Adaptive Traffic Light Signal Control Using Fuzzy Logic Based on Real-Time Vehicle Detection from Video Surveillance

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ABSTRACT

Intersections often become the focal points of congestion due to poor traffic signal management, reduced productivity, increased travel duration, gas emissions, and fuel consumption. Existing traffic light systems maintained constant signal duration regardless of traffic situations, resulting in green signals for lanes with no vehicle queues that increased waiting times in other lanes. Therefore, a real-time traffic signal optimization system using Fuzzy Logic control, utilizing vehicle queue and flow rate real-time data from video surveillance, is needed. This research used recorded video from surveillance cameras in Banten Province, Indonesia, during daylight conditions. Vehicle queues and flow rate data were used as parameters to determine traffic light signals. The YOLO algorithm obtained these parameter values, then served them as inputs for the Fuzzy Logic system to determine signal duration. The accuracy of the traffic situation estimation system fluctuated within a range of 40% to 100%. Simulation results showed an improvement of approximately 18% by evaluating the total number of vehicles that exited the queue and reduced vehicle waiting time by about 21% compared to the existing system on intersection efficiency. Consequently, the proposed system can reduce pollution and fuel consumption, contributing to urban sustainability and public well-being enhancement. Despite the improvements over the previous systems, the accuracy of the vehicle detection system may vary with traffic density based on the extent of occlusions present, which is an area that needs further refinement. This research's contributions include utilizing real-time video footage from surveillance cameras above traffic lights to obtain real traffic conditions and identify potential errors such as occlusion of overlapping vehicle due to very congested roads. Another contribution is the adjustment of the Fuzzy membership function based on the vehicle detection system's ability to ensure precise determination of green signal duration, even when the input data contains errors.

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1. INTRODUCTION

Intersections often become traffic congestion hubs due to poor traffic light prioritization [1], where different traffic densities were given the exact duration of the green signal [2]. In some conditions, lanes with low traffic density resulted in wasted time, leading to undesirable delays. The significant waiting time worsened road congestion, causing issues in various aspects of life. Regarding the environment, congestion increases gas emissions and fuel consumption [3]. Economically, congestion reduces productivity and work efficiency. Health-wise, congestion increases stress and fatigue for drivers [4], [5].

Typically, traffic lights are controlled using fixed-timing methods [6], where the duration of signals remains constant regardless of traffic density [7]. Alternatively, some traffic lights use the time-of-day scheme, which employs predetermined patterns based on historical data [8]. However, these conventional methods have limitations. Fixed-timing systems and the time-of-day scheme do not adapt to dynamic traffic situations, thus undesirable waiting times often occur when traffic density is low [9]. At the same time, existing adaptive methods that have been developed using electronic sensors, radar technology, and wireless communication technology are expensive due to the need for numerous sensors to cover a wide area, with each sensor requires regular maintenance [10]. In recent years, area traffic control systems have increasingly utilized video surveillance and monitoring systems to enhance traffic safety, reduce the workload of traffic control officers at intersections, and provide real-time data to drivers [11]. Video surveillance enables the estimation of real-time traffic data by detecting and classifying passing vehicles to provide actual information on vehicle flow fluctuations [12], [13]. This study aims to minimize undesirable delays using an adaptive traffic light control system utilizing real-time data from video surveillance. This would improve vehicle flow efficiency and reduce congestion, thereby reducing fuel consumption and pollution levels [14].

Several studies have explored traffic light control systems using various methods. One study utilized Artificial Neural Networks (ANN) and Fuzzy Logic, processing images of parked cars to determine signal durations. The Fuzzy Logic control system has proven better in improving the vehicle flow rate, though it may not accurately reflect the real traffic conditions because it uses images of parked cars [15]. M. M. Gandhi et al. employed AI and the YOLO algorithm to estimate green signal timing based on traffic density, resulting in a 23% increase in vehicle throughput. However, the conducted simulation did not utilize the object detection results process, thus it failed to account for errors that occurred during the object detection process [16]. Prathap et al. used YOLOv4 to calculate traffic density and determine green signal duration, showing significant improvements in vehicle trips per unit time, although their duration decision system could not handle errors from vehicle detection results in estimating traffic situations [17]. S. A. Celtek proposed using Swarm Optimization methods were applied for real-time signal control, achieving a 28% improvement in average travel time per vehicle. However, this study used survey data and did not involve real-time traffic data acquisition [18].

The literatures described above show that various techniques have been proposed to optimize traffic light duration. However, there is a lack of real-time traffic data acquisition and methods to handle potential errors that may arise during this process. This study proposes a real-time adaptive traffic light system using the vehicle queues and the vehicle flow rate were obtained from real-time object detection from surveillance cameras as input variables for Fuzzy Logic to calculate traffic signal duration.

In real-time object detection, processing speed is also a crucial factor along with accuracy. The YOLO algorithm uses a single regression, which excels in processing speed. The number of vehicles in the queues is counted during red signal, and the vehicle flow rate is the number of vehicles crossing intersections during green signal per unit time. To account for each vehicle type's effects on the flow quality [19], vehicles are classified into cars, motorcycles, and buses/trucks. The vehicles are then converted into passenger car units to estimate traffic capacity and flow more accurately [20].

