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# Adaptive Traffic Control and Management Using Yolo V8

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**ABSTRACT:** Traffic congestion is a pressing issue exacerbated by population growth and increased automobile usage in urban areas. Megacities are particularly affected, necessitating real-time traffic density calculations for improved signal control and management. Our proposed solution utilizes live camera feeds for traffic density analysis and employs AI algorithms to dynamically adjust traffic signals based on vehicle density. This approach aims to reduce congestion, decrease travel times, and mitigate environmental impact. By optimizing traffic control, our system offers faster transit and contributes to a more sustainable urban environment.

**KEYWORDS:** Traffic control, Traffic light system, Traffic management, Intelligent transport systems, Smart surveillance, Computer Vision, Machine Learning, Object detection, YOLOV8.

## I. INTRODUCTION

Traffic congestion has emerged as a pressing concern in cities worldwide, significantly impacting daily life, fuel consumption, travel time, and air quality. In the United States alone, travellers collectively spend nearly seven billion extra hours stuck in traffic annually, equating to approximately 42 hours per traveller. Similarly, Europe incurs significant financial costs due to traffic congestion. Factors contributing to this issue include inadequate traffic infrastructure, mismanagement of traffic signals, and the relentless increase in population and vehicles on the roads. While improving traffic infrastructure could offer a solution, its implementation is costly and insufficient without effective traffic signal management. Adaptive traffic management is crucial in modern transportation systems due to the dynamic and unpredictable nature of traffic conditions. Traditional traffic management approaches, such as fixed-time signal control or static route planning, often fall short in responding to fluctuating traffic volumes, incidents, or changing environmental factors. Consequently, congestion, delays, and safety risks persist, negatively impacting overall transportation efficiency and user experience. It addresses these challenges by continuously monitoring traffic conditions in real-time and adjusting control strategies accordingly. By leveraging data from sensors, cameras, and other monitoring devices, adaptive systems can detect changes in traffic flow, identify congestion hotspots, and predict potential incidents before they escalate. This proactive approach enables traffic managers to implement responsive measures, such as dynamically adjusting signal timings, deploying traffic management strategies, or providing real-time traveller information to motorists. Adaptive traffic management systems play a crucial role in addressing the complexities and challenges of modern transportation systems effectively. By providing real-time monitoring, proactive intervention, and dynamic control strategies, adaptive systems improve traffic flow, reduce congestion, enhance safety, and optimize overall transportation efficiency, ultimately providing a better experience for road users and contributing to sustainable urban mobility.

Intelligent Transportation Systems (ITS) present a viable approach to addressing traffic congestion by leveraging real-time traffic information where infrastructure can be connected and communicated with each other. An ITS provides information, communication, and sensor technologies to vehicles and transportation infrastructure to offer real-time traffic information for road users and transportation system operators to make better decisions. ITS mainly focuses on five application areas: Advanced Traveller Information Systems, Advanced Transportation Management System (ATMS), ITS-Enabled Transportation Pricing Systems, Advanced Public Transportation Systems, and Vehicle-to-Infrastructure Integration and Vehicle-to-Vehicle Integration. The ATMS improves the flow of vehicles on the road by considering adaptive traffic signal and phase timing rather than the fixed signal and phase. It uses real-time traffic data from road intersections and makes dynamic traffic signalling based on the incoming data. Traditionally, traffic signals are controlled by predefined fixed time plans. The fixed time is determined by historical traffic demand for all green traffic signal phases without considering real-time traffic fluctuation. There is another type of traffic signal control system named vehicle-actuated method.

Our proposed system aims to design a traffic light controller based on Computer Vision that can adapt to the current traffic situation. It utilizes live images from CCTV cameras at traffic junctions for real-time traffic density

calculation, detecting the number of vehicles at the signal and adjusting the green signal time accordingly. By using YOLO for vehicle detection, the system sets the timer of the traffic signal based on vehicle density, optimizing green signal times to reduce delays, congestion, and waiting time, thereby decreasing fuel consumption and pollution. We will explore the underlying technologies and methodologies employed in these systems, examine case studies of successful implementations, and discuss future directions and opportunities for further research and development in this field. Overall, adaptive traffic control and management systems represent a promising approach to addressing the complex challenges of urban traffic congestion and improving the overall quality of urban transportation.

