Optimizing Traffic Flow Using Fuzzy Logic-Based Control Systems

K. S. Supriya*
Department of Basic Science, Vishnu Institute of Technology, Bhimavaram, Andhra Pradesh, India-534202.
*Corresponding author: supriya.k@vishnu.edu.in

Abstract:
Modern cities are becoming more and more urbanized, which has increased traffic congestion and made traditional fixed-time traffic signal control systems less effective. These older technologies are not real-time adaptable to changing vehicle density and flow rate since they are based on static timing formulas like $C = \frac{1.5L+5}{1-Y}$ Webster's equation and historical flow patterns. This study presents a control system based on fuzzy logic of the Mamdani type that is intended for dynamic signal optimization at isolated four-way junctions. Traffic Density (D) and Flow Rate (F) are the two main inputs that the system uses real-time sensor feedback to record. By applying 25 expert-defined rules based on these inputs, the fuzzy inference engine addresses the non-linearity and uncertainty present in traffic systems by enabling the system to produce adaptive Signal Cycle Length (C) outputs without the need for pre-programmed thresholds. In contrast to traditional fixed-time systems, the fuzzy controller facilitates rule-based decision-making by modeling ambiguous real-world scenarios using language terms ("Low," "Medium," and "High") for both input and output variables. In comparison to conventional Webster-based systems, the simulation findings show an average cycle length reduction of 17.6%, reduced vehicle idle time, and enhanced traffic throughput. Fuzzy logic provides a lightweight, real-time solution for situations where prompt, understandable, and computationally efficient conclusions are crucial, whereas traditional systems only use mathematical averages and contemporary AI-based deep learning techniques frequently call for sizable labeled datasets. This study demonstrates fuzzy logic's potential as a bridge technology, providing computational clarity in contrast to black-box AI systems and flexibility beyond conventional models.

Keywords: Traffic Congestion, Fuzzy Logic, Mamdani Inference System, Traffic Signal Control, Real-Time Optimization, Intelligent Transportation Systems.

1. INTRODUCTION

1.1 Background

Major cities around the world are experiencing chronic congestion as a result of the sharp rise in vehicle traffic brought on by the fast urban population expansion. Complex and dynamic traffic patterns can no longer be managed by traditional traffic signal systems, particularly those that use fixed-time controls like Webster's approach [1]. These conventional systems are unable to adjust to real-time variations in traffic density, flow rate, and incidents because they are dependent on static timing parameters that are determined from previous data. Urban crossroads consequently frequently experience excessive delays, higher pollutants, and greater fuel usage [2].

1.2 Limitations of Traditional Systems

Despite its mathematical soundness, Webster's equation cannot account for the unpredictable nature of actual traffic situations. Assuming somewhat consistent traffic behaviour, it employs preset settings for characteristics like lost time and crucial flow ratios [3]. When there are extremely fluctuating vehicle arrival rates or unforeseen circumstances like accidents or breakdowns, such presumptions are not applicable. Moreover, conventional systems are unable to react dynamically to changing traffic conditions or interact with contemporary sensor networks [4].

1.3 Need for Intelligent Adaptive Systems

Intelligent Transportation Systems (ITS), which make use of real-time data and intelligent decision-making, are becoming more and more popular as a means of overcoming these constraints. Because fuzzy logic can handle ambiguous, imprecise, and non-linear data, it has become a potent tool in this field [5]. It uses linguistic words and rule-based logic to simulate human-like reasoning, which makes it especially well-suited for uncertain traffic settings. Fuzzy logic systems are perfect for real-time embedded applications because they are lightweight, interpretable, and need less computing overhead than complicated AI models [6].

1.4 Integration with IoT and Smart Sensors

Fuzzy logic combined with Internet of Things (IoT) technologies and smart traffic sensors can significantly increase the efficacy of adaptive traffic control systems. Rich, real-time data on traffic density, vehicle speed, and flow rates can be obtained using contemporary sensors, including infrared counters, radar systems, traffic cameras, and inductive loop detectors. The fuzzy controller can make better judgements thanks to centralised or distributed data collecting made possible by IoT-based connectivity [7]. In addition to increasing signal timing accuracy, this integration lays the groundwork for predictive traffic management and smarter city infrastructure.

