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Controlling Traffic for Clean Air and Healthy Cities with Multi-Fuzzy Inference Systems for a Sustainable Future

Mengawal Trafik untuk Udara Bersih dan Bandar Sihat dengan Sistem Inferensi Multi-Fuzzy untuk Masa Depan yang Mampan

Muhammad Aria Rajasa Pohan, Jana Utama*

Electrical Engineering Department, Faculty of Engineering and Computer Science, Universitas Komputer Indonesia, 40132 Bandung, West Java, Indonesia

**Corresponding author: muhammad.aria@email.unikom.ac.id*

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ABSTRACT

Surging urbanization and vehicle emissions exacerbate traffic congestion in major cities, leading to increased air pollution and high gasoline emissions as traditional traffic signal systems fail to adapt to real-time traffic conditions. To address this critical issue, this research proposes an innovative traffic control strategy using multi-fuzzy inference systems (mFIS) distributed at adjacent intersections in areas experiencing high traffic volumes. These distributed traffic light control systems collaborate to reduce congestion gradually in areas of high congestion. The mFIS system optimizes the traffic light settings based on the length of the vehicle queue, the duration of the vehicle stopping time, the number of vehicles in front of the lane, and the number of vehicles entering the lane. Our simulations demonstrated that the proposed mFIS controller effectively reduced average vehicle delay by up to 23.6% compared to the Proportional-Integral-Derivative (PCT) controller, 19.9% compared to the Variable Speed (VA) controller, and 14.1% compared to the traditional Fuzzy Logic System (FIS) controller. This significant performance improvement was consistently observed across various traffic conditions, including heavy traffic scenarios. The advantages of the proposed algorithm lie in restricting vehicles entering high-congestion lanes, speeding up the outflow of vehicles from congested areas, and using distributed control principles within areas experiencing high traffic volumes. Therefore, the algorithm in this study has the potential to be further developed to help reduce traffic congestion in big cities; thus, it can be a sustainable solution to create cleaner, healthier, and more sustainable cities in the future.

Keywords**:** Multi-Fuzzy Inference System, air pollution, sustainable solution, traffic signal optimization, distributed control.

ABSTRAK

Peningkatan urbanisasi dan pelepasan kenderaan memburukkan lagi kesesakan lalu lintas di bandar besar, membawa kepada peningkatan pencemaran udara dan pelepasan petrol yang tinggi kerana sistem isyarat trafik tradisional gagal menyesuaikan diri dengan keadaan trafik masa nyata. Untuk menangani isu kritikal ini, kajian ini mencadangkan strategi kawalan trafik yang inovatif menggunakan sistem inferensi multi-fuzzy (mFIS) yang diedarkan dipersimpangan bersebelahan di kawasan yang mengalami jumlah trafik yang tinggi. Sistem kawalan lampu isyarat yang diedarkan ini bekerjasama untuk mengurangkan kesesakan secara beransur-ansur di kawasan kesesakan tinggi. Sistem mFIS mengoptimumkan tetapan lampu isyarat berdasarkan panjang giliran kenderaan, tempoh masa berhenti kenderaan, bilangan kenderaan di hadapan lorong dan bilangan kenderaan yang memasuki lorong. Simulasi kami menunjukkan bahawa pengawal mFIS yang dicadangkan berkesan mengurangkan kelewatan kenderaan purata sebanyak 23.6% berbanding dengan pengawal Proportional-Integral-Derivative (PCT), 19.9% berbanding dengan pengawal Variable Speed (VA) dan 14 .1 % berbanding dengan pengawal Sistem Logik Kabur (FIS) tradisional. Peningkatan prestasi yang ketara ini diperhatikan secara konsisten merentas pelbagai keadaan trafik, termasuk senario trafik yang padat. Kelebihan algoritma yang dicadangkan terletak pada mengehadkan kenderaan yang memasuki lorong dengan ketumpatan tinggi, mempercepatkan aliran keluar kenderaan dari kawasan sesak, dan menggunakan prinsip kawalan teragih di kawasan yang mengalami jumlah trafik yang tinggi. Oleh itu, algoritma dalam kajian ini berpotensi untuk dikembangkan lagi bagi membantu mengurangkan kesesakan lalu lintas di bandar-bandar besar; oleh itu, algoritma ini boleh menjadi penyelesaian yang mampan untuk mewujudkan bandar yang lebih bersih, sihat dan lebih mampan pada masa hadapan.

Kata kunci**:** Sistem Inferensi Multi-Fuzzy, pencemaran udara, penyelesaian mampan, pengoptimuman isyarat lalu lintas, kawalan teragih.