This system aids decision-making processes related to determine traffic light signal duration. Fuzzy Logic, precisely Mamdani Fuzzy Logic, will be employed to determine green signal duration based on real-time vehicle queues and vehicle flow rates from video surveillance cameras. This intuitive representation closely resembles human decision-making processes from Fuzzy Mamdani, simplifying the complex task of deciding green signal duration in traffic light phases [21]. The flexibility of Fuzzy Logic is able to overcome errors resulting from estimating real-time traffic situations by adjusting it with the ability of the YOLO algorithm to estimate traffic conditions.

The research conducted thus far has not utilized real conditions from actual locations and situations, nor has it accounted for errors that may arise while estimating traffic situations. Some research relies on assuming the vehicle demand in simulation scenarios without precisely estimating them, while others utilize the data collected from field surveys. Additionally, some studies employed images of parked vehicles that might not accurately represent the real traffic conditions at traffic lights. Hence, this study seeks to bridge this gap by employing real-time video footage from video surveillance cameras installed above traffic lights to represent the real conditions in the field better and to identify potential errors that may occur during the traffic situation estimation process like occlusion of overlapping vehicle due to very congested roads that reduce accuracy in traffic situation estimation. The errors in the estimation traffic situation process will become a problem in determining the green signal duration. In previous studies, the green signal duration was determined using mathematical equations and directly inputting vehicle estimation results that contained errors, which could lead to errors in determining the green signal duration. As a result, the subsequent contribution of this research is to calibrate the vehicle detection system's capability to match the actual situation by adjusting the Fuzzy membership function. This aims to ensure that the green signal duration system can still make accurate decisions even if the input contains minor or significant errors.

This paper is structured into four sections. Second section outlines the research methodology and simulation for research evaluation and implementation. Third section presents the traffic estimation system results and traffic light simulations using the Simulation of Urban Mobility software. Lastly, Section 4 provides the conclusions drawn from the research.

2. METHODS

The proposed system utilizes real-time traffic situation data to estimate and adjust flow rate fluctuations accurately. The system comprises video surveillance for real-time data acquisition. The proposed adaptive traffic light flowchart is shown in Fig. 1, including real-time acquisition traffic data and signal duration decision-making. These cameras capture real-time traffic video and process it using image-processing techniques to obtain actual traffic situations. The system detects the count of vehicles for each class, including motorcycles, cars, and trucks/buses, that queued at the red light phase to calculate the vehicle queues. Similarly, the system also detects the number of vehicles crossing the intersection during the green signal phase to calculate the vehicle flow rate. The duration of the green signal dynamically adjusts based on the vehicle queues and vehicle flow rate at that time using Fuzzy Logic computation. Fig. 2 shows the diagram of proposed adaptive traffic light system. The duration of the green signal is constrained within minimum and maximum limits to prevent increased waiting time on other lanes [22]. In this research, the minimum duration for the green signal is 3 seconds and the maximum duration is 65 seconds. The signal changes cyclically in a clockwise direction, similar to the existing system. The signal cycle remains unchanged regardless of traffic density changes to avoid confusion for drivers [23]. Traffic light simulations are conducted using the Simulation of Urban and Mobility (SUMO) software to validate the system's performance [24]. These simulations compare the proposed adaptive system with the existing fixed-timing system in terms of waiting time and the number of vehicles that successfully exited the intersection.

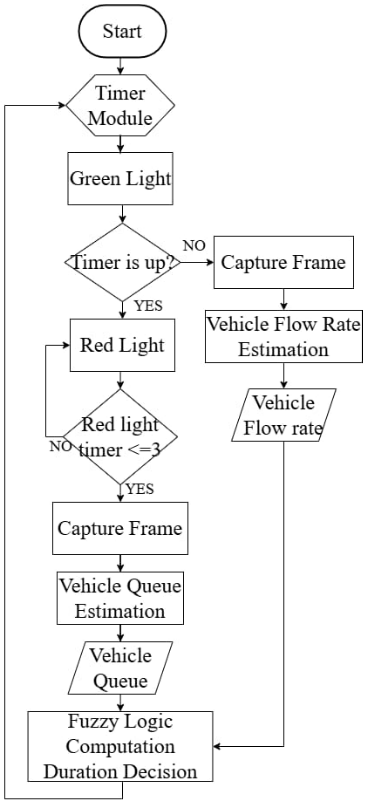


Fig. 1. Proposed adaptive traffic light flowchart

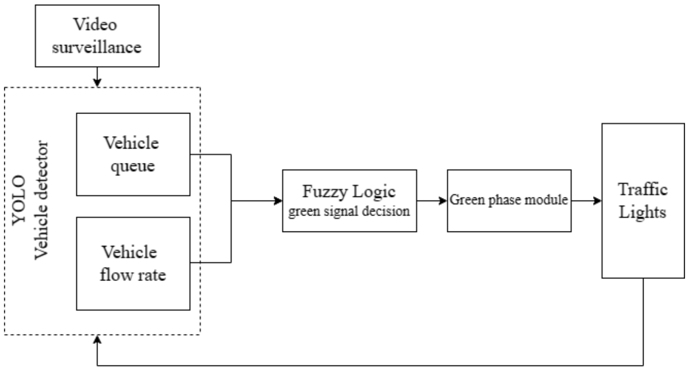


Fig. 2. Proposed adaptive traffic light system diagram

2.1. Vehicle Detection System

Object detection aims to determine an object's presence, size, and position in an image [25]. Typically, this process involves searching every part of the image to find segments that match the target object, either photometrically or geometrically, based on the training database. Detection is declared if the similarity between the template and the image is high. This similarity can be measured using correlation. Vehicle detection identifies vehicles within a specified observation area and precisely categorizes their types to accurately determine their positions [26].