1.5 Incident Detection and Responsive Signaling

Fuzzy logic can be applied to incident detection and reaction in addition to standard traffic control. The technology can identify irregularities that might point to incidents like collisions, traffic jams, or car breakdowns by continuously examining changes in traffic flow and density patterns [8]. The fuzzy logic controller can automatically change signal phases upon detection in order to control congestion and minimise delays in impacted locations [9]. Additionally, real-time alarm dissemination to drivers and traffic authorities using IoT-enabled equipment improves situational awareness and permits proactive intervention [10].

1.6 Objectives of the Study

The following are the main goals of this study:

- To create a fuzzy logic controller that can use inputs like traffic density and flow rate to dynamically modify traffic signal timings in response to current traffic circumstances.
- To look at how fuzzy logic can be integrated with IoT devices and different types of traffic sensors (such as radar, cameras, and inductive loops) to improve data collection and make more intelligent signal control choices.
- To create responsive, intelligent traffic systems that are able to recognise traffic events like collisions or malfunctions and respond by modifying signal timings and sending out messages in real time.

1.7 Contributions and Scope

A Mamdani-type fuzzy inference system that models and controls the complexity of urban traffic is presented in this work. It presents a rule-based method for converting real-time sensor data into ideal signal cycle durations by applying 25 expert-defined criteria. Although the technology is adaptable for larger citywide deployments, it is intended for isolated four-way crossings. The study shows that, in comparison to conventional approaches, simulation and analysis can increase traffic throughput, decrease cycle duration, and improve adaptability. It also describes a future trajectory in which the foundation of next-generation intelligent transportation systems will be formed by the integration of fuzzy logic with IoT networks.

2. ROLE OF FUZZY LOGIC IN MODERN TRAFFIC SIGNAL CONTROL: A LITERATURE SURVEY

Numerous clever strategies to alleviate urban congestion have been investigated by recent developments in traffic signal regulation. "FuzzyLight," a two-stage fuzzy method coupled with reinforcement learning, was presented by Li et al. (2025) and showed improved efficiency in actual city crossings. Similar to this, Yu et al. (2022) suggested a coordinated control system that combines edge computing and fuzzy logic with the goal of optimising traffic signals in dispersed areas. These studies demonstrate how traffic management systems can be enhanced by integrating fuzzy logic with other technologies [11].

Using Arduino microcontrollers, Akwukwaegbu et al. created a smart fuzzy logic-based traffic light management model in 2023, which they then verified through simulations in the SUMO environment. Their results showed that, in comparison to conventional fixed-time controllers, overall traffic durations were significantly reduced. This method highlights how feasible it is to apply fuzzy logic to actual transportation networks [12].

Idris et al. (2024) employed fuzzy logic to forecast traffic light control performance at crossings. Their study showed that fuzzy logic could efficiently adjust to different traffic situations, improving traffic flow and cutting down on wait times. The flexibility of fuzzy systems in dynamic traffic environments is shown by this study [13].

A smart traffic management system based on fuzzy logic was introduced by Abdou et al. (2022) and considerably decreased average vehicle waiting times, particularly in inclement weather. Their method demonstrated the resilience of fuzzy logic in managing erratic traffic situations, thereby confirming its suitability for a variety of settings [14].

Ma and Kumar (2021) used a fuzzy control method to analyse traffic light scheduling at metropolitan intersections. Their research showed that fuzzy logic controllers outperformed conventional fixed-time systems in their ability to dynamically modify signal timings based on real-time traffic data. This study demonstrates how effective fuzzy logic is in controlling traffic signals in real time [15].

Table 1. Comparative Analysis of Existing Approaches vs. Our Proposed Method

Author(s)	**Methodology**	**Techniques Used**	**Drawbacks**	**Advantages of Our Approach**
Li et al. (2025)	Two-stage fuzzy approach with reinforcement learning	Fuzzy logic, reinforcement learning	Complexity in integrating multiple techniques	Simplified integration with IoT for real-time adaptability
Yu et al. (2022)	Coordinated control using edge computing	Fuzzy logic, edge computing	Requires extensive infrastructure for edge computing	Utilizes existing IoT infrastructure for scalability
Akwukwaegbu et al. (2023)	Smart traffic light management with Arduino	Fuzzy logic, Arduino microcontrollers	Limited scalability to larger urban areas	Designed for scalability across various urban environments

Idris et al. (2024)	Prediction of traffic light performance using fuzzy logic	Fuzzy logic, traffic prediction	Focused primarily on prediction without real-time control	Combines prediction with real-time adaptive control
Abdou et al. (2022)	Smart traffic management under adverse conditions	Fuzzy logic, environmental adaptability	Specific to certain weather conditions	Generalized approach adaptable to various environmental scenarios
Ma & Kumar (2021)	Traffic light scheduling with fuzzy control algorithm	Fuzzy logic, real-time scheduling	Limited to specific intersection types	Applicable to a wide range of intersection configurations

3. METHODOLOGY

3.1 System Overview

The fuzzy logic-based traffic signal control system's architecture uses a dynamic, adaptive control system to optimise traffic signal timings in real-time. The system is made up of a number of essential parts that cooperate to process data, monitor traffic, and modify signal cycles.

