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TRAFFIC LIGHT CONTROL USING FUZZY LOGIC SUGENO METHOD

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ABSTRACT Urban traffic congestion, particularly at intersections, has become a critical issue due to the limitations of fixed-time traffic lights, which can not adapt to real-time traffic conditions. This study proposes an adaptive Sugeno-type fuzzy logic traffic signal controller that optimizes green light durations based on queue length, vehicle density, and vehicle size. The system was evaluated through MATLAB-SUMO co-simulations under various traffic scenarios, measuring queue lengths, vehicle departures, and green light durations. The results of the study reveal that the proposed fuzzy logic controller significantly reduces waiting times and queue lengths while increasing intersection throughput compared to traditional fixed-time control.

Keywords: sugeno fuzzy logic, queue length, vehicle size, intelligent transportation system, MATLAB-SUMO simulation.

التحكم في إشارات المرور باستخدام المنطق الضبابي بطريقة (Sugeno)

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المستخلص: أصبح الازدحام المروري في المناطق الحضرية، ولا سيما عند التقاطعات، مشكلةً بالغة الأهمية بسبب المحددات التي تواجه إشارات المرور ذات التوقيت الثابت، التي لا تستطيع التكيف مع ظروف حركة المرور الفعلية في الوقت الحقيقي.

تقترح هذه الدراسة نظامًا تكيفيًا للتحكم في إشارات المرور يعتمد على المنطق الضبابي من نوع (Sugeno)، بهدف تحسين زمن الإشارة الخضراء استنادًا إلى طول طابور المركبات، وكثافة المركبات، وحجم المركبات.

جرى تقييم النظام باستخدام المحاكاة المشتركة بين برنامجي MATLABوSUMO، وذلك في ظل سيناريوهات مرورية متنوعة، مع قياس أطوال طوابير المركبات، وعدد المركبات التي اجتازت التقاطع، وزمن الإشارة الخضراء.

وتُظهر نتائج الدراسة أن وحدة التحكم المقترحة القائمة على المنطق الضبابي تحقق انخفاضًا ملحوظًا في أزمنة الانتظار وأطوال طوابير المركبات، مع زيادة معدل تدفق المركبات عبر التقاطع، مقارنةً بأنظمة التحكم التقليدية ذات التوقيت الثابت.

الكلمات المفتاحية: المنطق الضبابي (Sugeno Fuzzy Logic)، طول طابور المركبات، حجم المركبات، نظام النقل الذكي، المحاكاة المشتركة بين برنامجي MATLABوSUMO .

1. BACKGROUND

Urban congestion remains a critical challenge affecting sustainability and quality of life, while also contributing significantly to air pollution from the transportation sector. Addressing congestion and emissions jointly has been shown to yield more effective outcomes than treating them independently [1]. However, completely eliminating congestion is neither practical nor economically feasible, as it would require substantial infrastructure

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investment; thus, moderate congestion is often considered a sign of urban vitality, necessitating balanced and efficient traffic management strategies [2], [3].

Promoting alternative transportation modes such as public transit, cycling, and off-peak travel is essential to mitigate congestion, though achieving this requires supportive policies and regulations [4], [5]. Traditional traffic control systems, particularly fixed-time signals, lack adaptability to dynamic traffic conditions, leading to inefficiencies and increased delays, while manual control remains limited by human constraints [6], [7].

Recent advancements in artificial intelligence, particularly fuzzy logic, offer adaptive and efficient solutions for traffic management. Fuzzy logic systems effectively handle uncertainty and dynamically optimize signal timings, improving traffic flow compared to conventional approaches [8]- [11]. Originally introduced by Zadeh in 1965, fuzzy logic extends classical binary logic by incorporating degrees of truth, making it suitable for complex and uncertain environments [12]–[14].

Fuzzy inference systems, particularly Mamdani and Takagi-Sugeno-Kang (TSK) models, are widely used in traffic control. While Mamdani systems provide intuitive rule-based reasoning, TSK models offer higher computational efficiency suitable for real-time applications [15], [16]. These systems rely on fuzzy sets and membership functions to process imprecise data, making them highly effective for real-time traffic control scenarios in which conditions are dynamic and uncertain [17], [18].