## II. BACKGROUND STUDY

Khushi [1], proposed a solution for Traffic control using video processing. The video from the live feed is processed before being sent to the servers where a C++ based algorithm is used to generate the results. Hard code and Dynamic coded methodologies are compared, in which the dynamic algorithm showed an improvement of 35%. A. Vogel, I. Oremovic, R. Simic and E. Ivanjko [2], proposed an Arduino-UNO based system that aims to reduce traffic congestion and waiting time. This system acquires images through the camera and then processes the image in MATLAB, where the image is converted to a threshold image by removing saturation and hues, and traffic density is calculated. Arduino and MATLAB are connected using USB and simulation packages, which are preinstalled. Depending on traffic count and traffic density, the Arduino sets the duration of green light for each lane. However, this method has several flaws. The cars often overlap with each other, making it difficult to obtain an accurate count of vehicles on the road. Moreover, different objects interfere with detection, as they too are converted to black and white, without distinction from regular objects like billboards, poles, and trees.

A. A. Zaid, Y. Suhweil, and M. A. Yaman [3], proposed a fuzzy logic-controlled traffic light that can adapt to the current traffic situations. This system makes use of two fuzzy controllers with 3 inputs and one output for primary and secondary driveways. A simulation was done using VISSIM and MATLAB, and for low traffic density, it improved traffic conditions. Renjith Soman [4], in his article titled "Traffic Light Control and Violation Detection Using Image Processing" published in IOSR Journal of Engineering (IOSRJEN), vol. 08, no. 4, 2018, pp. 23-27, proposed a smart traffic light system using ANN and fuzzy controller. This system makes use of images captured from cameras installed at traffic sites. The image is first converted to a grayscale image before further normalization. Then, segmentation is performed using a sliding window technique to count the cars irrespective of size, and ANN is run through the segmented image. The output is used in a fuzzy controller to set timers for red and green lights using crisp output. Results had an average error of 2% with an execution time of 1.5 seconds. A. Kanungo, A. Sharma, and C. Singla [5], used support vector machine algorithm along with image processing techniques. From live video, images in small frames are captured and the algorithm is applied. Image processing is done using OpenCV, and the images are converted to grayscale images before SVM is applied. This system not only detects traffic density but also detects red light violations.

Siddharth Srivastava, Subha deep Chakraborty, Raj Kamal, Rahil Minocha [6], in their article proposed the use of adaptive light timer control using image processing techniques and traffic density. Their system consists of a microcontroller-controlled traffic light timer, high image sensing devices, MATLAB, and transmission using UART principles. However, this system fails to prioritize authorized emergency vehicles nor to detect accidents on the intersection. Ms. Saili Shinde, Prof. Sheetal Jagtap [7] reviewed various techniques used for traffic light management systems. This paper observes that each technique has a common architecture: choose input data, acquire traffic parameters from input data, process it, determine density, and update parameters. Cao et al [8], employed machine learning techniques to forecast impending congestion based on the proximity of relevant roads and the driving intentions of associated vehicles. However, their approach relies on knowing the driving intentions of those vehicles, which entails substantial computational expenses for real-time congestion prediction. Additionally, certain unpredictable events, akin to black swans, cannot be foreseen. Consequently, addressing congestion incidents after they occur becomes crucial.

Brennand et al [9], proposed a traffic congestion control scheme aimed at mitigating the issues arising from traffic congestion in a distributed manner. Their approach involves constructing road classifications and providing recommendations for alternative routes to relevant vehicles. In the pursuit of efficient urban traffic flow management, grid-based traffic management has emerged as a prominent research area. However, constructing an effective management model for large-scale urban grid-based traffic networks remains a significant challenge. Qi et al. [10], proposed a dynamic strategy to reduce accident-induced traffic congestions by informing accident information to related drivers and facilitating detours in urban areas. Their scheme utilizes a time-based shortest path algorithm to generate a sub-road-network, enabling related vehicles to receive accident updates promptly.