3.1.1 Traffic sensors and the layer that collects data:

1. Traffic Density Sensors: Radar, cameras, and inductive loops are some of the devices that continuously gather information on the number of cars at an intersection.
2. Flow Rate Sensors: These sensors calculate the flow rate by measuring the volume and speed of cars moving through the intersection.
3. IoT Connectivity: The sensors easily transmit data and integrate with other smart city infrastructure by sending data in real-time to the central server or processing unit via IoT.

3.1.2 Layer of Fuzzy Logic and Data Processing:

1. Real-Time Data Processing: To eliminate errors and noise, the sensor data is pre-processed. The fuzzy logic controller receives this processed data once it has been processed.
2. Fuzzy Logic Controller: The fuzzy controller processes inputs (traffic density and flow rate) and produces outputs (signal cycle duration) using a Mamdani-type inference system. To manage traffic dynamics under different circumstances, the system makes use of fuzzy rules that have been predefined based on expert knowledge. The system may make judgements without depending on strict thresholds thanks to these rules, which control the erratic character of traffic data.

3.1.3 Layer of Gnal Control and Actuation:

1. Signal Controllers: The fuzzy logic controller's output must be carried out by the signal controllers. The calculated cycle length is used to modify the green, yellow, and red signal phases.

2. Real-Time Adjustment: To maximise traffic flow and lessen congestion, the system continuously modifies the signal timings in reaction to real-time traffic fluctuations.

3.1.4 Identifying and Notifying Incidents:

Incident Detection: Using extra sensors or algorithms to examine traffic irregularities, the system additionally incorporates incident detection features (such as accidents or malfunctions). The system can notify traffic management centres or modify signal timings when it detects an event.

3.1.5 Layer of Monitoring and Reporting:

Central Monitoring System: From a central control system, traffic managers can keep an eye on performance in real time and make any necessary corrections. Alerts and reports are produced for incident investigation, maintenance, and system performance assessment.