The YOLO (You Only Look Once) algorithm is implemented to detect object [27]. YOLO is a real-time object detection approach that uses a single regression based on a Convolutional Neural Network [28]. This algorithm only requires to look once at an image to predict the type and location of the object [29]. This research uses the YOLOv8 pre-trained version to estimate the vehicle queue and the vehicle flow rate at signalized intersections for control purposes. The YOLOv8 is one of the real-time object detection architectures capable of detecting objects quickly and accurately, and created by Ultralytics. YOLOv8 represents a substantial advancement over YOLOv5, as highlighted by its official documentation and source code. The major improvements consist of a refined backbone network, an innovative anchor-free detection head, and fresh loss functions tailored to enhance these modifications. With this new detection head, every pixel has the capability to forecast the relative offset of an object's top-left and bottom-right coordinates, removing the necessity for predefined anchor boxes. Furthermore, YOLOv8 separates forecasting box locations and classifying them are separated into distinct branches., reducing the joint learning load present in previous versions. This separation leads to a significant improvement in overall performance [30]. It represents performance, speed, and enhanced efficiency compared to its predecessors [31]. The YOLOv8 vehicle detection system is trained using the COCO dataset and achieves a Mean Average Precision value (mAP 50-95) of 50.2 in vehicle detection [32]. The YOLOv8 model has been utilized for vehicle identification and detection, leveraging a dataset comprising 2,042 images for training, 204 images for validation, and 612 images for testing. It achieved an accuracy rate of 77% [33]. Compared to the previous YOLO model, YOLOv8 achieved the highest mean average precision with the fewest parameters, making the YOLOv8 model lighter than other YOLO models. With the same latency, the YOLOv8 model also achieved the highest mean average precision. Consequently, YOLOv8 offers better processing speed and accuracy [34].

The traffic situation estimation process diagram can be seen in Fig. 3. When the program is executed, the video will progress frame by frame. Each frame will be fed into the YOLO model as input. The input frame is divided into grid cells, and each cell is tasked with predicting whether objects are present within its assigned region. Each grid cell goes through a feature extraction process utilizing convolutional layers. Based on the extracted features, each grid cell predicts several bounding boxes that potentially surround objects. The bounding box predictions include geometric coordinates as well as object confidence scores. The probability of object classes within each bounding box is also predicted. Applying the Non-max Suppression technique to handle bounding boxes with low confidence scores and resolve overlap while retaining those with the highest confidence scores [35]. The requirement of detected vehicle objects must have a probability exceeding a certain threshold [36]. In this study, the threshold for object identification is set at 15%.

The vehicle queue is the output of the traffic situation estimation system, representing the total number of vehicles detected 3 seconds before the red signal ends, then converted into Passenger Car Units (PCU) by multiplying each by the equivalent PCU value listed in Table 1 for their respective vehicle classes. A tracking technique is employed to calculate another output, which is the vehicle flow rate. This tracking method relies on Pythagorean theory. It calculates distances using previously obtained midpoint values. If the calculated distance falls below a certain threshold, specifically 35 pixels in this study, the object in the current frame is identified as the same object from the previous frame. Once YOLO successfully detects an object, it continues to recognize it in the following frames until it is no longer visible in the video [37]. By tracking objects, vehicles that have exited the intersection can be counted. If the midpoint of the bounding box falls within the range of a virtual line, in this case, 6 pixels before and after the virtual line, then the object will be counted as a vehicle that has exited the intersection. Flow rate is the number of vehicles that have crossed the intersection with the unit of PCU/minutes.

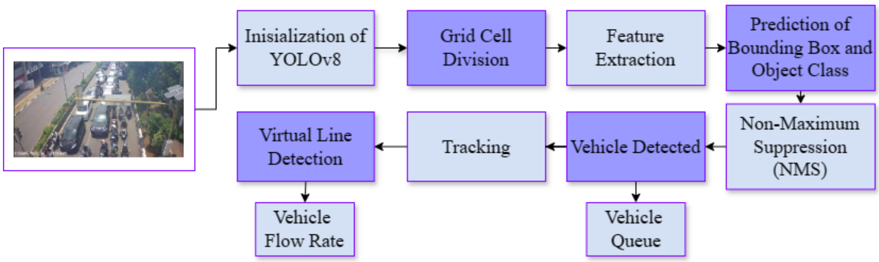


Fig. 3. Traffic situation estimation process diagram

Passenger car unit is a metric used in traffic engineering to assess and compare the impact of different types of vehicles on road traffic flow. By converting various vehicle types into a standard unit, traffic engineers can can be better in understanding and managing traffic flow on different types of roads [38]. PCU values also help to determine the capacity of roads, intersections, and other traffic facilities. PCU values are essential in traffic simulation models, allowing for more accurate predictions of traffic behavior under different scenarios. The specific PCU value for each vehicle type can vary depending on several factors including road conditions (urban vs. rural roads), traffic density, road geometry (number of lanes, width, etc.), traffic regulations and management practices [39]. In this case, the equivalence number of passenger car units is shown in Table 1.