INTRODUCTION

Surging urbanization and increasing vehicle emissions have become critical global challenges in major cities, including Jakarta, Indonesia (Prastiyo et al., 2020 ; Damayanti and Suryanto, 2022). In Jakarta alone, there is an average of 60 minutes of traffic congestion every day, causing economic losses estimated at two billion USD per year (Sahara and Nugroho, 2023; Saraswati and Adi, 2022; Syafey and Putra, 2023). These losses include wasted fuel costs, lost productive time, and health impacts due to air pollution. Air pollution alone causes at least 3.7 million premature deaths annually worldwide (Sudaryanto et al., 2022; Maizara et al., 2024), emphasizing the importance of effective traffic management.

Traditional fixed-time traffic control systems, which are commonly used in many cities, need to be upgraded to adapt to dynamic traffic conditions (Atta et al., 2018; Essa and Sayed, 2020; Permana et al., 2020; Ujianto, 2022). Often, fixed-time traffic control systems have difficulty coping with the high variability of traffic demand, resulting in suboptimal use of green signal duration in each cycle (Vuong et al., 2021). To overcome this drawback, intelligent traffic signal control systems such as Fuzzy Inference Systems (FIS) (Aria, 2019) and Artificial Neural Networks (ANN) (Hong et al., 2022) are emerging as promising alternatives.

Traffic signal control has shown significant progress with the application of Artificial Intelligence (AI) techniques. Traditional approaches based on fixed timing control, such as those outlined in Webster's formula (Ali et al., 2021), are still in use but have difficulty adjusting to real-time traffic variations. In contrast, modern approaches utilize AI to dynamically adjust signal timing, which has been shown to improve traffic control efficiency.

Fuzzy logic offers a powerful approach to managing uncertainty in traffic flow. Its ability to translate expert knowledge into control decisions has proven to be effective in reducing vehicle waiting times compared to fixed-time control. For example, research conducted by Van et al.

(2020) showed that fuzzy logic systems are capable of reducing vehicle waiting times. In addition, multi-stage fuzzy logic systems with optimization algorithms show promising results, especially in heavy traffic situations, as conducted by Mahmood et al. (2019) and Jiang et al. (2021)

Neuro-fuzzy systems, which combine fuzzy logic with neural networks, offer a data-driven approach to traffic control. Research conducted by Vuong et al. (2021) has illustrated the potential of these systems in optimizing traffic light sequencing and control. In addition, various other AI algorithms, such as Petri-nets, Bee Colony Optimization, and deep reinforcement learning, have shown potential in optimizing traffic flow (Luo et al., 2020; Hao et al., 2018; Kodama et al., 2022; Bokade et al., 2023; Zhu et al., 2022). These algorithms performed better than traditional fixed-time control and other optimization algorithms in simulation studies.

Although AI-based approaches offer significant advantages, there are still limitations. Most studies focus on isolated intersections, so implementation in complex urban traffic networks still requires further research. Therefore, to fill the gap in adaptive traffic signal control systems for complex mixed traffic flows, this study proposes an adaptive signal control method using multi-FIS (mFIS) for complex intersections with dynamic phasing to optimize vehicle movements, both straight and right turns.

In the proposed mFIS, a fuzzy system is installed at each intersection and can communicate with other fuzzy systems at adjacent intersections. The mFIS system optimizes the traffic light settings based on the length of the vehicle queue, the duration of the vehicle stopping time, the number of vehicles on the opposite side of the lane, and the number of vehicles entering the lane.

The performance of the proposed method is compared with Preset-Cycle-Times (PCT) control, Vehicle-Actuated (VA) control, and traditional FIS (FIS without cooperation between controllers at adjacent intersections). The tests were conducted through a microscopic traffic simulator.

The rest of the paper is organized as follows: Section II presents the details of the proposed method. The simulation experiments are given in Section III, and Section IV concludes the paper with conclusions.

RELATED WORK

Significant research has been conducted in the field of adaptive traffic signal control. Since Webster introduced the optimal cycle formula for delay minimization in 1958, it has become a standard for controlling fixed-time traffic signals at isolated intersections. However, its application is limited to using historical data to calculate the optimal cycle in fixed-time signal systems. Several modifications to Webster's formula have been proposed, including those by Wolput et al. (2016) and Zakariya and Rabia (2016).

Fuzzy logic has been widely applied in traffic signal control systems. Van et al. (2020) proposed a two-phase fuzzy traffic signal control system for mixed traffic conditions, where green time is determined by queue length and arrival rate. Garg and Kaushal (2017) integrated wireless sensor networks into fuzzy traffic control, reducing waiting times during heavy traffic.

Shiri and Maleki (2017) applied fuzzy logic to determine the maximum green time based on real-time traffic flow.

