

## Development of a Modified Fuzzy Logic Traffic Light Controller Using Fuzzy Time Series for Predicting Traffic Flow

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### ABSTRACT

*This research work developed a modified fuzzy logic traffic light controller using Fuzzy Time Series (FTS) to predict traffic flow for single intersection with the aim of minimizing the average waiting time of vehicles at the intersection or junction. The static nature of green light timing in traditional traffic light control systems may lead to high traffic congestion and results in a huge delay of traffic at intersection. The technique applies fuzzy time series which predicts the future state of the phase based on the previous state. This technique allows the fuzzy controller to make its decision taking into account not only the current traffic situation as detected by the Wireless Sensor Network, but also the probable short-term evolution of the traffic conditions. In this way, the choice of the phases depends on the number of vehicles in the queue, while the green time duration of the traffic lights would be determined based on the traffic flow forecast by the fuzzy time series. The performance of the modified fuzzy logic light controller using FTS is compared with the traffic lights dynamic control system that incorporate wireless sensor network for real-time traffic observing with multiple fuzzy logic controller, using average waiting time per phase as performance metrics. All are carried out in MATLAB 2015a. The performance of the developed controller was compared with the standard fuzzy logic controller and it was found that for the standard controller, the average waiting time in scenario I for phase I, II, III and IV were 18.71, 18.26, 26.10 and 27.32 respectively while that of the developed controller were 17.86, 17.39, 25.54 and 26.25 which is an average of 3.8% improvement across the four phases. For scenario II standard controller the average waiting time for phase I, II, III and IV were 20.36, 19.82, 19.48 and 18.25 while that of the developed controller were 19.99, 19.31, 18.79 and 17.80 respectively which has an average of 2.8% improvement across the four phases. The scenario III average waiting time for phase I, II, III and IV were 21.20, 22.46, 26.23 and 27.35 respectively, while that of the developed controller were 20.45, 19.99, 25.67, 25.97 respectively and have an average of 5.43% improvement across the four phases.*

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### INTRODUCTION

Intelligent Transportation Systems (ITS) are automatic road traffic management systems that manage road traffic with the aim of improving traffic safety, optimizing the speed of traffic flow,

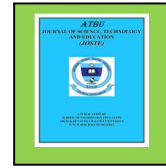
and reducing the energy consumption of cars moving on the roads. Intelligent transportation systems consist of four sub-systems, namely: surveillance system, a communication system, an energy efficiency system and a traffic light control

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system [1]. One of the main objectives of ITS is to ensure road efficiency, especially where traffic congestions are very likely to occur, for instance, in traffic lights junctions [2]. The main aspects to be considered in traffic lights control are both the cycles and the phases of the traffic lights. A traffic light cycle is the sequence of traffic lights signals (such as green, yellow and red) at the end of which the same signals configuration that occurred at the beginning of the sequence itself restarts.

A traffic light phase is the time period during which it is possible, for a given set of lanes, to move in the direction that is allowed. In the case of more than two phases, it is important to determine the activation sequence of the individual phases, also known as phase sequence [3]. Most of the current traffic light control systems uses one of the three control approaches namely [4]: fixed-time, actuated and adaptive. In Fixed-time control, a signal timing plan is selected according to a fixed schedule such as time-of-day, day-of-week. These sets of predetermined plans were developed offline based on historical traffic information. The duration and order of all green phases remain fixed and traffic demand.

In actuated control, the control scheme is adapted to fluctuations in traffic demand, but placing traffic detectors that indicate the presence or absence of vehicles. Using this data, green phases are extended or terminated depending on the present traffic demands. Thus, adaptive control continuously optimizes the signal plan according to the actual traffic load. Changes to the active signal plan parameters are automatically implemented in response to the present traffic demand as measured by a vehicle sensing system. In each case, the overriding aim is the same, to maximize safety, speed, and energy efficiency or minimize waiting time, number of vehicle stops. This is not a simple constrain in a dynamically changing traffic environment in which each traffic light system must take account of a wide range of variables, which include an intersection type of being single-lane or multiple-lane, traffic volume, time of day, the effects on other roads, and the involvement of pedestrian traffic [5].

There are two main traffic control systems that are presently in use, these includes Scoot-split, Cycle and Offset Optimization Technique (SCOOT) [6] and Sydney Coordinated Adaptive Traffic System (SCAT) [7]. Various computational intelligence techniques have been used for the design and implementation of adaptive light control systems, such as Genetic Algorithm [8], Fuzzy Logic Control [9][10], Neural Network [11][12] and Queueing Network technique [14]. This research work proposes the development of a modified Fuzzy Logic Traffic Light Controller using Fuzzy Time Series Model for prediction of traffic flow on single intersection.