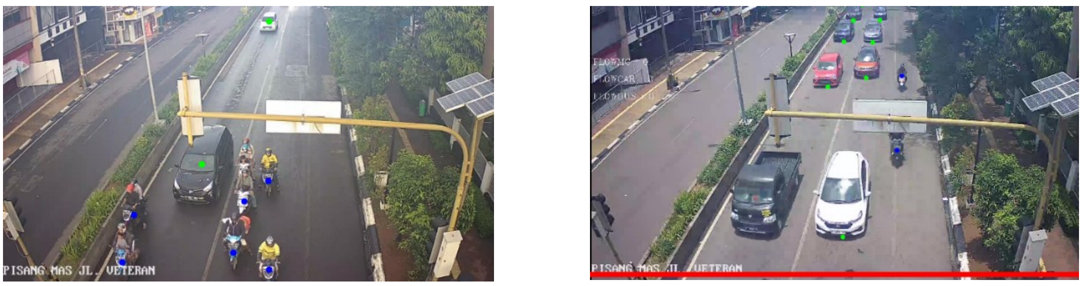
Table 1. Equivalence Number of Passenger Car Units

Vehicle Class	PCU Value
Light Vehicle (Car)	1.0
Heavy Vehicle (Truck/Bus)	2.3
Motorcycle	0.4

After estimating traffic queues and flow, the image is shown in Fig. 4. Vehicles with prediction values of more than 15% are labeled with a circle. Motorcycles are labeled with a blue circle, cars with a green circle, and buses or trucks with a red circle. Fig. 4(a) shows the image after estimating the vehicle queue. In the estimation of the vehicle flow rate, in Fig. 4(b), a red-colored virtual line is placed at the end of the intersection, so when vehicles have crossed the virtual line, it indicates that they have successfully exited the intersection.

Accuracy is used as an indicator for evaluating the vehicle detection system as stated in (1). In a confusion matrix, accuracy is a key measure of a classifier's performance, particularly in multi-class classification. Accuracy indicates how accurate the model classifies correctly.

$$Accuracy = \frac{TruePositive \ + \ TrueNegative}{(TruePositive + FalsePositive + TrueNegative + FalseNegative)} x \ 100\% \quad (1)$$



(a) (b)

Fig. 4. Image of estimating traffic situations process (a) Queue (b) Flow Rate

2.2. Fuzzy Logic Control for Green Signal Duration Decision

Over time, the demand for control systems that can handle a wide range of input and output values, as opposed to the binary 0 and 1 values of traditional Boolean Logic, has grown. Fuzzy Logic allows system inputs and outputs to adjust to various values, ensuring seamless state transitions. This flexibility has led to numerous opportunities for creating highly refined control systems. Fuzzy Logic has become especially crucial in designing dynamic and complex control systems, such as those used for adaptive traffic light control [40].

Fuzzy Logic is employed for decision-making regarding the duration of green signal at intersections, following the estimation of traffic situations using image processing. Fuzzy Logic is used to manage uncertainties in traffic data. Input variables such as vehicle queues and vehicle flow rate are fuzzified to determine optimal green signal duration based on predefined rules. Fuzzy Logic is selected due to its flexibility and capability to handle uncertainty [41]. The Mamdani Fuzzy Logic Control method, often referred to as the Max-Min method, which is intuitively represented, closely resembles human decision-making processes, simplifying the determination of complex traffic light green signal duration [42].

Two factors influence the determination of the green signal duration, serving as inputs to the Fuzzy Logic Control. The input variables for Fuzzy Logic Control are vehicle queues and vehicle flow rate while the output variable is green signal duration. Given that the primary goal of this research is to optimize the vehicle flow to reduce congestion, it is crucial to highlight the importance of the correlation among the Fuzzy inputs. This is particularly significant because some combinations of inputs can lead to undesirable outcomes, while others can facilitate better optimization. Variable of input and output used can be seen in Table 2. Fuzzy rules consist of 8 rules representing all combinations of the Fuzzy sets. Fig. 5 shows the process of Fuzzy Logic Control to decide green signal duration. Fuzzification is performed using the Zadeh min-max AND and OR operations. A part of the fuzzy rules used in this paper is shown in Table 3. When the vehicle queues are high and the traffic flow rate is high, this situation requires the most extended traffic light duration. As either or both of these input values decrease, the required traffic light duration also decreases. The defuzzification process involves multiplying each fuzzy output by its corresponding singleton position and then dividing the sum of these products by the total sum of all fuzzy outputs. This process yields the final single output for the green duration.

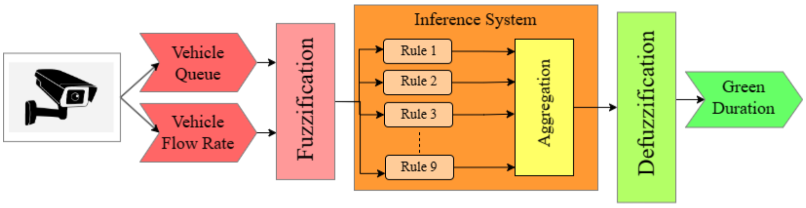


Fig. 5. Fuzzy Logic Control process diagram

Table 2. Membership Function

Membership Function	Queue	Flow	Green Duration
Very Low	0.4-5	-	-
Low	0.4-12.5	0-60	-
Medium	5-20.5	-	-
High	12.5-25	30-90	-
VVS (*very very short*)	-	-	5-10
VS (*very short*)	-	-	10-20
S (*short*)	-	-	20-30
M (*medium*)	-	-	30-40
L (*long*)	-	-	40-50
VL (*very long*)	-	-	50-60
VVL (*very very long*)	-	-	60-65

There are several factors that were considered in developing the membership functions:
1) The total number of vehicles for each class was obtained through object detection.
2) The duration of green signal in existing systems in the field.
3) The capability and accuracy of the vehicle detection system.