Alam (2015) proposed a two-stage fuzzy logic-based traffic light system for isolated intersections, using two modules: the Traffic Urgency Decision Module (TUDM) and the Time Extension Decision Module (ETDM). Similarly, Mahmood et al. (2019) proposed a system to reduce the average waiting time for vehicles. Jiang et al. (2021) developed an optimized version using a differential evolution algorithm to improve fuzzy rules. In addition to pure fuzzy logic, neuro-fuzzy systems have also been applied in traffic control. Udofia et al. (2014) proposed an adaptive neuro-fuzzy inference system (ANFIS) model to determine the phase sequence of traffic signals at isolated intersections.

While AI-based approaches offer significant advantages, there are still limitations. Most studies focus on isolated intersections, and implementation in complex urban traffic networks requires further research. To address this gap in adaptive traffic signal control systems for complex mixed traffic flows, this study proposes an adaptive signal control method using multi-FIS (mFIS) for complex intersections with dynamic phasing to optimize vehicle movements, including straight and right turns.

METHODOLOGY

VEHICLES SENSORS

Two detectors, rear and front, are used to count the number of vehicles in a lane. The rear detector, placed behind the lane, increases the vehicle count when it detects a vehicle (grey boxes in Figure 1), while the front detector, located near the intersection, decreases it when it detects a vehicle (black boxes in Figure 1). The outermost lane is for left-turning vehicles, the center lane is for straight vehicles, and the inner lane is for right-turning vehicles.

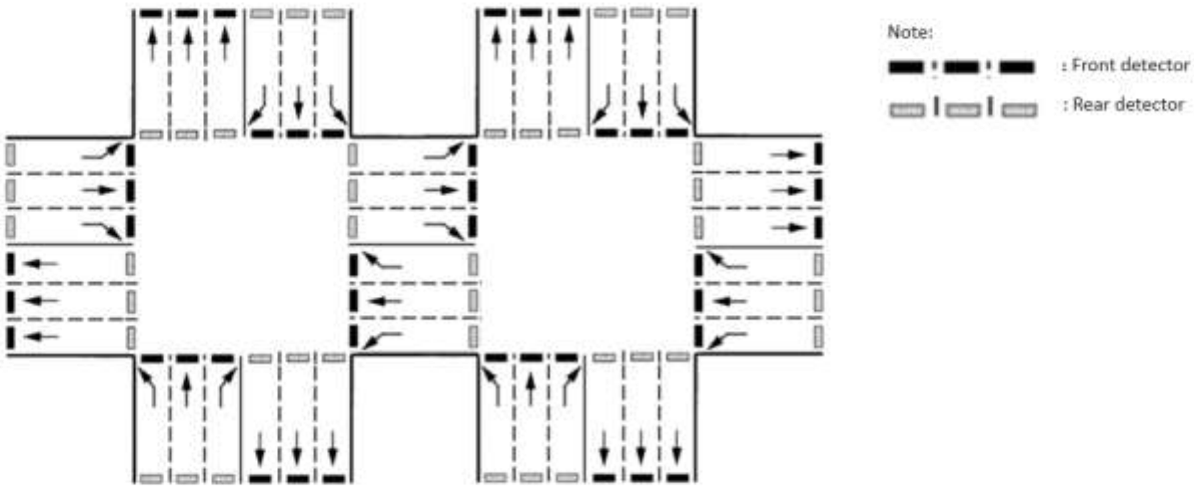

FIGURE 1. Example position of the vehicles sensors.

CONTROLLER SYSTEM OVERVIEW: MULTI-FUZZY INFERENCES SYSTEMS

The proposed controller is a multi-fuzzy inference system (mFIS) to control multiple adjacent intersections with dynamic phasing to optimize vehicle movements, both straight and right turns, in areas of high congestion. The controllers not only manage local traffic but also collaborate with their neighbours. The mFIS system optimizes the traffic light settings based on the length of the vehicle queue, the duration of vehicle stopping time, the number of vehicles in the opposite lane, and the number of vehicles entering the lane. The FIS will determine the direction of vehicle flow at the intersection and the time length of that flow adaptively based on traffic conditions. In this study, we propose four FIS inputs and the use of 20 alternative vehicle flow forms at the intersection, an increase from the previous study (Pohan, M.A.R. 2019), which only used three FIS inputs and 16 alternative vehicle flow forms at the intersection. Three FIS modules were used, namely the green phase module, the red phase module, and the decision module.

THE GREEN PHASE MODULE

The green phase module calculates the degree of urgency to extend the green phase time based on the length of the vehicle queue (QueueNum), the number of vehicles in front of the lane (FrontNum), and the number of vehicles entering the lane (ArrivalNum). This module generates the ExtendDegree, which is the degree of urgency to extend the green phase. When there is more than one traffic flow with a green phase, this module evaluates the extension degree of each flow. The minimum value of all these extension levels becomes the ExtendDegree value for that phase.

