated intersection and vehicles on the screen. This loop ensures the dynamic and adaptive nature of the traffic signal control system.

3.3 Flowchart

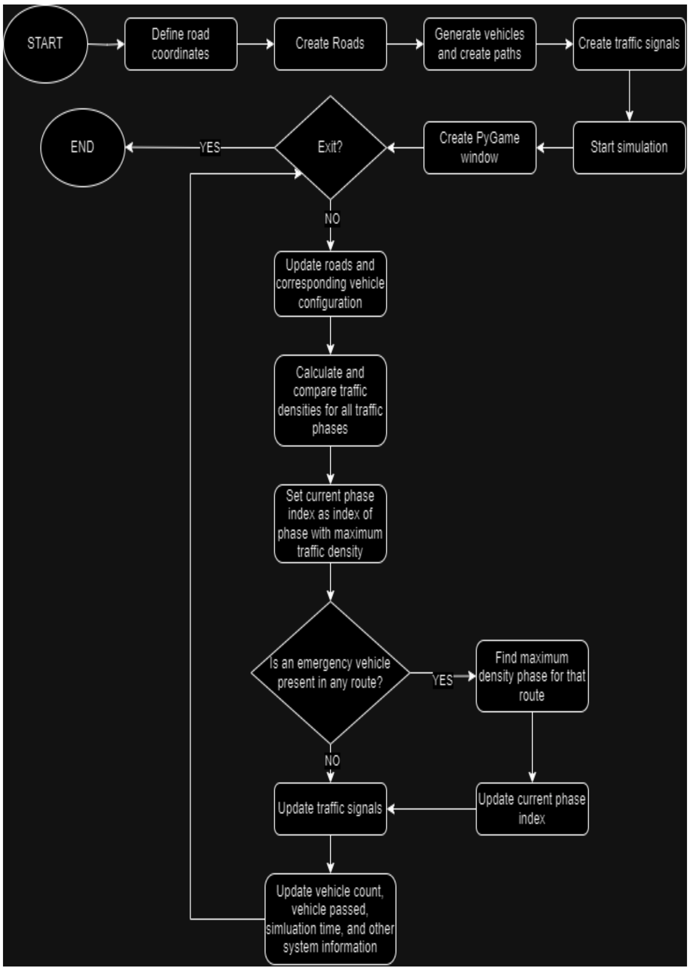

Figure 3. Flowchart

4. RESULTS

In this section, we present the outcomes of our simulation experiments. The results highlight congestion levels, response times, and the efficiency of our traffic management system. Each figure and table corresponds to specific observations made during the simulations, providing insights into the impact of various factors on traffic flow and emergency vehicle prioritization.

Figure 4 illustrates the scenario at the beginning of the simulation, with 74 seconds having elapsed. At this point, the congestion is low, and an emergency vehicle has been granted passage through the traffic.

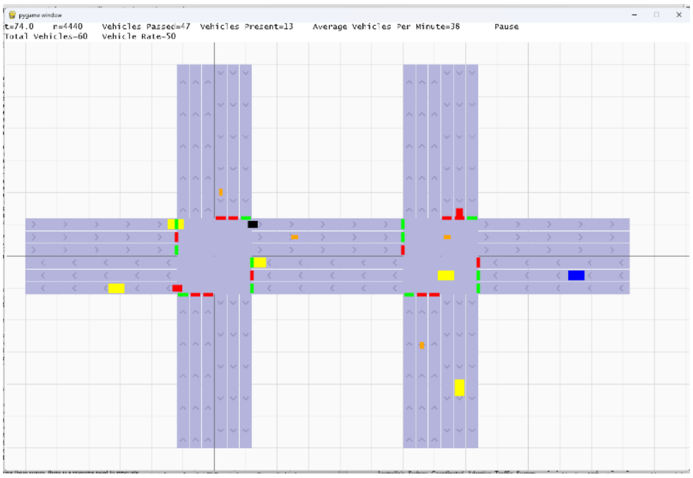

Figure 4. At 74 seconds

Figure 5 depicts the scenario at 167 seconds, where traffic congestion remains low, and no significant queues have formed.

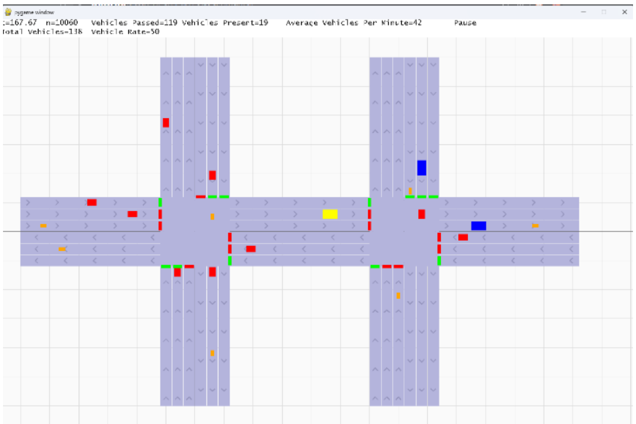

Figure 5. At 167 seconds

Figure 6 shows the scenario at 441 seconds into the simulation, where traffic congestion has risen. Despite the increased congestion, vehicles continue to flow at regular intervals, and the emergency vehicle is given priority.