4) The minimum and maximum time limits for green signal duration are set to prevent increased waiting times in other lanes.

The input membership function for the vehicle flow rate variable is divided into two classes (Low and High). The range of this variable is determined by observing the estimation of vehicle flow rate results. In real conditions, the vehicle flow rate ranges from 0 PCU/min to 82 PCU/min. However, in the real-time vehicle detection results, the vehicle flow rate ranges from 0 PCU/min to 88 PCU/min, as in heavy traffic conditions where vehicles move slowly, some vehicles are detected more than once on the virtual line. This occurs because the midpoint of the bounding box is within the virtual line range for more than one frame. Therefore, the input flow rate variable range is set from 0 PCU/min for the lower limit of the Low class and 90 PCU/min for the upper limit of the High class. Fig. 6 shows the plot of the vehicle flow rate membership function.

Table 3. Fuzzy Rule Base

[R1]	If flow = low	&	queue = very low	then	green duration = VVS
[R2]	if flow = low	&	queue = low	then	green duration = VS
[R3]	If flow = low	&	queue = medium	then	green duration = S
[R4]	if flow = low	&	queue = high	then	green duration = M
[R5]	if flow = high	&	queue = very low	then	green duration = M
[R6]	if flow = high	&	queue = low	then	green duration = L
[R7]	if flow = high	&	queue = medium	then	green duration = VL
[R8]	if flow = high	&	queue = high	then	green duration = VVL

The input membership function for the vehicle queues is divided into four classes (Very low, Low, Medium, High). The plot of the vehicle queue membership function is shown in Fig. 7**.** The range is determined based on the traffic situation estimation system's capability in estimating vehicle queues. According to the manual counting results, the vehicle queues range from 0 PCU to 45 PCU, whereas the object detection system's counting results show the vehicle queues ranging from 0 PCU to 25 PCU. This discrepancy occurs because in oversaturated traffic conditions, occlusions cause some vehicles, especially motorcycles, to be undetected by the system. Therefore, the input variable for the queue is in the range of 0.4 PCU to 25 PCU. The lowest vehicle queue range is 0.4 when only one motorcycle is present in the queue, with a PCU value of 0.4.

The output membership function of the green signal duration variable is divided into seven levels with a range from 5 seconds to 65 seconds. This range is determined based on the traffic signal duration in existing systems in the field. The plot of the green signal duration membership function can be seen in Fig. 8. In situations where the vehicle queue value is 0 PCU, meaning there are no vehicles in the queue, Fuzzy Logic computation process is not carried out, and the duration of the green signal directly equals 3 seconds. Giving 0 seconds to a lane without vehicle queues is beneficial if the vehicle estimation system does not contain errors. However, in this case, 3 seconds is provided to avoid starvation in the event of an error in the vehicle estimation system.

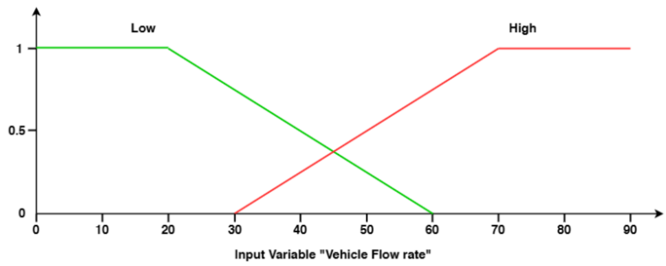


Fig. 6. The plot of the vehicle flow rate membership function

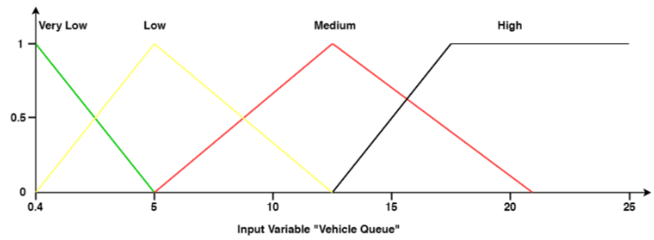


Fig. 7. The plot of the vehicle queue membership function

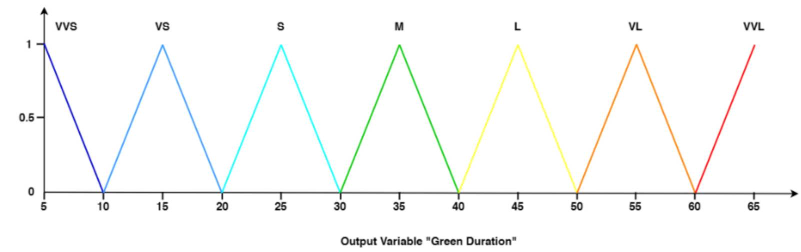


Fig. 8. The plot of the green signal duration membership function

2.3. Traffic Light Simulation

A simulation was developed using the Simulation of Urban Mobility (SUMO) software. SUMO is an open-source traffic simulation package widely used in research to investigate various topics [43]. Within SUMO, traffic light simulation can be performed, allowing for adjustments to the demand for each lane and the traffic light signals.