## LITERATURE REVIEW

A sensor is a device, module, or subsystem whose aim is to detect events or changes in its environment and send the data to other electronics, frequently a computer processor. It can also be defined as a sensing unit with generally limited capabilities in terms of memory, energy, computation power and communication [14]. Sensor network is a type of network which is capable of making decisions without external assistance. When sensors are networked to a base station, they can be used to control one or more intersection(s) of a particular area. A wireless sensor network (WSN) is a network composed of a large number of low-power and low-complexity wireless nodes that can detect a variable parameter from the physical environment and transmit the collected information to a sink (or possibly multiple sinks), typically, through multiple hops as depicted in

Figure 1. Also, wireless sensor networks can have actuators that are nodes that execute actions in the physical environment. Because of their inherent functionality, the actuators have higher complexity than the sensors. The main desired features of this type of network are [15]: Robustness, Scalability, Self-organization, Extended lifetime, and Low cost and size. Wireless sensor networks can be used for different applications, ranging from military applications such as enemy intrusion detection and home automation [16]. Sensing units used to

detect vehicles are magnetometers, as they are accurate, small and relatively cheap [14].

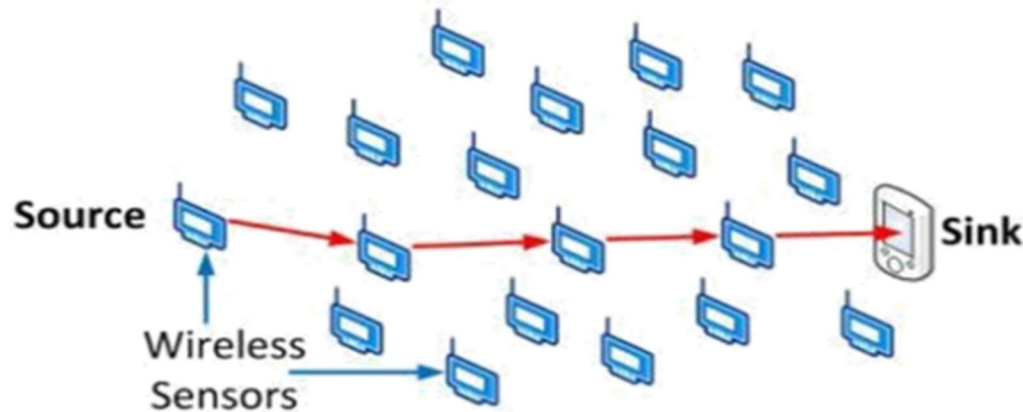


Figure 1. Wireless Sensor Network [17]

An inductive loop is a wire circuit that begins and ends at the same point, connecting to a loop extension cable and a vehicle detector. When powered, it creates a magnetic field that resonates at a steady frequency [18]. When a metal object like a vehicle passes over, the frequency increases, triggering the detector to close a relay. The relay remains closed until the vehicle exits, returning the frequency to normal. This mechanism can control devices like traffic lights or gates. Inductive loops are often embedded in roadbeds to detect passing vehicles, with basic detectors counting them over time [19]. Figure 2 illustrates an inductive loop system, consisting of a loop (preformed or saw-cut), an extension cable, and a detector.

Video vehicle detection offers a non-intrusive way to monitor traffic using cameras. These cameras capture video, which processors analyze to track vehicle movements and identify violations like lane crossing or illegal parking [20]. Cameras are usually mounted on poles or

structures above roads, sending real-time data to a central control room for analysis and traffic management. Figure 2 depicts an urban road network with integrated cameras for vehicle detection. These cameras are mounted on poles or structures and transmit data to a central control room for monitoring.

Wireless Sensor Detection (WSD) uses IEEE 802.15.4 protocol to collect traffic data, linking lane-specific information to traffic signals (IEEE, 2006). The system consists of Reduced Function Devices (RFDs) along roadsides that detect vehicles by sensing disruptions in the Earth's magnetic field. Full Function Devices (FFDs) gather data from RFDs and relay it to the First Pan Coordinator (FPC) for processing [3]. This communication occurs through a beacon-enabled protocol to avoid data collisions. The FPC is integrated into the intersection manager, which controls traffic signals at intersections. Figure 2 represents the WSD system, where the coordinator manages traffic flow at intersections by preventing data collisions using a time-slot mechanism.

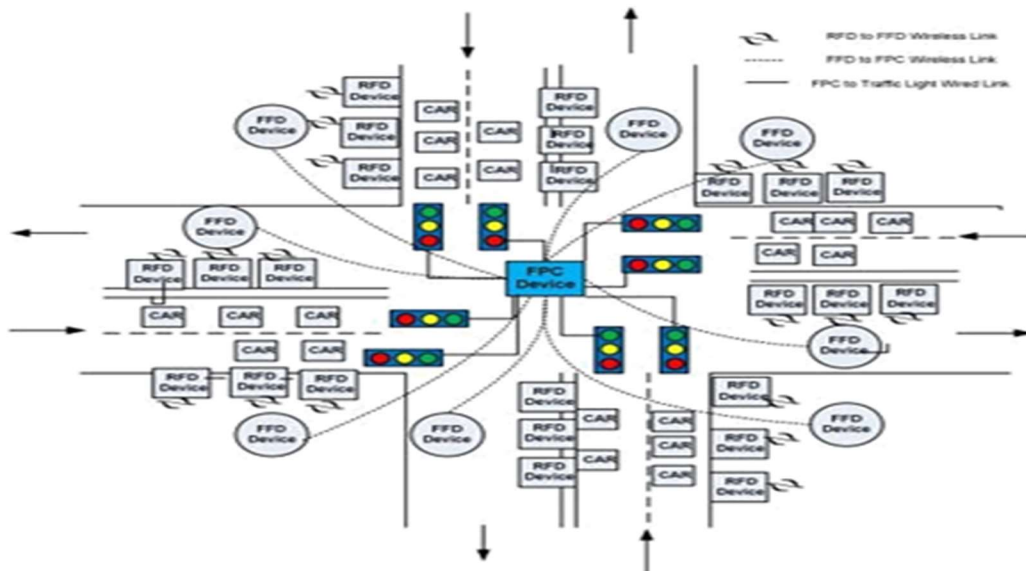


Figure 2. The WSD based traffic system architecture [3].