For example, for intersection conditions with east to west and west to east vehicle flows, the ExtendDegree for east-to-west (EW) traffic is calculated based on QueueNum(EW), FrontNum(EW), and ArrivalNum(E). A similar process is applied for west-to-east (WE) traffic, resulting in ExtendDegree(WE). The minimum value of ExtendDegree(EW) and ExtendDegree(WE) becomes the ExtendDegree for that phase. The membership function parameters for the Green Phase Module inputs are shown at Table 1. The Capacity variable in Table 1 indicates the maximum capacity of vehicles that can occupy the lane.

TABLE 1. Membership function parameters for the Green Phase Module inputs

Linguistic Variable	Linguistic Value	Triangular Membership Function Parameters		
		a	B	c
QueueNum	Zero	0	0	0
	Small	$-1/3\ Capacity$	0	$1/3\ Capacity$
	Medium	0	$1/3\ Capacity$	$2/3\ Capacity$
	Large	$1/3\ Capacity$	$2/3\ Capacity$	$Full\ Capacity$
	Very Large	$2/3\ Capacity$	$Full\ Capacity$	10000
FrontNum	Zero	0	0	0
	Small	$-1/3\ Capacity$	0	$1/3\ Capacity$
	Medium	0	$1/3\ Capacity$	$2/3\ Capacity$
	Large	$1/3\ Capacity$	$2/3\ Capacity$	$Full\ Capacity$
	Very Large	$2/3\ Capacity$	$Full\ Capacity$	10000
ArrivalNum	Zero	0	0	0
	Small	$-1/3\ Capacity$	0	$1/3\ Capacity$
	Medium	0	$1/3\ Capacity$	$2/3\ Capacity$
	Large	$1/3\ Capacity$	$2/3\ Capacity$	$Full\ Capacity$
	Very Large	$2/3\ Capacity$	$Full\ Capacity$	10000
ExtendDegree	Small	-1	0	1
	Medium	0	1	2
	Large	1	2	3
	Very Large	2	3	4

In the theory of Fuzzy Logic and Fuzzy Inference Systems, a Linguistic Variable is a variable whose values are words or sentences in a natural or artificial language rather than numerical values. Linguistic Values are the possible values that a linguistic variable can take, usually expressed as fuzzy sets that represent the degree of membership of an element within a set. Triangular Membership Function Parameters define the shape of the triangular membership functions used to represent these fuzzy sets. These functions are characterized by three parameters: the lower limit (a), the peak (b), and the upper limit (c), forming a triangular shape. This structure helps in defining how the degree of membership rises from zero to its maximum value at the peak and then falls back to zero. For further explanation on "Linguistic Variable," "Linguistic Values," and "Triangular Membership Function Parameters" in the theory of Fuzzy Logic and Fuzzy Inference Systems, readers can refer to literature such as (Lee, 2021; Dubois and Prade, 2012; Lowen, 2012).

This module consists of 125 rules. The example rules for the Green Phase Module are shown at Table 2. The urgency of the phase will decrease if QueueNum is small. An increase in the number of vehicles at the intersection ahead (FrontNum) will also reduce the QueueNum level. As the number of arriving vehicles (ArrivalNum) increases, the QueueNum value will increase.

TABLE 2. Example Rules for the Green Phase Module

	Input Variable		Output
QueueNum	FrontNum	ArrivalNum	ExtendDegree
Zero	Small	Zero	Zero
Small	Small	Zero	Small
Medium	Small	Zero	Medium
Large	Small	Zero	Large
Zero	Large	Zero	Zero
Small	Large	Zero	Small
Medium	Large	Zero	Small
Large	Large	Zero	Small
Zero	Small	Large	Small
Small	Small	Large	Small
Medium	Small	Large	Small
Large	Small	Large	Medium

THE RED PHASE MODULE

The decision module, which receives inputs from the red phase module (PhaseUrgency) and green phase module (ExtendDegree), is in charge of determining the change or extension of the green signal. When PhaseUrgency exceeds ExtendDegree, it indicates that the traffic on the other lane is heavier than the lane that is currently green. The module then gives green signal priority to the phase with the highest PhaseUrgency.This module has four inputs: the length of the vehicle queue (QueueNum), the number of vehicles in front of the lane (FrontNum), the number of vehicles entering the lane (ArrivalNum), and the duration of the vehicle stopping time (RedTime), which is the duration of the vehicle waiting due to the red signal. Fuzzy rules are created for the red phase module, where PhaseUrgency increases according to the increase of QueueNum, RedTime, and ArrivalNum, but decreases if FrontNum increases. Examples of fuzzy rules for this module and membership function parameters for FrontNum can be seen in Tables 3 and 4. The value of the membership function parameters of Urgency is the same as ExtendDegree.