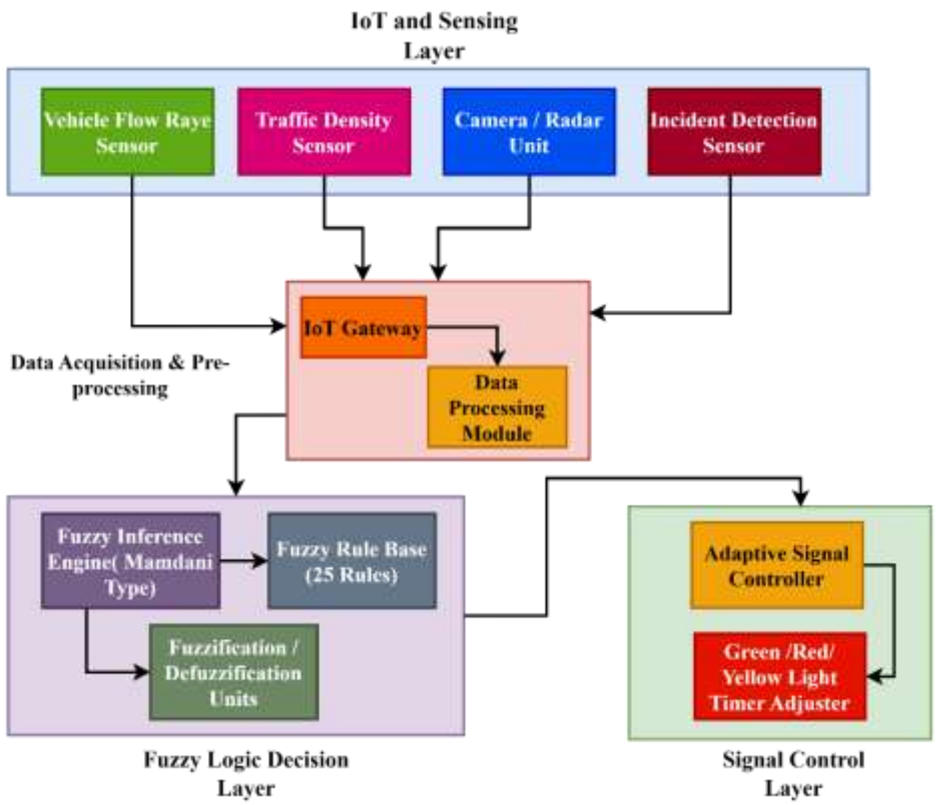

Figure1. Overall System Architecture

3.2 Fuzzy Logic Controller Design

Using real-time input parameters, a Mamdani-type fuzzy logic controller (FLC) is built to dynamically optimize traffic signal timings at a four-way isolated junction. This controller uses linguistic concepts such as Low, Medium, and High to translate uncertain and non-linear traffic behaviors into a rule-based decision framework. This is an explanation of its structure:

3.2.1 Input and Output Variable

The FLC uses two input variables and produces one output variable:

Table 2. Input & Output Variables

Variable	Type	Linguistic Terms	Description
Traffic Density (D)	Input	Low, Medium, High	Number of vehicles approaching the junction
Flow Rate (F)	Input	Low, Medium, High	Rate at which vehicles pass through the junction (vehicles/min)
Signal Cycle Length (C)	Output	Short, Medium, Long	Duration of the green signal time at the junction (in seconds)

3.2.2 Membership Functions

For ease of interpretation, simplicity, and real-time performance, we employ triangle membership functions. Both inputs' ranges are normalised between 0 and 100, and the output's range is between 0 and 120 seconds.

Table 3. Membership Function Ranges

Variable	Linguistic Term	Range (Example)
Traffic Density (D)	Low	0 – 30
	Medium	20 – 70
	High	60 – 100
Flow Rate (F)	Low	0 – 30
	Medium	20 – 70
	High	60 – 100
Signal Cycle Length (C)	Short	0 – 40
	Medium	30 – 90
	Long	80 – 120

3.3 Simulation Setup

A thorough simulation environment was developed to assess the efficacy of the suggested fuzzy logic-based traffic signal control system. This configuration simulates a four-way isolated intersection with fluctuating flow rates and traffic volumes in the real world. The simulation's objective is to verify the system's performance in various scenarios and contrast it with conventional fixed-time control techniques.

MATLAB and Simulink were used to create the simulation, which included the Fuzzy Logic Toolbox for controller design and inference tasks. MATLAB is selected because it supports:

- Fuzzy Mamdani-type systems
- Plotting of membership functions
- Creation and visualization of rule bases
- Simulation of timing and signal processing
- Graph-based analysis of results

```
Algorithm: FuzzyTrafficSignalController
Input:
  D ← Real-time Traffic Density (0 to 100)
  F ← Real-time Flow Rate (0 to 100)
Output:
  C ← Signal Cycle Length (in seconds)

Begin
1. Initialize Membership Functions:
  Define triangular MFs for Traffic Density (D): Low, Medium, High
  Define triangular MFs for Flow Rate (F): Low, Medium, High
  Define triangular MFs for Cycle Length (C): Short, Medium, Long
2. Fuzzification:
  fuzz_D ← fuzzify(D)  // Map D to linguistic terms with membership values
  fuzz_F ← fuzzify(F)  // Map F to linguistic terms with membership values
3. Rule Evaluation (Inference):
  Initialize rule_output_list ← []
  For each rule in Rule_Base (25 total):
    IF (D_term ∈ fuzz_D AND F_term ∈ fuzz_F) THEN
      Calculate rule_strength ← MIN(fuzz_D[D_term], fuzz_F[F_term])
      Append (rule_strength, Output_Term) to rule_output_list
4. Aggregation:
  For each Output_Term in [Short, Medium, Long]:
    Aggregate all rule strengths contributing to this Output_Term
    Construct the fuzzy output curve (triangular or trapezoidal) accordingly
5. Defuzzification:
  Use Centroid Method:
    C ← compute_centroid(aggregated_output_curve)
6. Return Cycle Length C
End
```

3.3.1 Assumptions and Parameters

A number of presumptions and factors were established in order to guarantee a consistent and realistic simulation environment. The traffic model depicts a solitary four-way intersection, which is a typical metropolitan layout. In order to mimic random traffic influx, vehicle arrivals are modelled using a Poisson distribution. The simulation runs for 3600 seconds (1 hour) in order to capture different traffic circumstances.