The idea of fuzzy set logic theory was first proposed by Lofti A. Zadeh in 1965 [21]. Fuzzy logic representations are founded on fuzzy set theory that try to capture the way humans represent and reason with real- world knowledge. A fuzzy set can be defined mathematically by given to each possible individual in the universe of discourse, a value characterizing its grade of membership in the fuzzy set. This grade corresponds to the degree to which that individual is similar with the concept represented by the fuzzy set. In other words, fuzzy set represent flexible sense of membership of elements to a set. When using fuzzy logic, truth values of variables can take on a continuous value in the range of [0; 1]. Decisions in fuzzy logic are usually made using a rule base which can be developed by expert knowledge or trial-and error [22]. Figure 3 shows the Flowchart describing the five steps in the design of a fuzzy system [23].

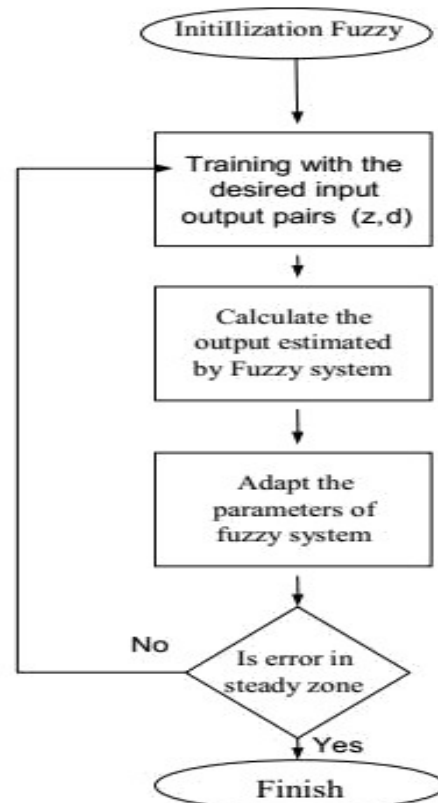


Figure 3. Flowchart for a Fuzzy System [23]

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## METHODOLOGY

The mapping between the traffic lights on the lanes of each road they control and their

allowed directions for the single intersection model adopted in this research is summarized in Table 1.

Table 1. Intersection roads and their associated traffic lights

Traffic lights	Road and lanes controlled	Allowed directions
SEM_A1	Road A-lane 1	Straight/Right
SEM_A2	Road A-lane 2	Left
SEM_B1	Road B-lane 1	Straight/Right
SEM_B2	Road B-lane 2	Left
SEM_C1	Road C-lane 1	Straight/Right
SEM_C2	Road C-lane 2	Left
SEM_D1	Road D-lane 1	Straight/Right
SEM_D2	Road D-lane 2	Left

The traffic lights are managed so as to make sure to prevent the cars coming from the different lanes of the same road from accessing the intersection simultaneously as it is depicted in Figure 4. This choice is made for the sake of avoiding the collisions that could occur when the trajectories of the two lanes of the same road

intersect. This way, the cars coming from the two lanes of ROAD A cannot go straight and turn left, respectively, during the same phase.

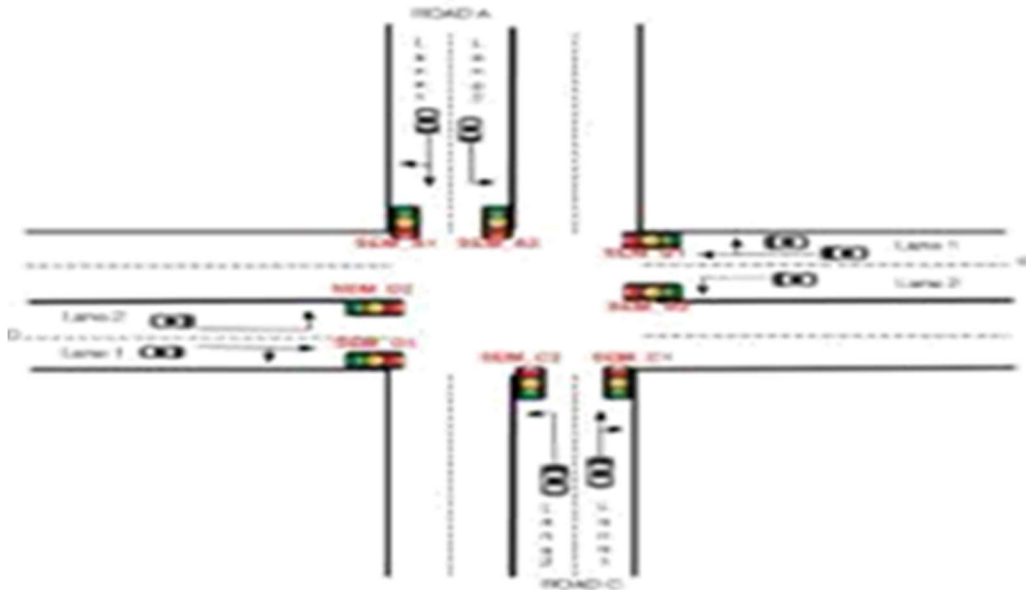


Figure 4. The isolated road intersection under study

The isolated intersection analyzed in this research consists of four phases, as illustrated in Figure 5. Each phase represents a time period

in which specific lanes are allowed to proceed while others remain halted. For example, when Phase 1 is active, vehicles in Lane 1 of Roads A