Cao et al.'s [11], proposed a novel pheromone-based traffic management framework aimed at reducing traffic congestion by integrating dynamic vehicle rerouting and traffic light control strategies. However, they acknowledged the challenge of predicting traffic congestion caused by unpredictable events like Black Swan occurrences.

Furthermore, the spread of congestion in urban road networks is recognized as a complex spatiotemporal phenomenon, necessitating analysis and modelling through computationally intensive microscopic models. Yildirimoglu et al. [12] proposed a hierarchical traffic management system utilizing Macroscopic Fundamental Diagram (MFD) principles. This system operates on two levels: at the upper level, a road guidance scheme optimizes road network performance guided by regional traffic split ratios, employing a model predictive control mechanism. Meanwhile, at the lower level, a path assignment mechanism recommends sub-regional paths for relevant vehicles, facilitated by an integer linear programming formulation.

### III. PROPOSED METHODOLOGY

#### a. Overview

Our proposed system utilizes images captured by CCTV cameras at traffic junctions to perform real-time traffic density estimation through image processing and object detection techniques. The captured image undergoes analysis using the YOLO vehicle detection algorithm, identifying vehicles such as cars, bikes, buses, and trucks to gauge traffic density. This information, along with other relevant factors, guides the signal switching algorithm in determining optimal green signal timers for each lane, with adjustments made to red signal times accordingly. To prevent lane starvation, the green signal duration is constrained within predefined maximum and minimum thresholds. Additionally, a simulation is developed to showcase the system's efficacy and compare it against the existing static system.

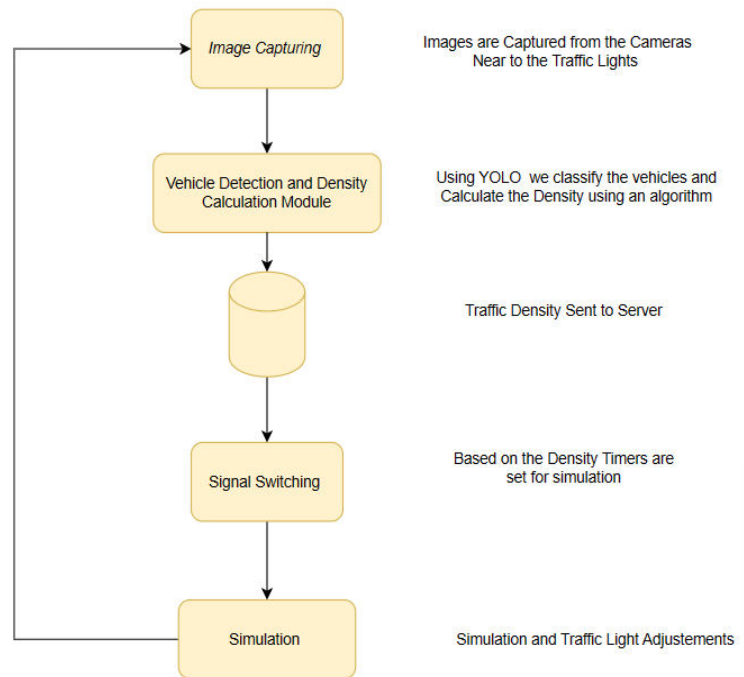


Fig 1: Architecture of proposed system

#### b. YOLO Implementation and Architecture

Our proposed adaptive traffic management system aims to revolutionize the way traffic is managed by utilizing state-of-the-art technology, particularly the YOLOv8 architecture, which is renowned for its highly efficient object detection capabilities. In our system, YOLOv8 serves as the backbone for real-time processing of traffic scenarios captured by surveillance cameras strategically positioned at key locations such as traffic junctions.