TABLE 3. Example Rules for the Red Phase Module

Input Variable				Output
QueueNum	FrontNum	ArrivalNum	RedTime	Urgency
Zero	Small	Zero	Medium	Zero
Small	Small	Zero	Medium	Small
Medium	Small	Zero	Medium	Medium
Large	Small	Zero	Medium	Large
Zero	Large	Zero	Medium	Zero
Small	Large	Zero	Medium	Small
Medium	Large	Zero	Medium	Small
Large	Large	Zero	Medium	Small
Zero	Small	Zero	Very Long	Zero
Small	Small	Zero	Very Long	Large
Medium	Small	Zero	Very Long	Very Large
Large	Small	Zero	Very Long	Very Large
Zero	Small	Large	Medium	Zero

TABLE 4. Membership function parameters for RedTime

Linguistic Variable	Linguistic Value	Triangular Membership Function Parameters		
		A	b	c
RedTime	Zero	-60	0	60
	Short	0	60	120
	Medium	60	120	180
	Long	120	180	240
	Very Long	180	240	10000

THE DECISION MODULE

The input of the Decision Module is the output of the Red Phase Module (PhaseUrgency) and the Green Phase Module (ExtendDegree). This module will decide whether to change or extend the green signal. If PhaseUrgency is higher than ExtendDegree, then traffic conditions on other lanes need to be prioritized for advancement over the current green phase. Therefore, this module will give the green signal to the phase with the highest PhaseUrgency value.

PROPOSAL OF ALTERNATIVE SIGNAL PHASE

The FIS will determine the direction of vehicle flow at an intersection and the length of time. It can select 20 alternative forms of vehicle flow at an intersection (see Figure. 2). The FIS adaptively selects the phase to be activated by adjusting to the existing traffic density. Figure 3 showcases a sample controller schematic diagram. It represents a situation where phase 1 of Figure 2 is presently in the green state.

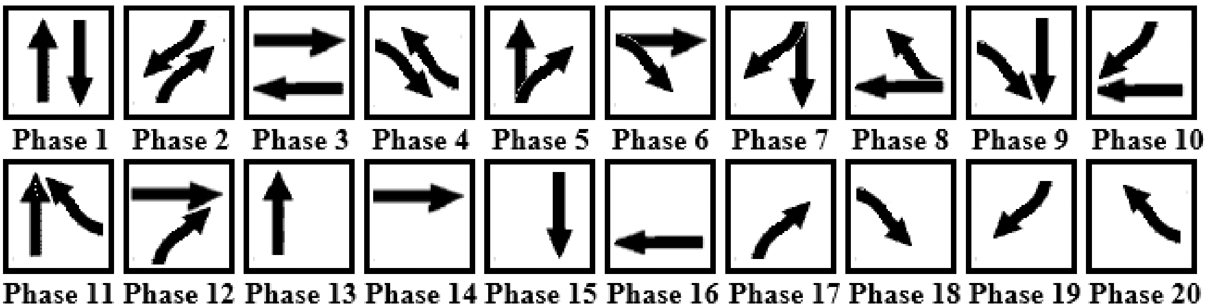

FIGURE 2. Alternative forms of vehicle flow at an intersection.