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and C can move straight or turn right, while all other lanes remain stopped at a red light.

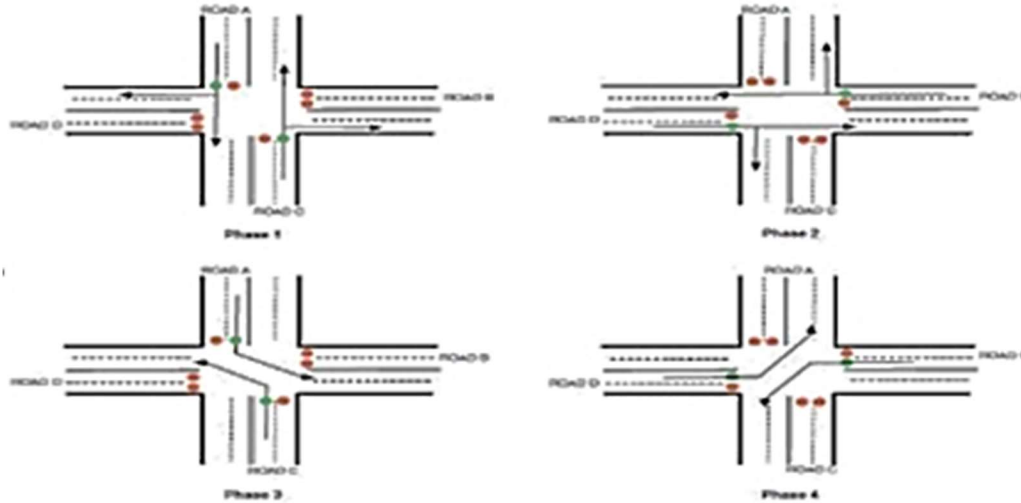


Figure 5. Traffic lights phases

To manage traffic flow effectively, a phase sorting module determines the execution sequence of phases within a traffic-light cycle. This sequence is arranged in descending order based on the number of queued vehicles. To enhance the realism of the simulated road traffic, each road section of length  $L$  is subdivided into smaller subsections of length  $l_i$ , as depicted in Figure 6.

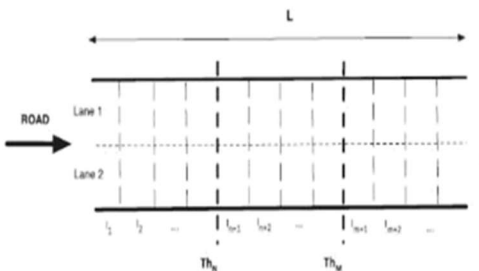


Figure 6. Section of road simulated

The queue length is estimated by counting the number of road subsections  $l_i$  in which vehicles are detected, classifying the queue length based on the number of vehicles present. The classification criteria are outlined in Table 2.

Table 2. Queue classification

Road Section	Meaning
$l_i \leq Th_N$	Normal queue
$Th_N < l_i \leq Th_M$	Medium queue
$l_i > Th_M$	Long queue

Threshold values  $Th_N$  and  $Th_M$  define the limits within which the queue length is considered normal or medium. Any value exceeding  $Th_M$  is classified as a long queue. Using Figures 4 and 5 as references, the priority level of each phase is calculated by summing the queue lengths in respective lanes during their red-light period, as defined in Equations (1) - (4).

$$Phase\_priority = queue\_len_{SEMA1} + queue\_len_{SEMC1} \quad (1)$$

$$Phase2\_priority = queue\_len_{SEM} + queue\_len_{SEMD1} \quad (2)$$

$$Phase3\_priority = queue\_len_{SEMA} + queue\_len_{SEMC2} \quad (3)$$

$$Phase4\_priority = queue\_len_{SEMB2} + queue\_len_{SEMD2} \quad (4)$$

Once computed, the Phase Selector determines the next phase to be executed based on priority levels, which are updated at the end of

each cycle during the yellow signal phase and sorted according to current traffic conditions.

A fuzzy logic controller is employed to optimize the green light duration for each phase. The use of four parallel controllers, as illustrated in Figure 7, ensures better fault tolerance, improved performance, and flexibility in managing phase-specific traffic conditions. Each controller

processes two input variables, corresponding to the queue lengths of the lanes controlled by a specific phase. For example, Controller 1 determines the green light duration for Phase 1 by evaluating the queue lengths of Lane 1 on Road A and Lane 1 on Road C. The same logic applies to other phases with their respective controllers.