2. LITERATURE REVIEW

Recent studies have widely explored fuzzy logic for intelligent traffic signal control to overcome the limitations of fixed-time systems. A fuzzy-based controller using sensors and simulation tools demonstrated improved traffic flow and reduced waiting time compared to conventional systems [19]. Similarly, a two-stage fuzzy controller for phase selection and green time allocation showed better adaptability to varying traffic conditions and reduced vehicle queues [20]. To address computational complexity, a hybrid fuzzy rule reduction approach was proposed, significantly decreasing execution time while maintaining high performance in complex intersections [21].

Likewise, integrating real-time data acquisition techniques such as video processing and machine learning (e.g., YOLO) has enhanced traffic estimation accuracy and system adaptability, although detection errors due to occlusion remain a challenge [22]. Some previous studies focused on infrastructure support using wireless sensor networks to enable reliable communication for intelligent transport systems [23]. Hybrid approaches combining fuzzy logic with optimization models like Webster formulas demonstrated improved performance in terms of delay and travel time under dynamic traffic conditions [24].

Additionally, optimization techniques such as differential evolution have been used to refine fuzzy rules and improve decision-making, though these methods are often limited to isolated intersections [25]. Advanced models also addressed these specific challenges such as congestion overflow and queue spillback using adaptive fuzzy-based prioritization strategies [26]. Furthermore, integrating road capacity analysis with fuzzy controllers has shown promising results in improving overall traffic efficiency in urban networks [27].

Despite recent advancements, most approaches are limited to small-scale intersections and fail to address scalability to larger networks. What is more, these approaches have not taken into consideration heterogeneous traffic characteristics, such as variations in vehicle size and type, leading to issues in accuracy and complexity. Therefore, an efficient fuzzy logic-based system that handles traffic diversity and performs reliably in real-world environments is needed.

3. MODELING OF TRAFFIC LIGHT

Fig. 1 shows the traffic system at Al-Zakhry Intersection, one of the busiest traffic lights in Sirte City. Real vehicle count data collected over a week were used to analyze traffic, with the fixed-time system evaluated based on averaged hourly vehicle movements.

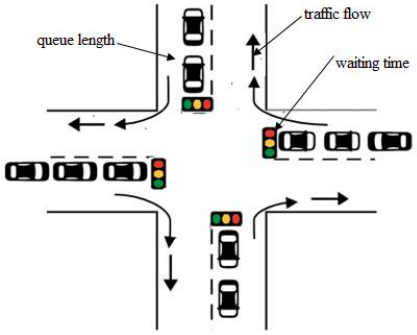


Fig.1: Layout of the Al-Zakhry intersection in Sirte City.

Table (I) presents a real dataset of vehicle counts observed during different hours of the day with a marked increase observed between 19:00–20:00.

Table I: Real vehicle count data collected at the Al-Zakhry intersection during different hours of the day.

Time	East	North	West	South		**Time**	East	North	West	South
7-8	181	78	155	132		**14-15**	329	133	309	296
8-9	413	201	389	411		**15-16**	396	206	417	380
9-10	471	306	442	535		**16-17**	410	271	482	463
10-11	521	398	513	498		**17-18**	583	319	803	477
11-12	623	432	589	510		**18-19**	894	487	1008	814
12-13	801	447	677	531		**19-20**	1240	765	1393	1175
13-14	672	261	504	499		**20-21**	713	391	809	667

Table II presents the fixed-time traffic light durations for each phase (red, yellow, green) per lane, totaling 472 seconds, resulting in excessive waiting for uneven queues.

Table II: Fixed cycle time settings (red, yellow, green) for each direction at the Al-Zakhry intersection.