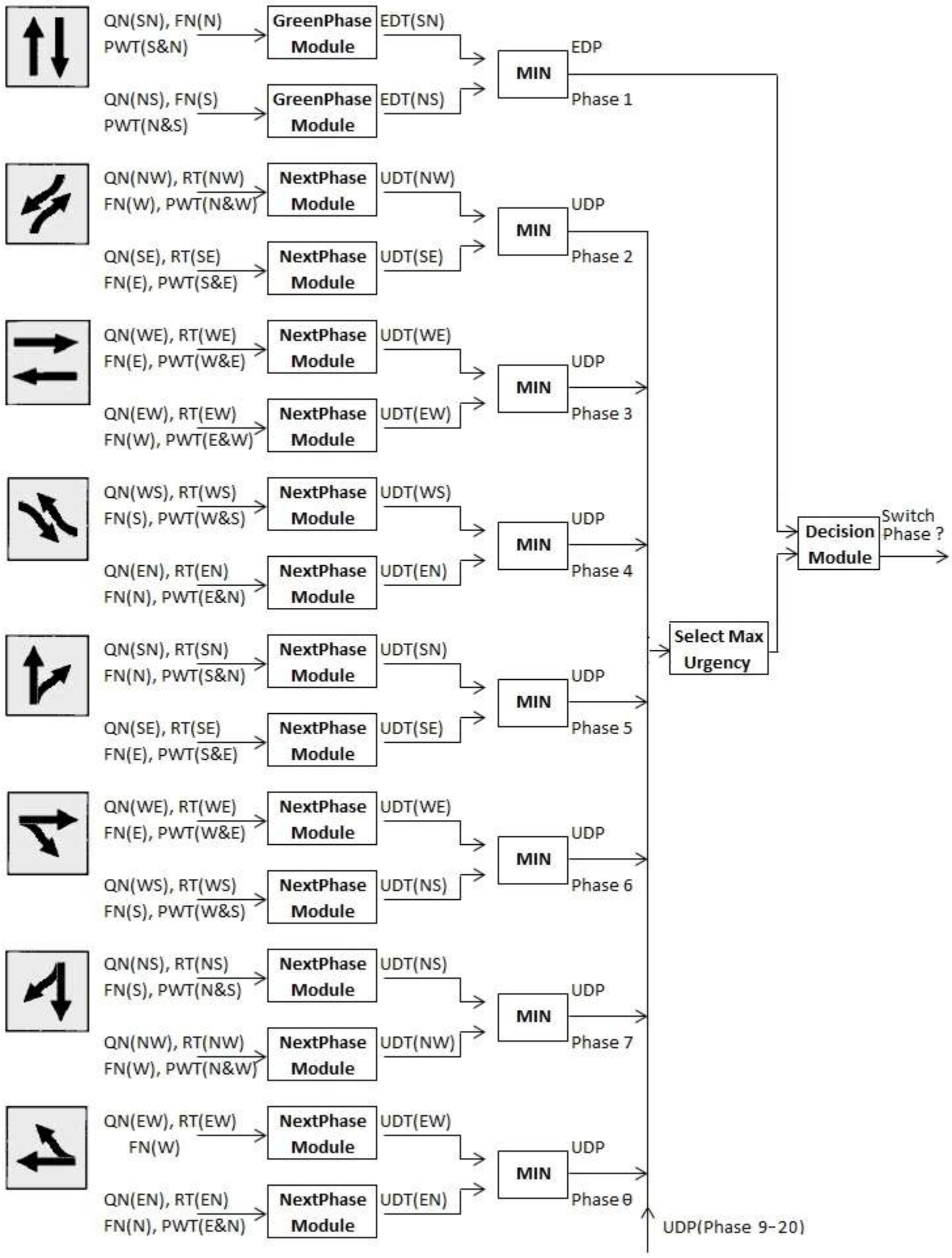

FIGURE 3. Example of a controller schematic diagram when phase 1 in Figure 2 is in the green phase.

RESULTS AND DISCUSSION

In this study, experiments were conducted using a microscopic traffic simulator to evaluate the performance of the proposed multi-fuzzy inference systems (mFIS) based traffic signal control system. The simulation environment was set up using the SUMO (Simulation of Urban MObility) traffic simulation software, which allows for realistic traffic flow simulations. The test area comprised an urban road network with multiple intersections experiencing high traffic volumes. Each simulation scenario was run for 1 hours of simulation time to obtain consistent and representative results. The mFIS system regulated the green light duration based on various parameters, including queue length, vehicle stop duration, the number of vehicles ahead in the lane, and the number of vehicles entering the lane. Additionally, each fuzzy system at an intersection could communicate with fuzzy systems at adjacent intersections to collaboratively optimize traffic flow.

We compared the proposed controller with the PCT, VA, and traditional FIS (Pohan, 2019) (FIS without cooperation between controllers at adjacent intersections) through simulations conducted across nine different traffic conditions. Initially, we explored scenarios where the traffic volume across the intersection remained constant at various levels: 600, 700, 800, 900, 1000, and 1100 vehicles per hour. After that, traffic conditions were changed every 20 minutes, including light, normal, and heavy traffic conditions. Table 5-7 presents the breakdown of vehicle counts for light, medium, and heavy traffic conditions across the four input links. Such a comprehensive evaluation enables a thorough assessment of the performance of the proposed fuzzy logic system under various traffic scenarios, which provides valuable insights for its potential real-world implementation and efficacy in controlling multiple traffic intersections.

TABLE 5. Vehicle volume in light traffic conditions.

	Time (minutes)			
	0-20	20-40	40-60	60-80
North	700	600	600	400
East	700	500	500	700
South	700	600	500	700
West	700	600	500	700

TABLE 6. Vehicle volume in medium traffic conditions.

	Time (minutes)			
	0-20	20-40	40-60	60-80
North	900	950	750	950
East	850	800	900	750
South	900	800	900	750
West	900	800	950	900

TABLE 7. Vehicle volume in heavy traffic conditions.