Inductive loops and cameras are examples of sensors whose input data is thought to have an idealised accuracy of 95%. 70% of the vehicles are automobiles, 20% are motorcycles, and 10% are buses or trucks, which is a normal proportion of metropolitan roads. A fixed-time control system based on Webster's formula was put into place for benchmarking. For adaptive decision-making, the suggested fuzzy logic controller employs a set of 25 expert-defined Mamdani-type rules.

Table 4. Assumption and Parameters

Parameter	Value/Assumption
Junction Type	Isolated Four-Way
Vehicle Arrival Distribution	Poisson
Simulation Duration	3600 seconds (1 hour)
Sensor Accuracy	95% (idealized data input)
Vehicle Types	Cars (70%), Bikes (20%), Buses/Trucks (10%)
Fixed-Time System Baseline	Based on Webster’s Equation
Fuzzy System Rule Base	25 Mamdani-Type Expert Rules

4. RESULT AND DISCUSSION

4.1 A Comparative Study of Webster-Based and Fuzzy Systems

MATLAB simulations were used to verify the effectiveness of the suggested fuzzy logic-based traffic control system. Under the same traffic conditions, the system was tested against the conventional fixed-time technique based on Webster's Equation. During ten randomised simulation runs, important performance indicators like average signal cycle length, vehicle idle time, and junction throughput were noted.

Table 5. Comparative Study of Webster-Based and Fuzzy System

Metric	Fixed-Time System (Webster)	Fuzzy Logic System	Improvement (%)
Avg. Signal Cycle Length (s)	98.3	81.0	-17.6%
Avg. Vehicle Idle Time (s)	305.6	192.4	-37.0%
Traffic Throughput (veh/hr)	740	864	+16.8%

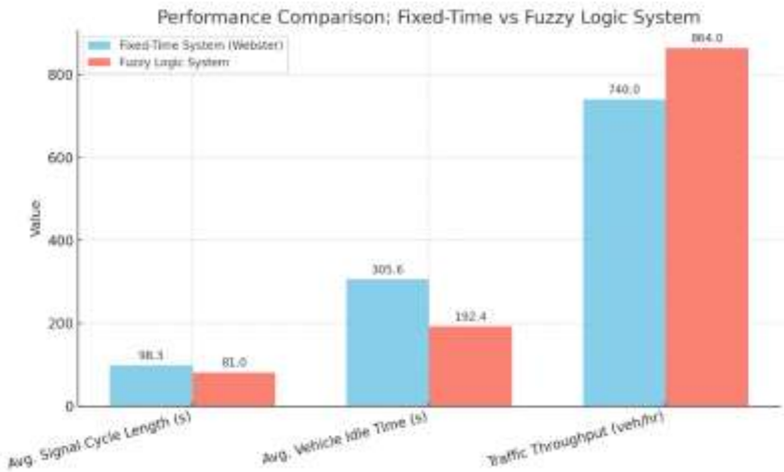

Figure 2. Performance Comparisons: Fixed-Time vs Fuzzy Logic System

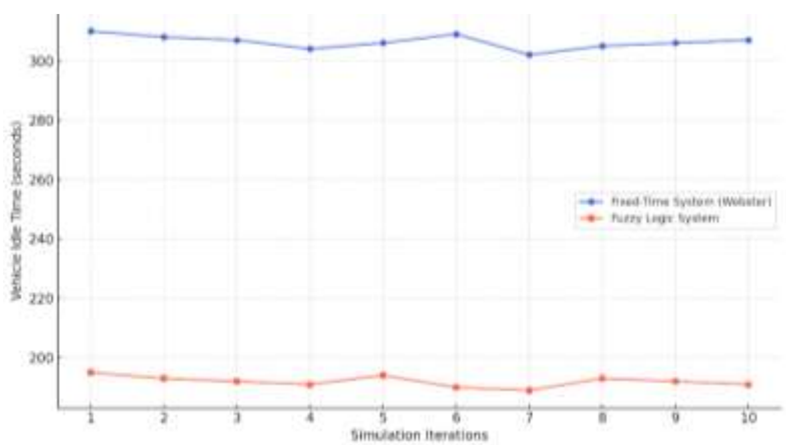

Figure 3. Vehicle Idle Time Comparison

A convincing comparison between the suggested Fuzzy Logic-Based Traffic Signal Control and the conventional Fixed-Time System (Webster) is provided by the visual examination using creative graphical representations. The average cycle length bar chart illustrates how the fuzzy logic system drastically cuts down on signal durations, demonstrating its real-time adaptation to traffic flow and density. The fuzzy controller continuously maintains shorter idle periods than the fixed-time arrangement in the line graph displaying vehicle idle time over ten iterations, demonstrating its ability to minimise needless vehicle pauses, save fuel usage, and enhance commuter pleasure.