Direction	Red(Sec)	Yellow(Sec)	Green(Sec)
East	88	3	27
North	93	3	22
West	88	3	27
South	93	3	22

3.1. Optimization of Fixed Traffic Light System

Observation of traffic flow at the intersection revealed congestion and inefficiency during peak hours. Hourly traffic volumes were estimated from shorter interval counts [28]. Data in Table I indicate the peak hour (19:00–20:00) with vehicle counts of East: 1,240; North: 765; West: 1,393; and South: 1,175.

First, calculate the cycle time using equation (1)

$$C_{ua} = \frac{(1.5 * LTI + 5)}{(1 - IFR)} \qquad (1)$$

Where **LTI** is the lost time per cycle, representing the time added to a signal cycle due to unexpected traffic effects such as delays or stops during the cycle. **IFR** represents the traffic flow-to-capacity ratio.

$$LTI = N \times (Y + C_\{clearance\}) \ ) \qquad (2)$$

Where N is the number of streets (N=4), Y is the yellow time (Y=3 s), and C is the clearance time between cycles (C=2 s).

$$\text{So, } LTI = 4 \times (3 + 2) = 20\text{sec}$$

The IFR equation is as follows:

$$\text{IFR} = \frac{\{\Sigma Q\}}{\{\Sigma S\}} \qquad (3)$$

Where ΣQ represents the total traffic flow on all streets (cars/hour), and ΣS denotes the total traffic capacity of all streets.

Table I presents the rush-hour traffic flow at the intersection. Therefore, the total number of cars (ΣQ) is:

$$\Sigma Q = 1240 + 765 + 1393 + 1175 = 4573 \text{ car/hour.} \qquad (4)$$

The traffic capacity is calculated using (5):

$$S = S_0 \times N \times f_w \times f_g \times f_p \times f_b \qquad (5)$$

Substituting the given values yields (S = 1900) cars/hour per street. Thus, the total flow and capacity are ΣQ = 4573 cars/hour and ΣS = 7600 cars/hour, resulting in an intersection flow ratio IFR $= \frac{\{\Sigma Q\}}{\{\Sigma S\}} \frac{\{4573\}}{\{7600\}} = \approx 0.6017$

The cycling time can be calculated as

$$C_{ua} = \frac{(1.5*20+5)}{(1-0.6017)} = \frac{(30+5)}{(0.3983)} \approx 87.9\text{sec}$$

Next, the green time for each road was calculated:

$$g_i = (C_{ua} - LTI) * PR_i \qquad (6)$$

The road priority ratio (PR_i) is defined as

$$\text{PRi} = \frac{\text{Q}_\text{i}}{\text{Q}_\text{total}} \qquad (7)$$

Where *Qi* is the traffic flow per road and *Qtotal* = 4573 cars/hour. The computed priority ratios are PR_1= 0.271, PR_2=0.167, PR_3=0.305 and PR_4=0.257. Using (6), the corresponding green times are g_1=19 s, g_2=12 s, g_3 =21 s, and g_4=18 s.

These optimized parameters were evaluated usin g MATLAB–SUMO simulation and compared with the existing Al-Zakhri intersection traffic system.

3.2. Sugeno-Fuzzy Traffic Control System

The fixed-time control method is inefficient due to its inability to adapt to dynamic traffic conditions, resulting in increased delays. To address this issue, a fuzzy logic-based controller was implemented for adaptive traffic management at the Al-Zakhri intersection. As can be seen in Fig. 2 below, the system utilizes two inputs—vehicle density and queue length—whose fuzzification is derived from real-time data presented in Table I."

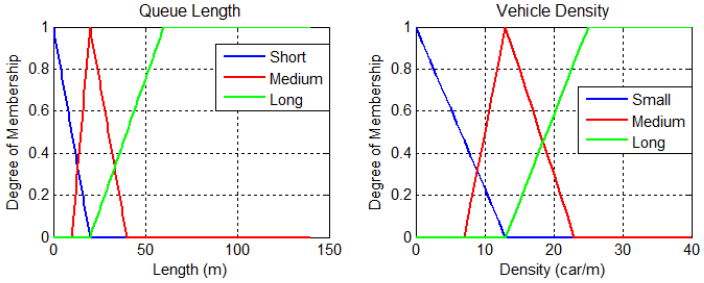


Fig. 2: Membership functions for the fuzzy controller input variables: vehicle density and queue length.