	Time (minutes)			
	0-20	20-40	40-60	60-80
North	1100	1050	1050	1100
East	1100	1000	1000	1000
South	1100	1000	1100	1100
West	1100	1000	1000	1100

The results of the tests for these scenarios are presented in Tables 8 and 9. Table 8 shows the test results for scenarios where the traffic volume across the intersection remained constant, while Table 9 shows the test results for scenarios where the traffic conditions were changed every 20 minute, as depicted in Tables 5-7. The measured performance metric is the average delay time for vehicles.

The proposed method performs well overall. In steady traffic, it reduces the average delay time by 13.5% to 23.6% compared to the PCT controller, 10.2% to 19.9% compared to the VA controller, and 6.5% to 10% compared to the traditional FIS controller. Under varying conditions, the improvements ranged from 10.6% to 23.6% with the PCT controller, 10% to 19.9% with the VA controller, and 5.3% to 14.1% with the traditional FIS controller. Interestingly, the proposed mFIS controller can maintain good improvements under heavy traffic conditions (5.3% to 14.1%). This is an improvement from previous FIS research in (Pohan, 2019). The advantages of the proposed algorithm lie in restricting vehicles entering lanes with high levels of congestion, accelerating the outflow of vehicles from congested areas, and using distributed control principles within areas experiencing high traffic volumes.

To illustrate how the improvement percentages in Tables 8 and 9 are calculated, consider the example of the 9.3% improvement shown for mFIS compared to FIS. The average waiting time for mFIS is 41.3 seconds, while the average waiting time for FIS is 45.6 seconds. By calculating the difference between the average waiting time of FIS and mFIS, and then dividing this difference by the average waiting time of FIS, we obtain the improvement percentage of mFIS over FIS. In this case, the difference is 45.6 - 41.3, which is 4.3 seconds. Dividing 4.3 seconds by 45.6 seconds and then multiplying by 100 gives an improvement percentage of approximately 9.43%.

TABLE 8. Case 1 average waiting time summary.

constant traffic volume	mFIS	FIS	VA	PCT	Improvement than FIS	Improvement than VA	Improvement than PCT
600	41.3	45.6	50.5	54.1	9.3%	18.1%	23.6%
700	46.5	51.7	58.1	59.3	10.0%	19.9%	21.5%
800	56.6	61.3	66.9	70.3	7.6%	15.3%	19.4%
900	62.1	66.4	72.4	73.7	6.5%	14.3%	15.8%
1000	81.2	89.9	94.4	94.3	9.7%	14.1%	13.9%
1100	91.4	99.3	101.8	105.6	8.0%	10.2%	13.5%

TABLE 9. Case 2 average waiting time summary

varying traffic conditions	mFIS	FIS	VA	PCT	Improvement than FIS	Improvement than VA	Improvement than PCT
Light	42.8	49.8	51.9	53.9	14.1%	17.5%	20.6%
Normal	59.0	63.8	69.7	73.1	7.5%	15.4%	19.3%
Heavy	88.7	93.6	98.5	99.2	5.3%	10.0%	10.6%

To verify the performance improvement of the proposed mFIS algorithm, we conducted a statistical analysis of the results of the four algorithms. We explored the statistical significance of these performance differences further using an independent samples t-test. Table 10 presents the t-test results, specifically providing p-values comparing the mFIS algorithm with the three other comparison algorithms. The p-values indicate the level of significance of the observed differences between mFIS and the comparison algorithms. A p-value less than the predetermined significance level of 0.05 indicates statistically significant performance differences between these algorithms. As illustrated in Table 10, the mFIS algorithm shows low p-values below the significance threshold when compared to VA and PCT, but the mFIS algorithm does not surpass the significance threshold when compared to the FIS algorithm.

TABLE 10. Results of statistical analysis using independent samples t-test (p-values) comparing the mFIS algorithm with three other comparison algorithms

Algoritma	p-values
mFIS compared to FIS	0.631303916
mFIS compared to VA	0.048524291
mFIS compared to PCT	0.034291689

This reduction in congestion will correlate with a decrease in CO_2 emissions and vehicle fuel consumption, improving environmental sustainability in urban centres, enhancing the quality of urban life, and improving mobility. In addition, it is important to pay attention to other measures that can help reduce congestion, such as developing path-planning algorithms that can provide the best route for vehicles (Pohan et al., 2024; Mashayekhi et al., 2020; Pohan et al., 2021; Aria, 2021; Pohan and Utama, 2023; Rahajoeningroem and Gunastuti, 2024; Pohan and Utama, 2024), avoid congestion, and effectively manage overall traffic. By integrating smart solutions such as traffic signal optimization and path-planning, we can create a more efficient, environmentally friendly and sustainable transportation system for a better future. If this research utilizes Type 1 fuzzy logic, future work could explore the use of Type 2 fuzzy logic (Pohan et al., 2023; Taufiqurrahman, and Pohan, 2023) as a potential enhancement