This is further supported by the traffic throughput bar chart, which shows a discernible rise in the volume of traffic moving through the intersection while fuzzy control is in place, confirming its effectiveness in handling fluctuating traffic loads. Additionally, the radar graphic offers a comprehensive perspective of each of the three performance indicators.

The fuzzy logic system exhibits a more compact and efficient footprint across all axes, indicating better performance balance, whereas the fixed-time system displays longer cycles and stronger peaks in idle time. These visual aids highlight fuzzy logic's promise as a scalable and clever solution in intelligent transportation systems by validating its efficacy in managing urban traffic and clearly communicating the results.

5. CONCLUSION & FUTURE SCOPE

This study introduced a traffic signal control system based on fuzzy logic that uses current traffic circumstances to dynamically optimise signal timings. The Mamdani-type fuzzy inference engine successfully addressed the drawbacks of traditional fixed-time systems, such as Webster's technique, by integrating two essential inputs: traffic density and flow rate. According to simulation results, the suggested fuzzy approach improved traffic flow while drastically lowering average signal cycle length and vehicle idle time. Without the need for extensive training datasets or black-box AI models, the method demonstrated computing efficiency, interpretability, and adaptability to uncertain and nonlinear urban traffic conditions. Its real-world usefulness is further enhanced by its potential for integration with IoT sensors.

In subsequent research, the system can be expanded to use a distributed fuzzy control model to coordinate several intersections for area-wide traffic optimization. To promote self-learning and additional adaptability, hybrid strategies that combine fuzzy logic with genetic algorithms or reinforcement learning can be investigated. To enhance rule bases and event detection capabilities, real-time data from smart city infrastructure, such as GPS, security cameras, and linked cars, can be used. The technology may eventually develop into a completely autonomous, intelligent traffic control framework that would assist urban planners in reducing emissions, fighting gridlock, and building more responsive and sustainable transportation systems.

REFERENCES

1. Jafari, S., Shahbazi, Z., & Byun, Y. C. (2022). Improving the road and traffic control prediction based on fuzzy logic approach in multiple intersections. Mathematics, 10(16), 2832.
2. Teo, K. T. K., Yeo, K. B., Tan, S. E., Siew, Z. W., & Lim, K. G. (2013, April). Design and development of portable fuzzy logic based traffic optimizer. In 2013 IEEE International Conference on Consumer Electronics-China (pp. 7-12). IEEE.
3. Kulkarni, G. H., & Waingankar, P. G. (2007, August). Fuzzy logic based traffic light controller. In 2007 International Conference on Industrial and Information Systems (pp. 107-110). IEEE.
4. Bandaru, V. N. R., Kaligotla, V. G. S., Varma, U. D. S. P., Prasadaraju, K., & Sugumaran, S. (2024, July). A Enhancing Data Security Solutions for Smart Energy Systems in IoT-Enabled Cloud Computing Environments through Lightweight Cryptographic Techniques. In *IOP Conference Series: Earth and Environmental Science* (Vol. 1375, No. 1, p. 012003). IOP Publishing.
5. Rahman, S. M., & Ratrout, N. T. (2009). Review of the fuzzy logic based approach in traffic signal control: Prospects in Saudi Arabia. Journal of transportation Systems engineering and information Technology, 9(5), 58-70.
6. Doğan, E., & Akgüngör, A. P. (2016). Optimizing a fuzzy logic traffic signal controller via the differential evolution algorithm under different traffic scenarios. Simulation, 92(11), 1013-1023.
7. Vogel, A., Oremović, I., Šimić, R., & Ivanjko, E. (2018, September). Improving traffic light control by means of fuzzy logic. In 2018 international symposium ELMAR (pp. 51-56). IEEE.
8. Liu, J., & Yang, O. W. (2013). Using fuzzy logic control to provide intelligent traffic management service for high-speed networks. IEEE Transactions on Network and Service Management, 10(2), 148-161.