Fig. 9 shows a snapshot display of the simulation. The simulated network's geometry replicates the intersection layout where video surveillance is captured. This intersection comprises four lanes and four traffic lights. Among these lanes, only one will have its signal controlled to be green, while the remaining three lanes will maintain a fixed green signal with constant traffic flow to observe the effects of the proposed system. The specifics of the traffic scenario for the simulation are outlined in Table 4. The lane under control, lane 1, will receive demand from nine predetermined traffic situations from video footage. Moreover, the queue of vehicles and traffic flow will be manually counted to get the real situation. The demand setting for Lane 1 is that the vehicle queues are given at the first red signal, and then the subsequent demand uses the vehicle flow rate. The vehicle demand for the other three lanes is a constant vehicle flow rate for each simulation.

Each traffic situation will undergo two simulations with the same demand but different traffic light modes. In the first nine simulations, the fixed timing mode is used, similar to the red signal mode in the field. Four lanes at the intersection will have a green signal consistent with their original state. In the second nine simulations, the proposed adaptive traffic light mode is used. The duration of the green signal for lane 1 will be determined based on Fuzzy Logic, using inputs from the result of the object detection process to estimate traffic situations from the video surveillance cameras. The duration of the red signal for the other three lanes will be the same as their original conditions. The unit of vehicle queues in the simulation is PCU, and the unit of vehicle flow rate is PCU/minute.

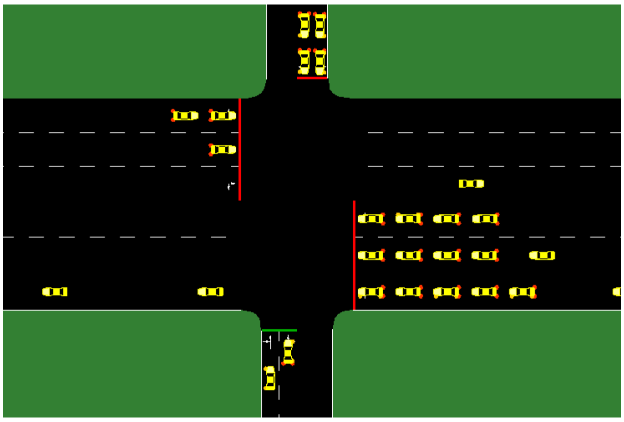


Fig. 9. Simulation display

The simulations are conducted with a duration of 5 minutes for each simulation. Vehicles successfully exited the queue from the four lanes during the 5-minute duration, and the waiting time of the vehicle is counted as an evaluation of the simulation results. To assess the performance of the proposed adaptive system, the waiting time of vehicle and the total number of vehicles successfully exiting queues in adaptive traffic light mode and fixed-timing mode are compared. An increase in the number of vehicles successfully exiting the queue indicates a decreased waiting time and faster vehicle queue dissolution.

Table 4. Traffic Scenario of 18 Simulations from 9 Traffic Situations

Traffic situation	GREEN SIGNAL DURATION: Lane under control Lane 1 – Fixed-timing mode	Adaptive timing mode	3 other lanes: Lane 2	Lane 3	Lane 4	DEMAND: Lane 1 Queue, Flow Rate (PCU, PCU/minute)	Lane 2	Lane 3	Lane 4
1	60	3	30	60	60	0, 0	3.33	6.67	5
2	60	6.35	30	60	60	0.4, 0.4	3.33	6.67	5
3	60	23.8	30	60	60	5.2, 63.4	3.33	6.67	5
4	60	17.2	30	60	60	6.6, 17.8	3.33	6.67	5
5	60	33.2	30	60	60	9, 56	3.33	6.67	5
6	60	22.7	30	60	60	16.2, 9,8	3.33	6.67	5
7	60	56.7	30	60	60	26.4, 71,2	3.33	6.67	5
8	60	36.1	30	60	60	36.8, 47.8	3.33	6.67	5
9	60	53.6	30	60	60	41.6, 76.5	3.33	6.67	5

3. RESULTS AND DISCUSSION

This section analyzes and discusses research results. The evaluation method for the traffic situation estimation results is the system's accuracy in estimating vehicle queues and traffic flow rate. The accuracy metric measures how correctly the model detects and classifies vehicles. Another result is from comparing the simulation of the existing traffic light system with the proposed adaptive system with the existing fixed-timing system. These results are evaluated by comparing both systems' vehicle throughput and waiting time.

3.1. Evaluation of Estimating Traffic Situations System

The vehicle detection system estimates the number of vehicle queues and traffic flow values. Fig. 10 — Fig. 18. show nine traffic situations that will be simulated. The nine traffic situations represent the entire traffic situation. Fig. 10(a)—Fig. 18(a) is the initial image before the estimation of traffic situation process. Fig. 10(b) —Fig. 18(b) is the image after the estimation of traffic situation process. Vehicles successfully detected by the system are marked with circles around their bounding boxes.

Table 5 shows the evaluation of the vehicle situation estimation process. The real traffic situation values are the manual calculations performed by the authors. The traffic situation values from vehicle detection are the results of vehicle detection obtained by the traffic situation estimation system. Testing the YOLOv8 vehicle detection system with various vehicle queue images from video surveillance during red signal revealed that the accuracy of estimating the number of vehicle queues ranges from 80% to 100% when there are few vehicles and 40% to 75% during busy traffic situations. The YOLOv8 vehicle detection system was tested with various traffic videos during green signal to estimate traffic flow values. The accuracy of estimating vehicle traffic flow values ranges from 65% to 100%.