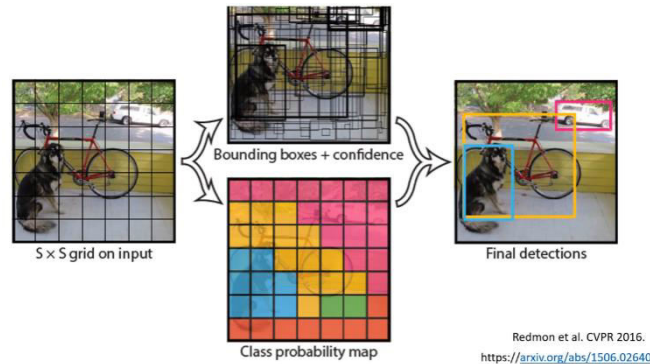


Figure 1. Object Detection using YOLOv8

### c. Image Capturing Module

Our traffic control system integrates CCTV camera technology, image processing, and object detection for real-time traffic density calculation. It comprises three modules: Vehicle Detection, Signal Switching Algorithm, and Simulation, pivotal for optimizing junction traffic flow. The Vehicle Detection module processes CCTV images through image processing and YOLO algorithm for vehicle classification. This forms the basis for traffic density calculation. The Signal Switching Algorithm adjusts signal timings dynamically based on vehicle detection data to enhance traffic flow and minimize congestion, ensuring balanced signal allocation across lanes. A Simulation module validates system effectiveness through comparative analysis with static systems, demonstrating tangible benefits in optimizing traffic flow. This approach highlights the superiority of our dynamic signal switching system over traditional methodologies.

### d. Vehicle Detection and Density Calculation Module

The proposed system opts for YOLO (You Only Look Once) for vehicle detection due to its optimal trade-off between accuracy and processing speed. To customize YOLO for our specific needs, a bespoke model was trained to identify various vehicle types, such as cars, bikes, buses, trucks, and rickshaws. Training began with dataset preparation, involving sourcing images from Google and manually labeling them using the Label IMG tool. We utilized pre-trained weights from the official YOLO website and adjusted the configuration file (.cfg) to align with our model's requirements. Training iterations persisted until the loss function minimized, signaling completion. The trained weights were then integrated into the system code, enabling vehicle detection via the OpenCV library. Detected vehicles are visually highlighted through bounding boxes drawn on images based on the received labels and coordinates.

### e. Traffic Density Storage at Server Module

At the core of our traffic control system is the vital aspect of storing traffic density data at the server level, crucial for real-time traffic management efficiency. This entails establishing a centralized server infrastructure equipped with robust hardware and software capabilities to manage incoming data from multiple traffic junctions. The collected data, processed through image processing and object detection algorithms, is stored in a structured format within the server's database, including timestamps, junction locations, traffic density values, and relevant metadata. Additionally, regular backups and redundancy measures are implemented to ensure data availability and system reliability, enhancing operational resilience under diverse conditions.

### f. Signal Switching Algorithm

The Signal Switching Algorithm coordinates traffic signal timing based on real-time traffic density data from the vehicle detection module, ensuring smooth traffic flow at intersections. It dynamically adjusts green signal timers based on detected vehicle count and class distribution, updating red signal timers accordingly and managing signal transitions cyclically. By parsing JSON data from the detection module, the algorithm computes total vehicle counts for each class, considering confidence levels and object coordinates for precise traffic density calculation. It calculates green signal times considering factors like processing time, lane count, and vehicle class speeds, while preventing lane starvation with minimum and maximum time limits. The algorithm's adaptability scales seamlessly to accommodate varying signal counts, optimizing traffic signal timing to alleviate congestion and enhance safety. During operation, detection threads capture snapshots for the next direction while the main thread handles current signal timing, ensuring seamless assignment and preventing lag. This efficient process allows for real-time adjustments, enhancing overall traffic efficiency and management effectiveness.

$$GST = \frac{\sum_{vehicleClass} (NoOfVehicles_{vehicleClass} * AverageTime_{vehicleClass})}{(NoOfLanes+1)}$$