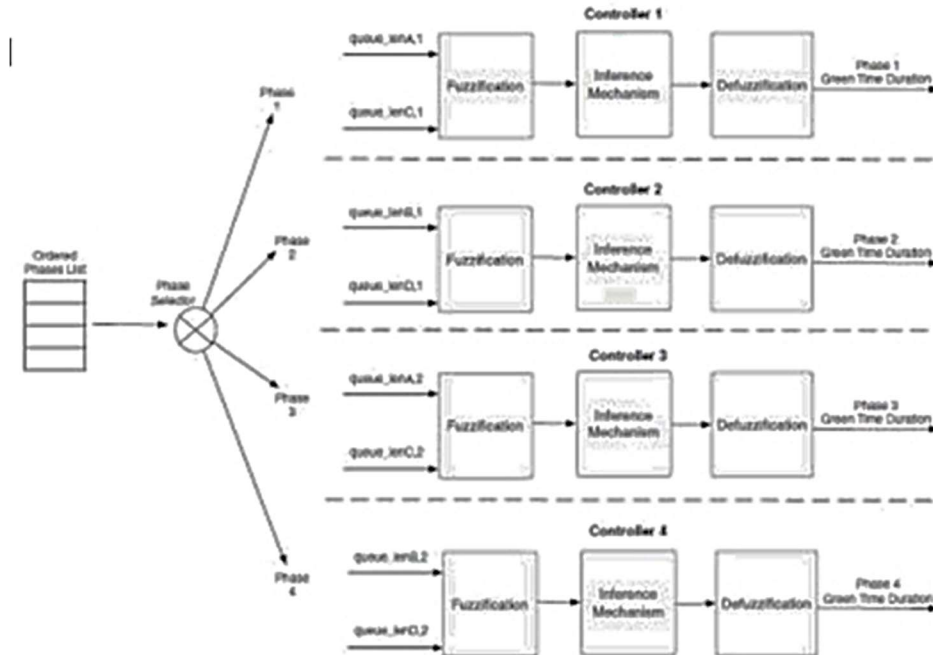


Figure 7. The four parallel fuzzy logic controllers

The fuzzy logic controller operates in three stages. In the first stage, known as fuzzification, input variables representing queue lengths are converted into crisp values within three membership functions: Normal, Medium, and Long. In the simulated scenario, each lane is monitored up to 400 meters, which can accommodate up to 80 vehicles per lane (160 per phase). The membership functions for the number of vehicles (input variables) are depicted in Figure 8, while those for the green light duration (output variables) are represented in Figure 9.

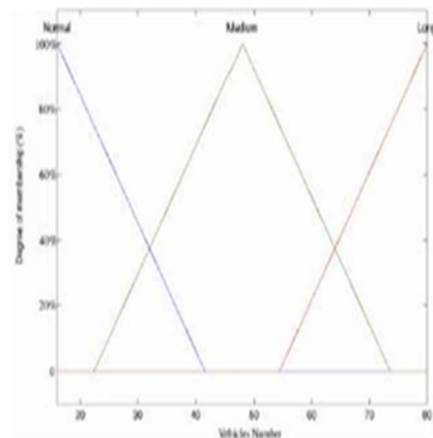


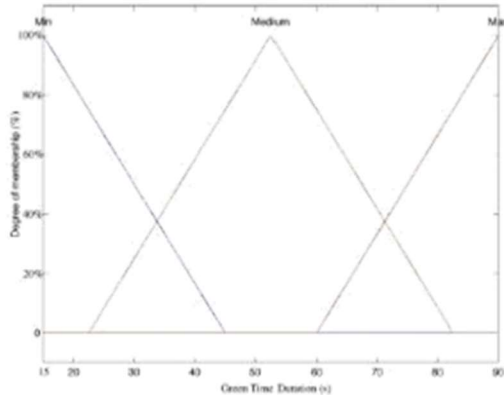
Figure 8. Membership functions for the number of vehicles (input variables)

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The second stage involves an inference mechanism that processes fuzzified data through IF-THEN rules. The inference rules for each controller are summarized in Table 3.

Figure 9. Membership functions for the green light duration (output variables)

Table 3. Inference rules for the *i*th controller

Rule	Road X length	W-lane length	Road Y-lane Z	<i>i</i> th Phase Green Time Duration
1		Normal	Normal	Min
2		Normal	Medium	Min
3		Normal	Long	Medium
4		Medium	Normal	Min
5		Medium	Medium	Medium
6		Medium	Long	Max
7		Long	Normal	Medium
8		Long	Medium	Max
9		Long	Long	Max

If both lanes in a phase experience long queues, the phase receives the maximum green time duration to alleviate congestion. However, if at least one lane has a normal queue length, extending the green light unnecessarily could adversely affect other phases. The final stage is defuzzification, where a single crisp output value for the green light duration is obtained using the center-of-gravity method, as expressed in Equation (5). The yellow light duration remains fixed since it does not permit new crossings, except for vehicles already within the intersection. The execution order recalculates at the end of each cycle, ensuring dynamic adaptation based on the latest priority levels.

$$\text{GreenTimeDuration} = \frac{\sum_{i=1}^n O_i * C_i}{\sum_{i=1}^n O_i} \quad (5)$$

The simulation model was run for three hours to evaluate vehicle arrivals and traffic conditions. Each lane was monitored up to 400 meters, allowing for the classification of queue lengths into three categories: short (less than 133 meters), medium (between 133 and 266 meters), and long (greater than 266 meters). Vehicle arrival rates were simulated under three different scenarios: low (1-10 cars per minute), medium (11-30 cars per minute), and high (31-60 cars per minute). These values were chosen based on practical traffic observations, ensuring realistic congestion levels. The simulation parameters are summarized in Table 4.