(a) (b)

Fig. 10. Image of traffic situation 1 (a) before the estimation of traffic situation process (b) after the estimation of traffic situation detection process

(a) (b)

Fig. 11. Image of traffic situation 2 (a) before the estimation of traffic situation process (b) after the estimation of traffic situation process

(a) (b)

Fig. 12. Image of traffic situation 3 (a) before the estimation of traffic situation process (b) after the estimation of traffic situation process

(a) (b)

Fig. 13. Image of traffic situation 4 (a) before the estimation of traffic situation process (b) after the estimation of traffic situation process

(a) (b)

Fig. 14. Image of traffic situation 5 (a) before the estimation of traffic situation process (b) after the estimation of traffic situation process

(a) (b)

Fig. 15. Image of traffic situation 6 (a) before the estimation of traffic situation process (b) after the estimation of traffic situation process

(a) (b)

Fig. 16. Image of traffic situation 7 (a) before the estimation of traffic situation process (b) after the estimation of traffic situation process

(a) (b)

Fig. 17. Image of traffic situation 8 (a) before the estimation of traffic situation process (b) after the estimation of traffic situation process

(a) (b)

Fig. 18. Image of traffic situation 9 (a) before the estimation of traffic situation process (b) after the estimation of traffic situation process

Table 5. Queue and Flow Estimation Results

Traffic Situation	Real Traffic Situation		Traffic Situation by Vehicle Detection		Accuracy(%)	
	Queue	Flow	Queue	Flow	Queue	Flow
1	0	0	0	0	100	100
2	0.4	0.4	0.4	0.4	100	100
3	5.2	63.4	4.4	39.4	80	67
4	6.6	17.8	7	16.2	93	88
5	9	56	10.2	46	71	84
6	16.2	9.8	12.2	9	63	90
7	26.4	71.2	20	61.7	72.2	86
8	36.8	47.8	22	36.4	56	77
9	41.6	76.5	17.3	76.9	43.6	94

According to vehicle detection results for estimating queues and traffic flows, the system shows high accuracy when the vehicle queues are shorter, and traffic flows are higher. However, occlusion occurs and lowers the accuracy of estimating vehicle queues when the queue is denser. Additionally, when traffic flow is lower, the vehicle speeds increase, resulting in some vehicles not being detected because the processing time is longer than the time the vehicles spend within the virtual line detection. The main reason for the low accuracy in estimating vehicle queue traffic situations is attributed to the camera angle and the occlusion of motorcycles by larger vehicles. The occlusion increases significantly during peak times when the lanes are oversaturated.

3.2. Evaluation of The Proposed Adaptive Traffic Light System

The simulations were conducted with varying traffic situations on one lane and consistent traffic situations on the other three lanes. In the fixed-timing system, the duration of the red signal is the same as the original. In the proposed system, the duration of the red signal is determined through Fuzzy computation using input from the results of vehicle detection calculations. The variation in traffic situations represents dynamic traffic situations, with Fuzzy Logic membership representing traffic situations with different values. The nine simulations conducted cover all possible traffic situations that may occur. Fig. 10—Fig. 18 show nine images of varying traffic situations used.

Performance is evaluated based on the number of vehicles that successfully exited the intersection within 5 minutes. In other words, the comparison is made by looking at the number of vehicles that left the intersection through each lane, with a higher number indicating reduced waiting time and vehicle queues [44]. Table 6 shows the simulation results of the current system, and Table 7 shows the simulation results of the proposed adaptive system.

As shown in Fig. 19, the proposed system consistently outperforms the current fixed-timing system. High performance estimation occurs when traffic density is low. In traffic situation 1, the number of vehicles that were able to exit the queue increases by 116%, and in traffic situation 2, it increases by 73%. On average, for all traffic situations, the number of vehicles successfully exited the intersection increases by 18% compared to the existing method. Fig. 20 shows the vehicle waiting time between the existing fixed-timing method and the proposed adaptive method. The current one do not work optimally at low traffic density due to the creation of unwanted waiting time when traffic conditions are quieter.

Table 6. Simulation Results of Current Fixed-Timing Traffic Light System

Traffic Situation	Green Duration (s)	Lane 1	Lane 2	Lane 3	Lane 4	Total
1	60	0	22	45	25	92
2	60	1.4	17	43	26	87.4
3	60	43.2	15	42	26	126.2
4	60	40.6	15	45	24	124.6
5	60	47	15	45	26	133
6	60	37.2	15	45	26	123.2
7	60	63.4	15	45	26	149.4
8	60	65.8	15	45	27	152.8
9	60	64.6	15	46	24	149.6

Table 7. Simulation Results of Proposed Traffic Light System

Traffic Situation	Green Duration (s)	Lane 1	Lane 2	Lane 3	Lane 4	Total
1	3	0	29	87	83	199
2	6.35	2.4	17	87	45	151.4
3	23.8	30.2	17	82	27	156.2
4	17.2	22.6	18	83	33	156.6
5	33.2	39	18	86	28	171
6	22.7	28.2	18	78	27	151.2
7	56.7	75.4	18	45	25	163.4
8	36.1	52.8	20	80	26	178.8
9	53.6	67.6	24	45	25	161.6

In the proposed traffic light system, this condition does not occur as the duration of the green signal adapts to the traffic system. Therefore, the length of green signal duration decreases when there is less traffic, resulting in better traffic flow and reduced waiting times compared to fixed-timing systems. For all simulated traffic situations, the proposed adaptive system has an average waiting time of 118 seconds, which is 21% less than the average waiting time of the fixed-timing system. Research [45] reported a 10% decrease in the waiting time of vehicles by directly applying estimation outcomes to decide the duration of the green signal. The improved decrease in waiting time in the suggested system is due to the tuning of vehicle detection outcomes with real-world data, which allows the system to handle errors more efficiently.