The fuzzy logic controller (FLC) rule base of table II was designed to dynamically adapt to real-time traffic by incorporating vehicle passage times and heterogeneity. Rules, derived from Al-Zakhri intersection data, relate vehicle size, queue length (≤ 60 m), and traffic density to determine optimal green durations. Vehicles were classified into motorcycles (≤2 m, 1.5–2 s), passenger cars (4–6 m, 2–3 s), light trucks (6–8 m, 3.5–4 s), and heavy trucks (10–15 m, 5–6 s).Using these classifications, output equations were derived to determine green time allocation. For instance:

$$V_c = f(L_q, N_v) where \begin{cases} (19,4) \rightarrow cars \\ (15,1) \rightarrow heavy\ truck \\ (30,7) \rightarrow 2trucks + 5cars \\ (50,15) \rightarrow motorcycles \\ (50,10) \rightarrow cars \end{cases}$$

This expresses queue length (L_q) and vehicle count (N_v) as inputs to the fuzzy logic mapping *f* that determines vehicle composition (V_c) for green time allocation.

Table III: Rule base of traffic control system.

Number of cars / queue length	Small	Medium	large
Short	Y1	Y4	Y7
Medium	Y2	Y5	Y8
Long	Y3	Y6	Y9

To derive the precise output of each fuzzy rule, the least squares regression (LSR) method is employed, generating rule-specific output equations that map input variables to green time adjustments.

Table IV presents the Sugeno-type fuzzy output equations, enabling the FLC to adapt to real-time traffic variations while ensuring robust and scalable performance across intersections.

Table IV**:** Output equations of the Sugeno-type fuzzy controller for green signal duration.

Fuzzy outputs	Type	Parameters,(ax+by+c)
Y1	Linear	0.464, 0.714, -0.545
Y2	Linear	0.43, 0.68, -0.047
Y3	Constant	88
Y4	Linear	0.29, -0.295, 2.732

Fuzzy outputs	Type	Parameters,(ax+by+c)
Y5	Linear	0.425, 0.665, 4.52
Y6	Constant	88
Y7	Linear	0.989, 0.0013, -4.731
Y8	Linear	0.5323,0.5587,-1.5179

To evaluate the rules For example:

*If0.545 =4.417-=(0.464*3)+(0.714*5)*y_1*=5(short), then* x_2 *=3(short) and* x_1

$$y' = \frac{\sum yi\ ui}{\sum ui}$$

$\mu d(short) = \frac{12-8}{12} = \frac{3}{4}$, *and* $\mu q(short) = \frac{20-5}{20} = \frac{3}{4}$, *and*

$$y' = \frac{4.417*0.75}{0.75} = 4.417SEC$$

if x_1=18(medium), x_2=30(medium) then y_5 =(0.764*18)+(0.102*30)+1.423=18.235

if x_1=18(medium), x_2=30(larg) then y_6 =(0.425*18)+(0.665*30)+4.520=32.12

if x_1=18(larg), x_2=30(medium) then y_8 =(0.989*18)+(0.0013*30)-4.731=13.11

$if x_1$=18(larg), x_2=30(larg) then then y_9=18-5=13

$\mu d(med)=\frac{21-18}{21}=\frac{1}{7}$, $\mu d(larg)=\frac{18-12}{12}=\frac{1}{2}$ And $\mu d(larg)=\frac{30-20}{20}=\frac{1}{2}$

$$y'=\frac{\left(\frac{1}{7}*18.235\right)+\left(\frac{1}{7}*32.12\right)+\left(\frac{1}{7}*32.12\right)+\left(\frac{1}{2}*13\right)}{\frac{1}{7}+\frac{1}{7}+\frac{1}{7}+\frac{1}{2}}=16.7634\text{SEC}$$