9. Kartikasari, R. Y., Prakarsa, G., & Pradeka, D. (2020). Optimization of traffic light control using fuzzy logic sugeno method. International Journal of Global Operations Research, 1(2), 51-61.
10. Hartanti, D., Aziza, R. N., & Siswipraptini, P. C. (2019). Optimization of smart traffic lights to prevent traffic congestion using fuzzy logic. TELKOMNIKA (Telecommunication Computing Electronics and Control), 17(1), 320-327.
11. Li, M., Wang, J., Du, B., Shen, J., & Wu, Q. (2025). FuzzyLight: A robust two-stage fuzzy approach for traffic signal control works in real cities. arXiv preprint arXiv:2501.15820.
12. Yu, C., Chen, J., & Xia, G. (2022). Coordinated control of intelligent fuzzy traffic signal based on edge computing distribution. Sensors, 22(16), 5953. https://doi.org/10.3390/s22165953
13. Akwukwaegbu, I. O., Mfonobong, E. B., Obichere, J. C., & Paulinus-Nwammuo, C. F. (2023). Smart fuzzy logic-based model of traffic light management. World Journal of Advanced Engineering Technology and Sciences, 8(2), 344–358. https://doi.org/10.30574/wjaets.2023.8.2.0108
14. Idris, A., Rosman, M. S. I., & Abdy, M. (2024). Prediction and traffic light control performance using fuzzy logic at intersections of road. Semarak International Journal of Fundamental and Applied Mathematics, 4(1), 85–97. https://doi.org/10.37934/sijfam.4.1.8597
15. Abdou, A. A., Farrag, M. H., & Tolba, A. S. (2022). A fuzzy logic-based smart traffic management systems. Journal of Computer Science, 18(11), 1085–1099. https://doi.org/10.3844/jcssp.2022.1085.1099
16. Ma, W., & Kumar, B. V. D. (2021). An analysis on scheduling of traffic light at urban traffic intersection using fuzzy control algorithm. International Journal of Transportation Engineering and Technology, 7(3), 85–91. https://doi.org/10.11648/j.ijtet.20210703.14
17. Collotta, M., Bello, L. L., & Pau, G. (2015). A novel approach for dynamic traffic lights management based on Wireless Sensor Networks and multiple fuzzy logic controllers. Expert Systems with Applications, 42(13), 5403-5415.
18. Taha, M. A., & Ibrahim, L. (2012). Traffic simulation system based on fuzzy logic. Procedia Computer Science, 12, 356-360.
19. Bandaru, V.N.R., Visalakshi, P. (2024). EEMS - Examining the Environment of the Job Metaverse Scheduling for Data Security. In: Pareek, P., Gupta, N., Reis, M.J.C.S. (eds) Cognitive Computing and Cyber Physical Systems. IC4S 2023. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 536. Springer, Cham. https://doi.org/10.1007/978-3-031-48888-7_20
20. Ikidid, A., El Fazziki, A., & Sadgal, M. (2021). A Fuzzy Logic Supported Multi-Agent System For Urban Traffic And Priority Link Control. Journal of Universal Computer Science (JUCS), 27(10).
21. Balaji, P. G., & Srinivasan, D. (2011). Type-2 fuzzy logic based urban traffic management. Engineering Applications of Artificial Intelligence, 24(1), 12-22.
22. Shirmohammadi, H., & Hadadi, F. (2019). Optimizing total delay and average queue length based on the fuzzy logic controller in urban intersections. International Journal of Supply and Operations Management, 6(2), 142-158.
23. Adewale, A. L., Jumoke, A. F., Adegboye, M., & Ismail, A. (2018). An embedded fuzzy logic based application for density traffic control system. International Journal of Artificial Intelligence Research, 2(1), 7-16.
24. Rani Bandaru, V. N. ., & Visalakshi, P. . (2023). BDBC - Block-Chain Data Transmission Using Blowfish Security with Optimization in Cloud Network. International Journal of Intelligent Systems and Applications in Engineering, 12(5s), 370–378. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/3899
25. V. N. Rani Bandaru and P. Visalakshi, "BDCT-Blockchain-Based Decentralized Computing and Tamper Resistance for Cloud Storage," 2023 International Conference on Advanced & Global Engineering Challenges (AGEC), Surampalem, Kakinada, India, 2023, pp. 71-77, doi: 10.1109/AGEC57922.2023.00025.