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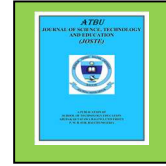


Table 4. Simulation parameters

Parameters	Value
Number of FFDs	8
Number of RFDs on each lane	80
Distance between each RFD	5 m
Duration of simulation	3 hours
Length of each lane monitored	400 m
Low Arrival Rate	[1,10] car/min
Medium Arrival Rate	[11,30] car/min
High Arrival Rate	[31,60] car/min
Crossing Rate	1 car/s
ThN	133 m
ThM	266 m

To assess the system's performance, three distinct traffic scenarios were simulated, each characterized by different arrival rates for the

four phases. The scenarios are outlined in Table 5.

Table 5. Simulated scenarios

Scenario	Phase I AR	Phase II AR	Phase III AR	Phase IV AR
I	Low	Low	High	High
II	Medium	Medium	Low	Low
III	Medium	Medium	High	High

Where AR= Arrival Rate

Performance evaluation was conducted by measuring the average waiting time for vehicles, with confidence intervals calculated to ensure accuracy. The waiting time is defined as the duration between a vehicle's arrival at the intersection and the moment it crosses. This metric provides an essential indicator of the system's efficiency in managing traffic flow and reducing congestion.

## RESULTS AND DISCUSSION

The results of the vehicle queue analysis and the predicted queue length for various scenarios are discussed in this section. The actual queue lengths were obtained using the Poisson distribution, while the predicted values were derived using the Fuzzy Time Series (FTS) model. The comparison of actual and predicted queue lengths across different phases highlights the performance of the FTS model under varying traffic conditions.

In Scenario I, Figure 10 [a-d] illustrate the actual and predicted queue lengths for Phases I to IV, respectively. The results indicate that the FTS model provides accurate predictions, particularly in Phases I and II, where traffic conditions are relatively stable. The RMSE values for these phases are 0.97 and 0.59, respectively, demonstrating minimal prediction error. However, as traffic conditions become more dynamic in Phases III and IV, the RMSE values rise to 2.39 and 2.48, respectively, indicating increased prediction errors. Figure 11 presents the RMSE values for all phases in Scenario I, highlighting the model's strength in stable conditions and its limitations under more variable traffic patterns.

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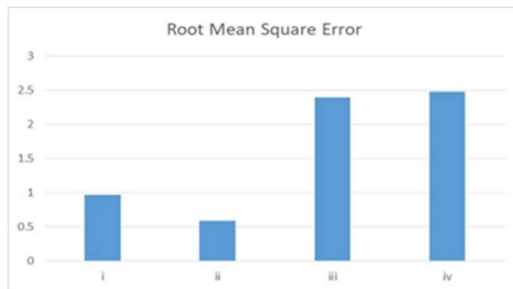


Figure 11. Root mean square for scenario I

Scenario II follows a similar pattern, with Figure 12 [e-h] displaying the actual and predicted queue lengths for Phases I to IV. The RMSE values, as shown in Figure 13, indicate a moderate level of prediction accuracy, with values of 2.00, 2.08, 1.08, and 0.41 for Phases I to IV, respectively. Notably, the RMSE for Phase IV is significantly lower, suggesting improved predictive accuracy. However, the near-zero predicted queue length throughout this phase requires further examination to understand the model's behavior under such conditions.



Figure 13. Root mean square for Scenario II

For Scenario III, Figures 14 [i-l] present the queue length comparisons across all phases. The RMSE values, depicted in Figure 15, reveal varying levels of prediction accuracy. Phase II exhibits the lowest RMSE of 0.57, indicating strong model performance in this phase. Conversely, Phases III and IV have the highest RMSE values of 2.74 and 2.59, respectively, suggesting challenges in accurately capturing queue lengths during more dynamic traffic periods. These findings reinforce the need for further refinements in the FTS model to enhance its predictive capabilities in highly variable traffic conditions.