4. RESULTS

The optimized fixed-time system, derived from eq.(1)–(6), was evaluated through simulation. Results Fig. 3 indicate a significant reduction in waiting time across all directions during the peak hour (19:00–20:00, Table I) compared with the existing fixed-time control system

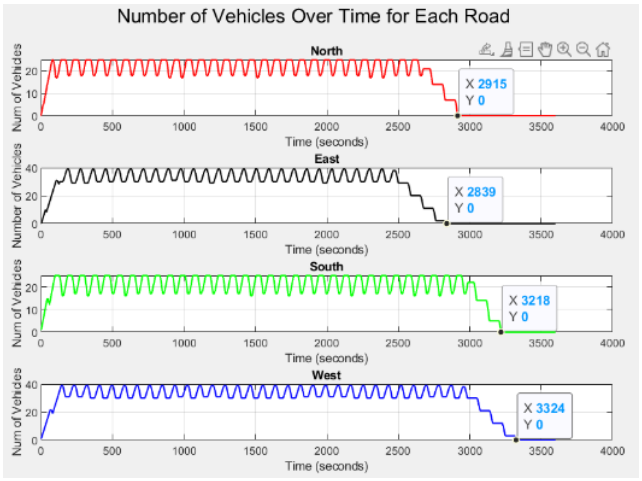


Fig. 3**:** Optimized fixed-time traffic signal system during peak-hour simulation.

The optimized fixed-time control improves traffic performance, yielding increased vehicle throughput and reduced queue length across all approaches. It ensures smoother phase transitions and efficient flow progression, with peak waiting time constrained to less than 20 s, Fig.4.

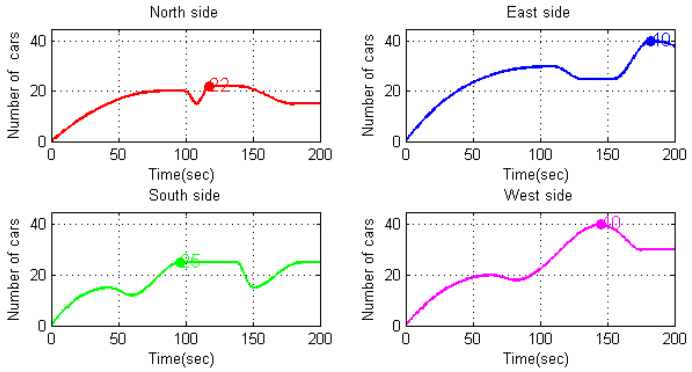


Fig. 4: One cycle of the optimized fixed-time traffic light system, illustrating smoother vehicle flow.

The Sugeno-type FLC Fig. 5 dynamically determines phase green times based on queue length, traffic density, and vehicle size. The results demonstrate reduced waiting time and queue length, along with increased traffic throughput under varying demand conditions.

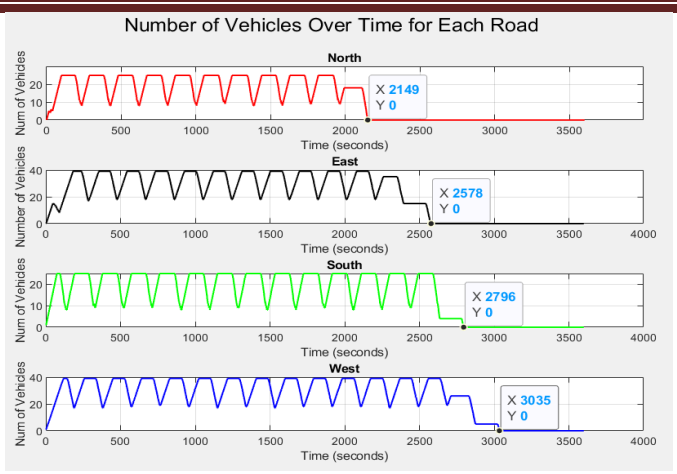


Fig. 5**:** Simulation of the Sugeno-type fuzzy traffic light controller with adaptive green durations.