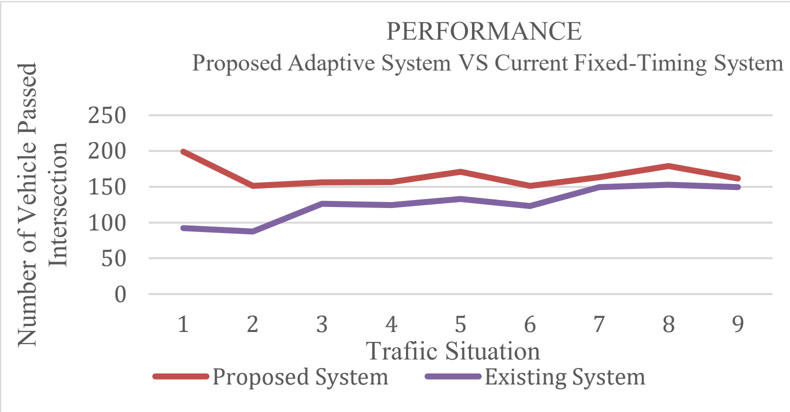


Fig. 19. Performance of the proposed adaptive system and current fixed-timing system

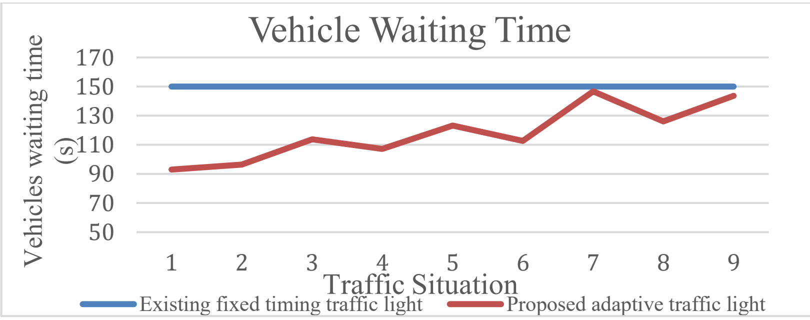


Fig. 20. Vehicle waiting time

The system successfully estimated real-time traffic situations using video footage from surveillance cameras. The system for determining green signal duration effectively addressed errors in traffic condition estimation. In the simulation of traffic situation 8, even with an estimation accuracy of only 56% for vehicle queues, the system was still able to provide an accurate green signal duration and perform better than the existing system. With an estimation accuracy range of 40%- 100%, the system consistently outperformed the existing system.

The system's performance can be further enhanced by adjusting motorcycle positioning and providing dedicated motorcycle stopping area to mitigate occlusion caused by larger vehicles. Video surveillance cameras producing high-quality images will also enhance vehicle detection accuracy. Lastly, the camera installation position needs to be carefully considered to ensure no obstructions and optimize vehicle detection results.

4. CONCLUSION

In this paper, the proposed adaptive traffic light system has successfully applied image processing and Fuzzy Logic to adaptively set the green signal time using real-time video surveillance video. The proposed traffic light system has changed the fixed duration of traffic lights to dynamic, adapting to fluctuations in traffic density —a lower traffic density results in decreasing green signal duration and vice versa [46]. The aim is to reduce vehicle waiting time, potentially decreasing pollution and fuel consumption [47], [48].

Estimating traffic conditions using surveillance cameras in real-world scenarios does not yield 100% accuracy. Detection and classification errors occur due to occlusion, especially during high traffic density. Utilizing Fuzzy Logic for estimating green signal duration offers advantages over using existing mathematical equations [17] because the Fuzzy Logic system can effectively compensate for the shortcomings of the vehicle detection system. This is achieved by adjusting the membership function according to the ability of the vehicle detection system. Despite the differences between the estimated traffic conditions by vehicle detection and the actual situation, the proposed system is still able to perform better, improving vehicle flow efficiency with an 18% increase compared to the current system regarding the overall count of vehicles that successfully exited the queue and a 23% decrease in vehicle waiting time.

The proposed surveillance camera system has many advantages over existing adaptive traffic light systems. The cost required for this method is almost negligible, as it leverages surveillance cameras already installed at traffic junctions [49]. In contrast, systems that use electronic sensors such as pressure mats and infrared sensors require significant costs for sensor procurement and maintenance [50].

This study focuses on optimizing traffic light functions by adjusting signal duration accurately in specific urban intersections during morning peak hours, targeting typical traffic patterns and volumes. Key variables include vehicle queues and flow rate, which influence the traffic light signals. The study excludes factors such as pedestrian movements, weather conditions, and unexpected road incidents, considering only daylight data. This focus is chosen because morning peak hours are critical for urban traffic management. Concentrating on that time enhances traffic flow efficiency during one of the most congested times of the day.

Future research could explore the larger and more complex traffic networks, and developing scalable algorithms for multiple intersections is essential. Expanding the system to detect emergency vehicles and adjust signal timers to prioritize their passage is essential for improving the safety of affected individuals. Addressing these areas will help the system evolve into an efficient and sustainable solution for urban traffic management.

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