Figure 15. Root mean square for Scenario III

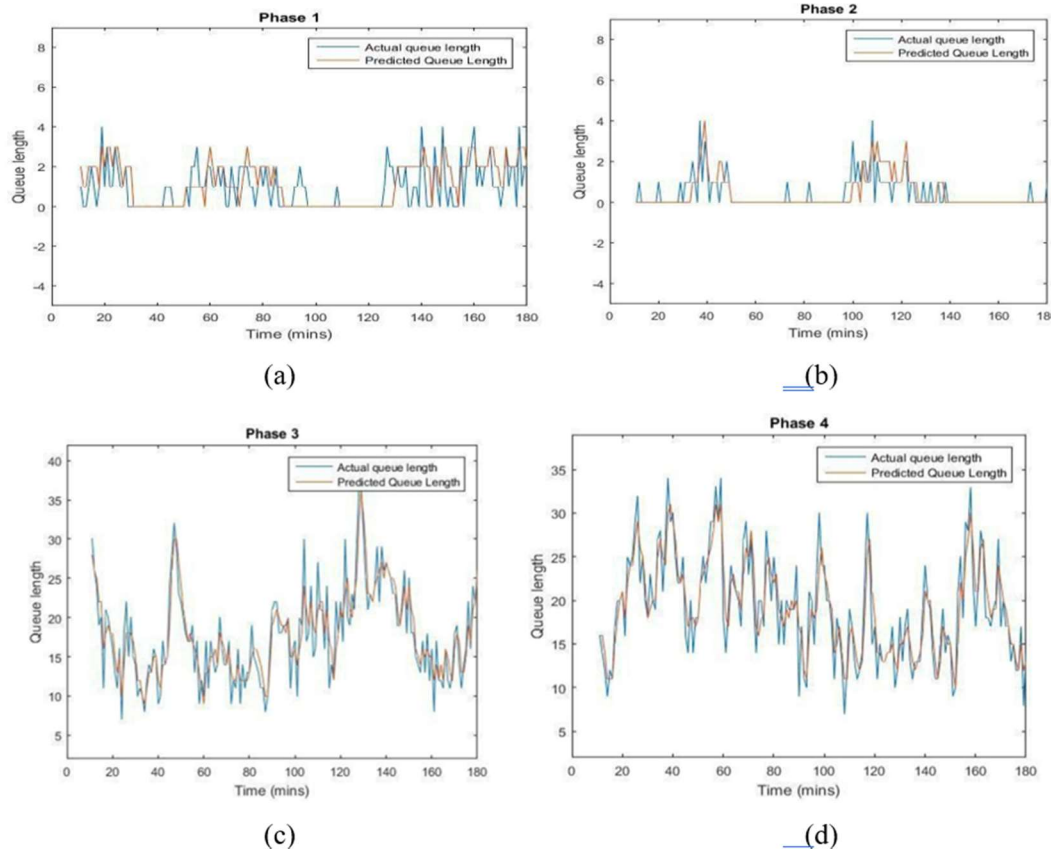
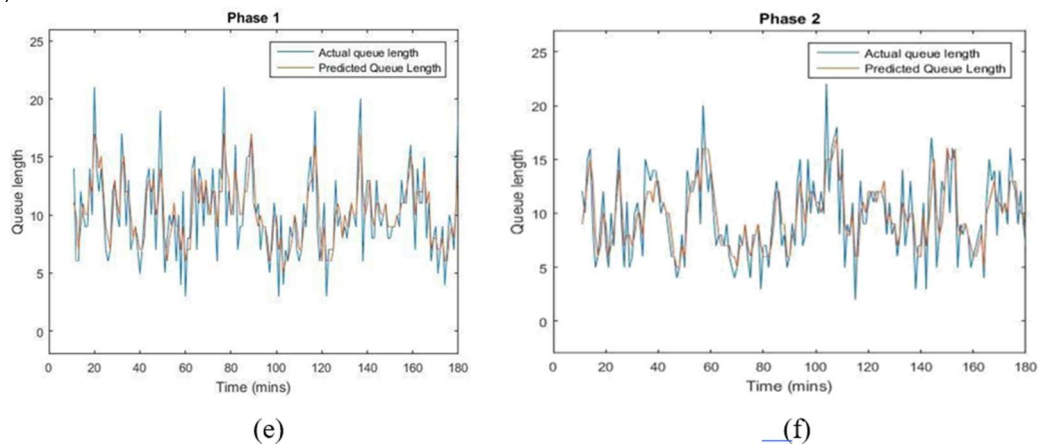


Figure 10. Scenario I actual and predicted queue length for: phase I (a), phase II (b), phase III (c), phase IV (d)



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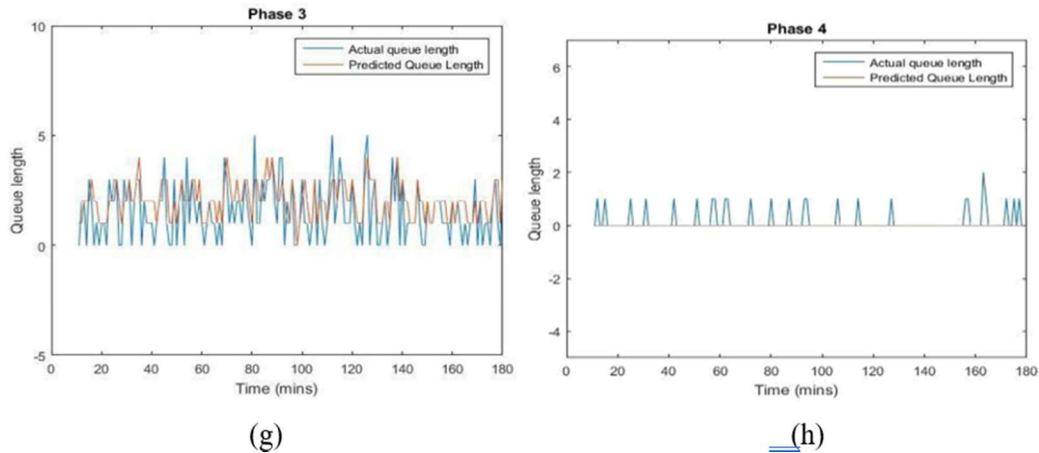