Fig. 6 illustrates a complete signal cycle of the Sugeno-based Fuzzy Logic Traffic Control System(FL-TCS), where phase durations are adaptively adjusted according to real-time traffic conditions. The controller allocates longer green times to highly congested approaches (e.g., east and south), resulting in reduced waiting time, faster queue dissipation, and improved overall traffic flow efficiency.

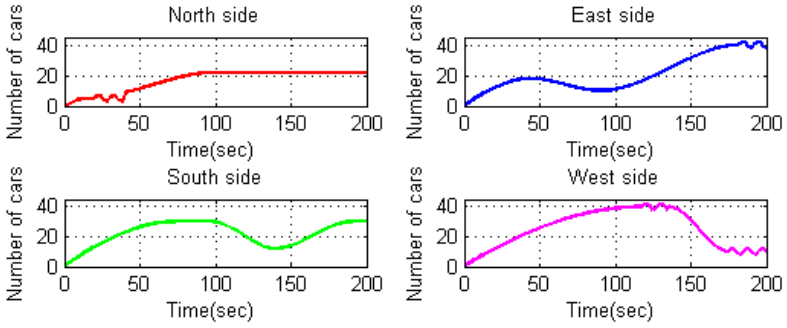


Fig. 6: Single cycle operation of the Sugeno-fuzzy traffic system, showing staggered congestion across directions.

Fig. 7 shows how the Sugeno fuzzy controller dynamically adjusts green phase duration under varying input scenarios.

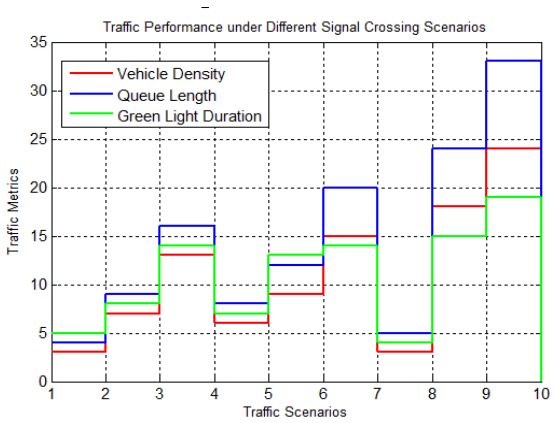


Fig. 7: Green phase duration adjustments under different traffic input scenarios.

The simulation of the Sugeno fuzzy control system, compared to the existing system, Fig. 8, demonstrates a reduction in vehicle exhaust emissions and fuel consumption. This improvement results directly from the dynamic adjustment of green phase durations and optimized vehicle flow.

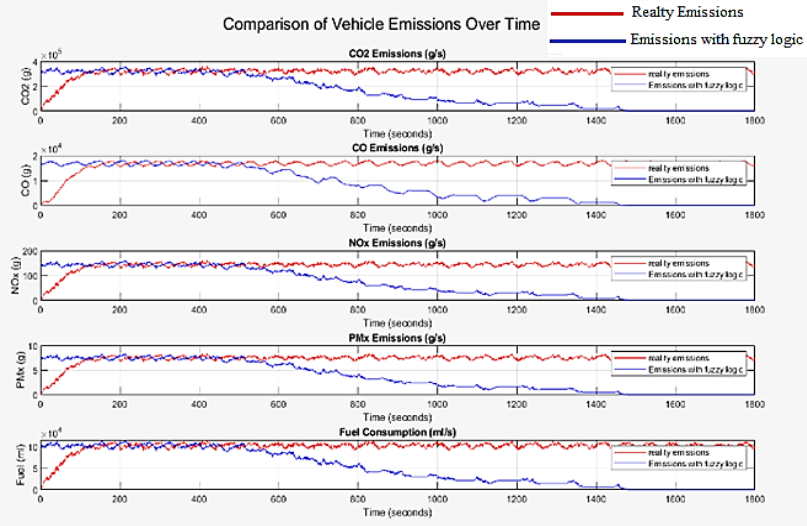


Fig. 8: Reduction of gas emissions using the Sugeno-fuzzy control system compared with the current system.