Where, GST is green signal time

**g. Simulation Module**

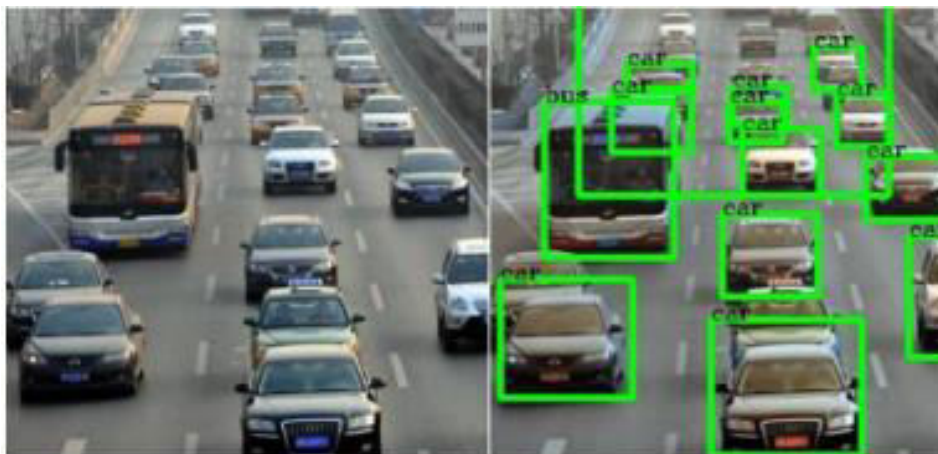
A Pygame simulation was meticulously crafted to visually depict real-world traffic scenarios and compare the proposed dynamic traffic control system with the existing static system. It showcases a 4-way intersection with timers on each traffic signal for signal transitions, along with vehicle counts. Various vehicle types enter from different directions, with some programmed to turn at the intersection based on random initialization. Elapsed time tracking aids in progress monitoring and data analysis. Key steps involved sourcing and resizing background and vehicle images, coding signal phases and vehicle behaviors, and introducing a bike lane for urban realism. By simulating realistic behaviors and intersection dynamics, the simulation offers valuable insights into dynamic traffic control system effectiveness.

**IV. RESULTS ANALYSIS**

Test images on which our vehicle detection model was applied. The left side of the figure shows the original image and the right side is the output after the vehicle detection model is applied on the image, with bounding boxes and corresponding labels. The vehicle detection module underwent rigorous testing with a diverse set of test images, each containing varying numbers of vehicles. Despite achieving a respectable accuracy range of 75-80%, it fell short of reaching an optimal level of performance. The primary bottleneck hindering further accuracy improvement was identified as the inadequacy of the dataset used for training the model.

To address this limitation and enhance the accuracy of the detection system, a proposed strategy involves leveraging real-life footage captured from traffic cameras to enrich the training dataset. By incorporating real-world scenarios captured in traffic camera footage, the model can learn from a more representative and diverse set of environments, lighting conditions, and vehicle configurations. This approach enables the model to generalize better and adapt to the complexities encountered in real-world deployment. Utilizing traffic camera footage offers several advantages over synthetic or curated datasets. Firstly, it provides a vast and constantly evolving source of data, ensuring the model's robustness and adaptability to dynamic traffic scenarios. Secondly, it offers a richer context by capturing the intricacies of traffic flow, vehicle interactions, and environmental factors, which are crucial for accurate detection. Additionally, real-life footage facilitates the annotation of ground truth data, essential for supervised learning and model evaluation.

By training the vehicle detection model on real-life traffic camera footage, the system can learn to detect vehicles more accurately, even in challenging conditions such as adverse weather, occlusions, and varying illumination. This approach not only enhances the performance of the detection system but also installs confidence in its reliability and applicability in real-world settings. Moreover, continuous refinement and fine-tuning of the model using updated datasets ensure that it remains effective in addressing evolving challenges and requirements in vehicle detection applications, ultimately leading to improved safety, efficiency, and performance in traffic management and related domains.