Furthermore, the following discussion will address the potential limitations, scalability, real-world implementation challenges, environmental impacts, and economic impacts of the proposed multi-fuzzy inference system (mFIS). While the mFIS demonstrates promising results in reducing traffic congestion and vehicle delays, several potential limitations must be considered. The system operates under the assumption of ideal traffic flow conditions, perfect sensor accuracy, and the absence of external disruptions such as accidents or roadworks. Its effectiveness heavily relies on accurate and real-time traffic data; any inaccuracies or delays in data can lead to suboptimal signal timings and decreased performance. Additionally, the performance of the mFIS can be sensitive to the initial settings of fuzzy rules and membership functions. Fine-tuning these parameters is crucial but can be both challenging and time-consuming.

The scalability of the proposed system has been tested through various traffic conditions, including light, medium, and heavy traffic scenarios. This comprehensive evaluation enables a thorough assessment of the performance of the proposed fuzzy logic system under diverse traffic scenarios, providing valuable insights into its potential real-world implementation and efficacy in controlling multiple traffic intersections.

Implementing the mFIS in real-world scenarios presents several challenges. One major challenge is the deployment of the necessary hardware, including sensors and controllers, as well as the communication infrastructure required in urban environments. Additionally, integrating the mFIS with existing traffic management systems and other urban infrastructure can be complex and require substantial effort to ensure compatibility and seamless operation. Ongoing maintenance and technical support are vital to ensure the continuous operation and effectiveness of the mFIS. This includes regular updates, troubleshooting, and system optimization to maintain optimal performance.

The environmental impacts of the proposed mFIS are also significant. Reduced air pollution can be quantified by estimating the potential reduction in air pollutants such as NO_x, CO_2, and $PM_{2.5}$ due to decreased traffic congestion and idling. Improved air quality can lead to health benefits, including reduced respiratory illnesses and increased life expectancy, supported by relevant studies. Additionally, smoother traffic flow may contribute to noise pollution reduction.

Economically, the mFIS offers several benefits. Potential fuel savings for drivers can result from reduced congestion and idling. Time savings for commuters and commercial vehicles due to improved traffic flow can be quantified in economic terms, reflecting increased productivity and reduced transportation costs. Moreover, improved traffic flow can positively impact economic growth and development by attracting businesses and improving accessibility to goods and services.

To further enhance the mFIS and address its current limitations, several specific future research directions are proposed. Integrating Internet of Things (IoT) technologies, including Vehicle-to-Everything (V2X) communication, can improve sensor accuracy and mitigate external disruptions such as accidents or roadworks, addressing the reliance on accurate and real-time traffic data. Additionally, exploring the incorporation of machine learning algorithms can optimize signal timings based on real-time data patterns, making the system more adaptive and efficient. Other potential research directions include investigating the integration of the mFIS with multi-modal transportation systems, such as public transit, biking, and walking, to optimize overall urban mobility. Another important area is energy efficiency, where research can explore optimizing traffic signals to minimize energy consumption for both vehicles and traffic signal infrastructure. Furthermore, a more in-depth analysis of the environmental impacts of the mFIS system should be conducted, focusing on the potential for reducing greenhouse gas emissions and improving air quality.

CONCLUSION

This paper has proposed a traffic control system using multi-fuzzy inference systems (mFIS) to control multiple adjacent intersections with dynamic phasing to optimize vehicle movements, both straight and turn right. The controller not only manages local traffic but also cooperates with their neighbours, from which the controller gets information in addition to the detectors. The mFIS system optimizes the traffic light settings based on the length of the vehicle queue, the duration of the vehicle stopping time, the number of vehicles in front of the lane, and the number of vehicles entering the lane. The FIS will determine the direction of vehicle flow at an intersection and the length of time. mFIS can select 20 alternative forms of vehicle flow at an intersection. The results obtained from the application of mFIS in the microscopic traffic simulator found that the proposed controller shows the proposed algorithm can reduce congestion levels in areas with high congestion levels compared to the comparison algorithm. The advantages of the proposed algorithm lie in restricting vehicles entering high-congestion lanes, speeding up the outflow of vehicles from congested areas, and using distributed control principles within areas experiencing high traffic volumes. This reduction in congestion levels will correlate with a decrease in CO_2 emissions and vehicle fuel consumption, which will improve environmental sustainability in city centres, enhance the quality of urban life, and improve mobility.

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