Fig. 9 and Fig. 10 illustrate the comparison between fixed time traffic system and Sugeno-fuzzy traffic system of total mass emissions of gases and fuel consumption over the periodic time of one hour of the fixed time traffic light

```
======= Total Emissions Over One Hour =
Total CO2 Emissions: 841235846.25 g
Total CO Emissions: 43810864.49 g
Total NOx Emissions: 376640.79 g
Total PMx Emissions: 19666.80 g
Total Fuel Consumption: 268329610.78 ml
```

Fig. 9: Gas emissions in the current fixed-time system.

```
======= Total Emissions Over One Hour =
CO2 Emission: 722813474.08 g
CO Emission: 40447943.62 g
NOx Emission: 327445.19 g
PMx Emission: 17432.74 g
Fuel Consumption: 230557491.14 mL
```

Fig: 10. Gas emissions in the Sugeno-fuzzy system.

Table V presents a comparison of the control systems, su arizing time savings and emission reductions as percentage ratios, highlighting the efficiency gains in traffic flow and environmental impact.

Table V: Performance comparison of fixed-time, optimized, and Sugeno-fuzzy traffic light systems.

Direction/ Lane	Number of Vehicles (#)	Fixed-Time Signal Duration (sec)	Optimized Signal Duration (sec)	**Optimized Time Savings (%)**	Fuzzy Logic Signal Duration (sec)	Fuzzy Logic Time Savings (%)
North	765	3600	2915	19.0%	2149	40.3%
East	1240	3600	2839	21.1%	2578	28.4%
South	1175	3600	3218	10.6%	2796	22.3%
West	1393	3600	3324	7.7%	3035	15.7%

In addition, the reduction in congestion emissions is evident when compared to the fixed-time system, as presented in Table (VI).

Table VI**:** Percentage reduction of exhaust gas emissions and fuel consumption using the Sugeno-fuzzy system.

Gas Emissions and Fuel Consumption	CO2	CO	NOx	POx	Fuel consumption
%reduction	14.1%	7.7%	13.1%	11.4%	14%

The evolution of vehicle flow over successive signal cycles is shown in Fig. 11a–b, with the MATLAB command window providing a real-time display of adaptive green phase adjustments for each intersection approach. These dynamic variations reflect changes in the input parameters.

```
======Time Step: 133======
Vehicles (N, E, S, W): [25, 30, 34, 23]
Queue Length (N, E, S, W): [75.00, 63.75, 71.25,
116.25] meters
Green Time (N, E, S, W): [33.57, 56.46, 56.60,
27.01] seconds
======================
```

Figure (11-a)

```
======Time Step: 194======
Vehicles (N, E, S, W): [20, 38, 28, 25]
Queue Length (N, E, S, W): [37.50, 138.75, 93.75,
41.25] meters
Green Time (N, E, S, W): [33.93, 33.01, 27.18,
53.92] seconds
======================
```

Figure (11-b)

Fig.12a–**b:**MATLAB command window outputs showing dynamic green phase adaptation at time steps 133 and 194.

5. Conclusion

This study analyzed and compared three traffic light control strategies: fixed-time, mathematically optimized, and Sugeno-fuzzy logic systems. Simulations in MATLAB and SUMO evaluated performance based on vehicle density, queue length, and traffic flow efficiency during peak hours. The fixed-time system lacked adaptability, causing unnecessary delays under variable traffic conditions. The optimized system improved green phase allocation but remained limited in responding dynamically to real-time traffic. In contrast, the Sugeno-fuzzy system demonstrated superior flexibility and efficiency, adjusting green phase durations according to vehicle density, queue length, and vehicle types, thereby reducing waiting times, idling, emissions, and fuel consumption.

It is recommended that future research could extend this approach to synchronized multi-intersection networks, combining real-time sensor data with advanced optimization methods, such as reinforcement learning or generative models. Such developments would enable adaptive traffic management at a larger scale, reducing congestion, emissions, and travel times across urban networks.

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