**Figure 2. Vehicle Detection Results**

Fig. 2 shows test images on which our vehicle detection model was applied. The left side of the figure shows the original image and the right side is the output after the vehicle detection model is applied, with bounding boxes and corresponding label



Figure 3. Simulation Output

With all simulation conditions same i.e distribution of traffic, speeds of vehicles, probability of vehicles turning, the gap between vehicles, and so on, the simulations were run for a total period of 1 hour 15 minutes, with 300 seconds i.e. 5 minutes for each distribution and it was found out that the proposed system, on an average, increased the performance by about 23% as compared to the current system with fixed times. This implies a reduction in idle green signal time as well as the waiting time of the vehicles. On comparing these results with some alternative adaptive system, it was found that the proposed system achieves an average performance improvement of 12% as compared to static systems while the proposed system achieves 23% improvement.

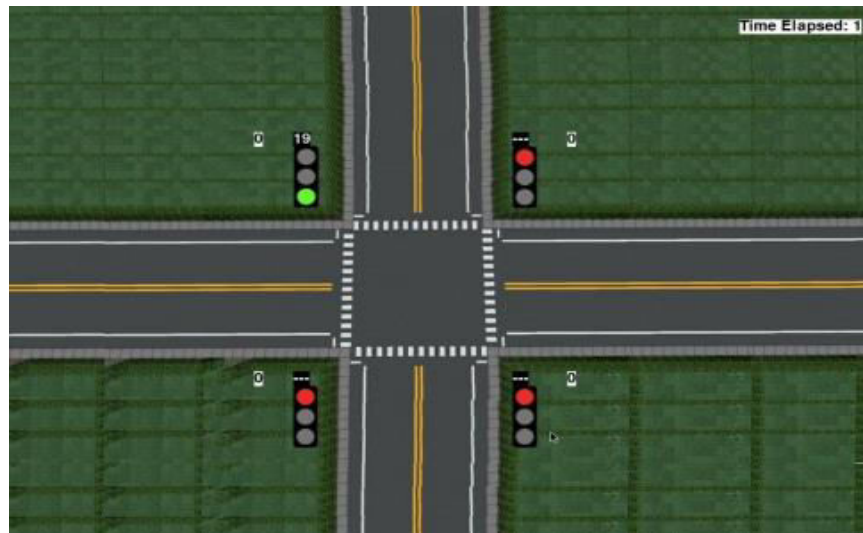


Figure 5. Simulation Output 1

Figure5, Simulation Output 1, just after start showing red and green lights, green signal time counting down from a default of 20 and red time of next signal blank. When the signal is red, we display a blank value till it reaches 10 seconds. The number of vehicles that have crossed can be seen beside the signal, which are all 0 initially. The time elapsed since the start of simulation can be seen on top right .



Figure 6. Simulation Output 2

Figure 6, Simulation Output2 showing green time of signal for vehicles moving up set to 10 seconds according to the vehicles in that direction. As we can see, the number of vehicles is quite less here as compared to the other lanes. With the current static system, the green signal time would have been the same for all signals, like 30 seconds. But in this situation, most of this time would have been wasted. But our adaptive system detects that there are only a few vehicles, and sets the green time accordingly, which is 10 seconds in this case.

Table-1: Simulation Results of Current Static System

No.	Distribution	Lane1	Lane 2	Lane 3	Lane 4	Total
1	[300,600,800,1000]	70	52	52	65	239
2	[500,700,900,1000]	112	49	48	31	240
3	[250,500,750,1000]	73	53	63	62	251
4	[300,500,800,1000]	74	44	65	71	254
5	[700,800,900,1000]	90	32	25	41	188
6	[500,900,950,1000]	95	71	15	14	195
7	[300,600,900,1000]	73	63	69	24	229
8	[200,700,750,1000]	54	89	10	67	220
9	[940,960,980,1000]	100	10	8	4	122
10	[400,500,900,1000]	81	29	88	37	235
11	[200,400,600,1000]	42	47	54	86	229
12	[250,500,950,1000]	39	52	93	22	206
13	[850,900,950,1000]	74	10	13	17	114
14	[350,500,850,1000]	49	46	69	50	214
15	[350,700,850,1000]	51	64	37	43	195