Figure 12. Scenario II actual and predicted queue length for: phase I (e), phase II (f), phase III (g), phase IV (h)

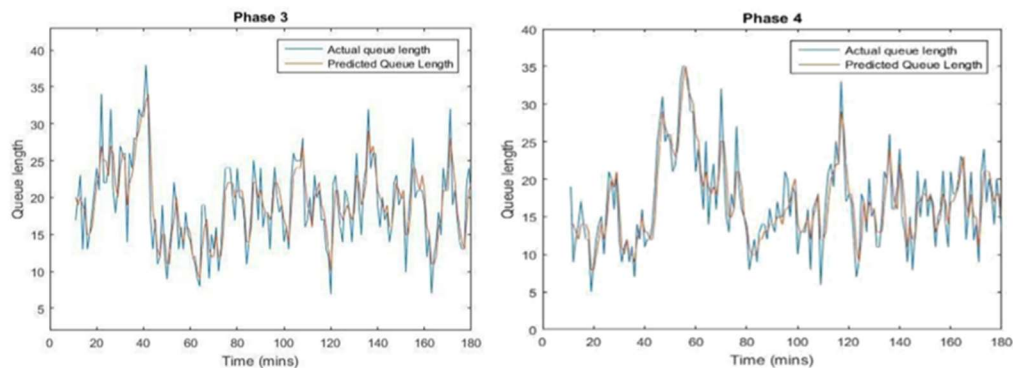
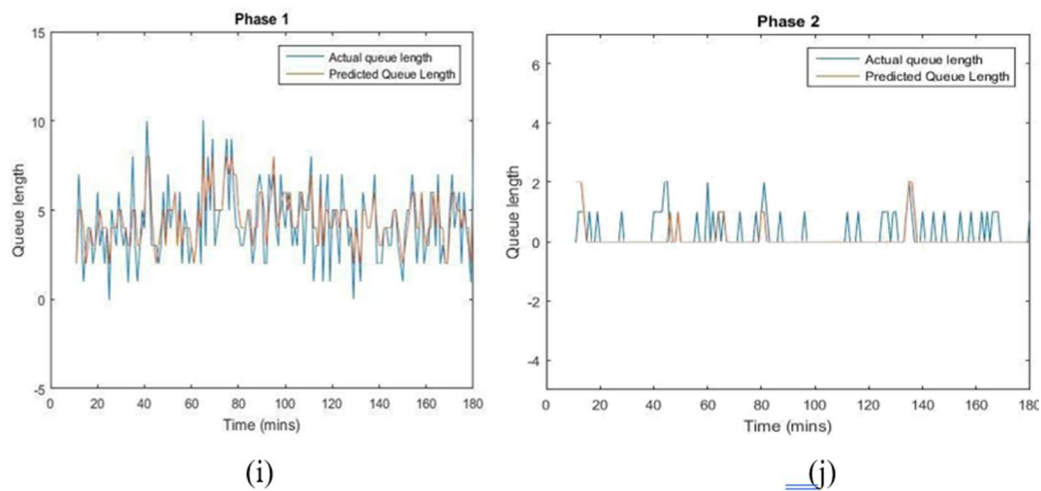


Figure 12. Scenario III actual and predicted queue length for: phase I (i), phase II (j), phase III (k), phase IV (l)

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## CONCLUSION

This research developed a fuzzy logic-based traffic controller capable of estimating green time duration for each phase of a single intersection by utilizing a queue length prediction model based on the ratio median length of intervals in higher-order fuzzy time series. The predicted queue length was used as input for the fuzzy logic controller, which then determined the appropriate green time duration for each phase. The controller was tested under three different traffic scenarios with varying vehicle arrival rates. In Scenario I, where phases I, II, III, and IV experienced low, low, high, and high arrival rates, respectively, the modified controller demonstrated an improvement of 3.8% in reducing average waiting time compared to the standard fuzzy logic controller. Similarly, in Scenario II, which featured medium, medium, low, and low arrival rates across the four phases, the developed controller achieved a 2.8% improvement. Lastly, in Scenario III, where the arrival rates were medium, medium, high, and high for the respective phases, the proposed controller outperformed the standard model by 5.4% in terms of average waiting time reduction. These results highlight the efficiency of

the developed fuzzy logic controller in optimizing traffic flow and reducing congestion. The significant contributions of this research include the development of a fuzzy logic-based traffic control system, the modeling of vehicle arrival patterns using the Poisson distribution, and the implementation of a fuzzy time series approach for queue length prediction, all of which contributed to improving traffic efficiency at signalized intersections. While the proposed model showed promising improvements, further enhancements can be explored in future studies. One potential improvement is incorporating additional factors, such as the average velocity of vehicles, to refine queue length predictions and further optimize traffic signal timing. Additionally, implementing the controller in a real-world intersection would provide valuable insights into its practical effectiveness and adaptability to dynamic traffic conditions. These recommendations will pave the way for continued advancements in intelligent traffic control systems, ensuring smoother traffic flow and reduced congestion in urban environments.

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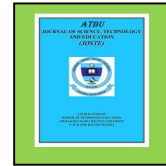
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