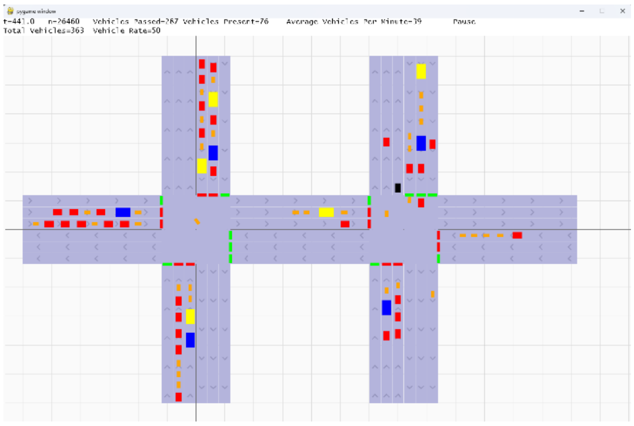

Figure 6. At 441 seconds

The vehicle counts at Intersection 1 are presented in Table 1, showing the number of vehicles waiting at each incoming road at different time intervals. At 74 seconds, traffic remains light with minimal congestion, as only one vehicle is waiting at each of the North, West, and East roads, while the South road has no waiting vehicles. By 167 seconds, the vehicle count has slightly increased, with small queues forming at the South and East roads. At 441 seconds, congestion rises notably, especially on the North and South roads, with 15 and 13 vehicles waiting, respectively, while the West road sees no vehicles waiting. As the simulation progresses, the traffic volume continues to grow, with significant queues forming at all roads by 600 and 750 seconds, reflecting an increase in overall congestion at the intersection.

Time Elapsed	North_in	East_in	South_in	West_in
74	1	1	0	1
167	1	1	1	3
441	15	0	13	13
600	20	2	18	22
750	25	4	22	28

Table 1. Readings at Intersection 1

The vehicle counts at Intersection 2 are presented in Table 2, showing the number of vehicles waiting at each incoming road at different time intervals. At 74 seconds, traffic is light with one vehicle waiting at each of the North, West, South, and East roads. By 167 seconds, the vehicle count has increased slightly, with two vehicles waiting at the North road while the other roads remain relatively unaffected. At 441 seconds, congestion rises, particularly at the North and East roads, where 10 and 14 vehicles are waiting, respectively, while the South and West roads see moderate queues. As the simulation continues, the number of waiting vehicles increases further, with more significant congestion at all roads by 600 and 750 seconds, indicating higher overall traffic volume at the intersection.

Time Elapsed	North_in	East_in	South_in	West_in
74	1	1	1	1
167	2	1	1	1
441	10	5	7	14
600	15	8	12	18
750	20	10	18	25

Table 2. Readings at Intersection 2

4. CONCLUSION

In conclusion, the results of the simulation demonstrate the impact of varying traffic conditions on congestion levels and the efficiency of traffic flow at the two intersections. The data presented reveals that while initial traffic volumes are manageable, congestion increases significantly over time, particularly during peak periods. The ability to prioritize emergency vehicles, even under high congestion, was effectively maintained throughout the simulation. The findings highlight the importance of dynamic traffic management systems that can adapt to changing conditions and ensure both the smooth flow of vehicles and the timely passage of emergency vehicles. Further studies and simulations could refine these models and incorporate additional factors to enhance the performance and scalability of traffic management systems in real-world scenarios.

REFERENCES

[1] TomTom.com, 'Tom Tom World Traffic Index', 2019. [Online]. Available: https://www.tomtom.com/en_gb/traffic-index/ranking/

[2] Khushi, "Smart Control of Traffic Light System using Image Processing," 2017 International Conference on Current Trends in Computer, Electrical, Electronics and Communication (CTCEEC), Mysore, 2017, pp. 99-103, doi: 10.1109/CTCEEC.2017.8454966.

[3] A. Vogel, I. Oremović, R. Šimić and E. Ivanjko, "Improving Traffic Light Control by Means of Fuzzy Logic," 2018 International Symposium ELMAR, Zadar, 2018, pp. 51-56, doi: 10.23919/ELMAR.2018.8534692.

[4] A. A. Zaid, Y. Suhweil and M. A. Yaman, "Smart controlling for traffic light time," 2017 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT), Aqaba, 2017, pp. 1-5, doi: 10.1109/AEECT.2017.8257768.

[5] Renjith Soman "Traffic Light Control and Violation Detection Using Image Processing"." IOSR Journal of Engineering (IOSRJEN), vol. 08, no. 4, 2018, pp. 23-27

[6] A. Kanungo, A. Sharma and C. Singla, "Smart traffic lights switching and traffic density calculation using video processing," 2014 Recent Advances in Engineering and Computational Sciences (RAECS), Chandigarh, 2014, pp. 1-6, doi: 10.1109/RAECS.2014.6799542.

[7] Sabeen Javaid, Ali Sufian, Saima Pervaiz and Mehak Tanveer,"Smart Traffic Management System Using Internet of Things",IEEE 2018.

[8] F. Tang, Y. Kawamoto, N. Kato, and J. Liu, "Future intelligent and secure vehicular network toward 6G: machine-learning approaches," Proceedings of the IEEE, vol. 108, no. 2, pp. 292–307, 2020.

[9] Y. Ni, L. Cai, J. He et al., "Toward reliable and scalable internet of vehicles: performance analysis and resource management," Proceedings of the IEEE, vol. 108, no. 2, pp. 324–340, 2020.

[10] H. Zhou, W. Xu, J. Chen, and W. Wang, "Evolutionary V2X technologies toward the internet of vehicles: challenges and opportunities," Proceedings of the IEEE, vol. 108, no. 2, pp. 308–323, 202