Table-1 Simulation Output showing green time of signal for vehicles moving up set to 10 seconds according to the vehicles in that direction. As we can see, the number of vehicles is quite less here as compared to the other lanes. With the current static system, the green signal time would have been the same for all signals, like 30 seconds. But in this situation, most of this time would have been wasted. But our adaptive system detects that there are only a few vehicles, and sets the green time accordingly, which is 10 seconds in this case.



**Table-2: Simulation Results of Proposed system**

No.	Distribution	Lane1	Lane 2	Lane 3	Lane 4	Total
1	[300,600,800,1000]	87	109	41	50	287
2	[500,700,900,1000]	128	55	49	25	257
3	[250,500,750,1000]	94	50	60	58	262
4	[300,500,800,1000]	89	46	69	59	263
5	[700,800,900,1000]	185	25	23	28	261
6	[500,900,950,1000]	94	118	11	16	239
7	[300,600,900,1000]	87	68	70	33	258
8	[200,700,750,1000]	56	108	19	78	261
9	[940,960,980,1000]	193	6	5	7	211
10	[400,500,900,1000]	97	29	100	34	260
11	[200,400,600,1000]	26	52	67	99	244
12	[250,500,950,1000]	52	75	101	7	235
13	[850,900,950,1000]	154	17	12	18	201
14	[350,500,850,1000]	64	53	80	47	244
15	[350,700,850,1000]	66	82	40	48	236

Table 1, displays the simulation results of the current static traffic signal system, providing insights into vehicle flow and intersection performance under fixed signal timings. The data offers valuable observations regarding traffic behavior and efficiency within the simulated environment. Table 2, illustrates the simulation outcomes of the proposed adaptive traffic signal system, showcasing enhanced intersection performance through dynamic signal adjustments based on real-time traffic conditions, resulting in improved traffic flow and reduced congestion. The distribution [a, b, c, d] means that the probability of a vehicle being in lane 1, lane 2, lane 3, and lane 4 is a/d, (b/a)/d, (c-b)/d, and (d-c)/d, respectively. For example, in simulation 1, the distribution is [300,600,800,1000] which means probabilities of 0.3, 0.3, 0.2, and 0.2. The results obtained were tabulated in the form of number of vehicles passed lane-wise and the total number of vehicles passed. When the distribution of traffic among the 4 lanes is equal or almost equal, then the proposed system performs only slightly better than the current system. This is the case in simulation numbers 1, 2, 3, and 4. The performance improvement is about 9% here. When the distribution of traffic is moderately skewed, then the proposed system performs significantly better than the current system. This is the case in simulation numbers 5, 6, 7, 8, 14, and 15. The performance improvement is about 22% here. Usually, this is the kind of traffic distribution seen in real life scenarios.



**Figure 4: Simulation result analysis of Current System Vs Proposed System**

As it can be seen in figure 4, the proposed adaptive system always performs better than the current static system, regardless of the distribution. The improvement in performance depends on how skewed the distribution of traffic is across the lanes. More the skewness of the distribution of traffic, more improved is the performance.

## V. CONCLUSION

In conclusion, the proposed adaptive traffic signal system dynamically adjusts green signal times based on traffic density, prioritizing longer durations for busier directions, thus reducing delays and congestion, lowering fuel consumption and pollution. Simulation results indicate a significant 23% improvement in vehicle throughput compared to current systems, with potential for further enhancement through real-life CCTV data calibration. This system offers advantages over traditional methods like Pressure Mats and Infrared Sensors, with negligible deployment costs and reduced maintenance, as existing CCTV infrastructure can be leveraged without additional hardware. Integration of this system with city-wide CCTV networks holds promise for improved traffic management.

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