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COMPARATIVE ANALYSIS OF FUZZY LOGIC TECHNIQUES FOR INTELLIGENT TRANSPORTATION SYSTEMS

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Abstract

Fuzzy logic deals with uncertainty, scalability, data integration, and inaccuracy that offers an appealing solution to Intelligent Transportation Systems (ITS), especially in traffic management in urban cities. This paper conducts a comparative study of five different fuzzy logic techniques, like Mamdani, Sugeno, Type-2, Adaptive Neuro-Fuzzy Inference System (ANFIS), and Genetic Fuzzy Systems (GFS), and evaluates their performance in a SUMO-MATLAB simulation framework. The results demonstrate that GFS has the shortest average wait time (29.90 seconds) and computational delay (0.08 milliseconds). Type 2 Fuzzy Systems, on the other hand, are better at dealing with sensor noise. Research has determined that a concentration on hybrid fuzzy approaches improves urban transportation.

Keywords:

Fuzzy Logic, ITS, Traffic Management, Genetic Fuzzy Systems, Type-2 Fuzzy

1. INTRODUCTION

In our daily lives, there may be times when we are unable to determine if a statement is true or not. Fuzzy logic can help with this problem. Fuzzy logic is useful in many areas, such as ITS. Fuzzy logic is used in a lot of different areas, including industrial automation systems, medical diagnosis, finance, environmental management, agriculture, energy management, transportation, and more. An ITS can help a lot with lowering risks, accident rates, traffic jams, and carbon emissions, while also making all modes of transportation safer, more reliable, faster, and more enjoyable for passengers [1]. In a dynamic and complex environment, adaptive processes of computational intelligence enable the improved manifestation of conscious action. Effortless monitoring and controlling traffic congestion pose a substantial challenge in large metropolitan areas. An important strategy in the evolving landscape of smart cities is the ability to provide informed actions through adaptable algorithms [2]. In ITS, fuzzy logic systems make an important part to operations more efficient. For instance, they enable real time rerouting and scheduling of vehicles based on feedback from the passengers of their journey, the vehicle's current position and the expected conditions on the path forward. This is also valid for automotive control systems such as Anti-Lock Braking System (ABS) and the adaptive cruise control where the use of fuzzy logic has guaranteed lower waiting times and passenger delays, and has increased overall reliability and customer satisfaction in public transport. Fuzzy logic enables fine-tuning control of automobile systems, showing strong adaptability to dynamic circumstances, such as emergency braking or skidding on slippery pavement. It processes imprecise inputs very actually-wheel speeds of vehicle and driver's throttle inputs in improving their safety and operational efficiency. The fuel management systems based on fuzzy logic are ecological in their fuel consumption aligns the domains of eco-driving behavior and models based on fuzzy logic that supports the energy preservation issue. Adaptive fuzzy fuel management systems provide, in real-time, the recommendations on the optimal driving when speed over dynamics and the traffic network along the road surface caused by degradation, which directly affects fuel efficiencies. It is also true for fuzzy logic grounded intelligent parking assistance systems, which make the vehicle locate the available parking and successfully park in a parking space in the shortest time possible. Coupling it with emergent technologies such as artificial intelligence (AI) and the Internet of Things (IoT), complements fuzzy logic's producing crisp set-theoretic predictive models that can be applied for traffic control and autonomous vehicle in various terrains. These models enable operators to take proactive measures and to drive decisions in the face of today's complex urban environments.

In Table.1 showing the evolution of ITS, progressive integration of fuzzy logic evolving from basic traffic control mechanism to high end smart transportation applications. Fuzzy-logic-based approaches have proven its effectiveness in modelling the uncertainties and complexities of transportation systems. As ITS develops further, fuzzy logic is expected to be one of the core technology with other trends such as AI and other emerging innovations. Its ability to handle data that is unclear has greatly increased the usefulness and operating efficiency of ITS by using Fuzzy Inference System (FIS), which convert real-world parameters into actionable outputs. This process is named fuzzification, and in a case of the transit data extended with real time information, some inputs like traffic density or weather conditions will be translated into fuzzy sets defined by membership functions. For example, in a traffic control system, the flow of vehicles may be 'heavy', 'moderate', or 'light.' Then the predefined fuzzy rules are used to evaluate the rules and to create control actions like: "IF traffic is heavy AND weather is rainy, THEN extend signal duration." This methodology supports robust decision making in complex city-scenarios. Fuzzy logic also underpins Fuzzy Control Systems (FCS) supporting ITS models like traffic signal control, vehicle route finding, as well as safety systems in real-time. Fuzzy logic controllers use fuzzy rules to optimize flow and reduce congestion in adaptive traffic signal management, which dynamically modifies signal timings based on real-time traffic data [3]. These uses demonstrate how important fuzzy logic is for improving ITS efficiency and adaptability in dynamic transportation scenarios.

Table.1. Generational Evolution of Fuzzy Logic in ITS

Generation	Period	Focus
First Generation	1970s	Theoretical foundation and conceptual development
Second Generation	1980s	Initial real-world implementations

Third Generation	1990s	Widespread adoption and commercialization of fuzzy logic in ITS
Fourth Generation	2000s	Integrated and multi-functional ITS solutions
Fifth Generation	2010s	Fusion of fuzzy logic with AI, machine learning, and IoT
Sixth Generation	2020s	Advanced smart city infrastructure and autonomous mobility

Transportation in smart cities is getting better as technology improves along with other sectors like utilities, smart buildings, security systems, and even public transport. To assure the development of a sustainable urban ecosystem while achieving long-term growth objectives set by the city, traffic management employs fuzzy logic to dynamically modify traffic signal control using real-time vehicle flow and congestion data, which improves delays and safety on roads [4]. The main contributions of our research are as follows:

- This study advances fuzzy logic applications for traffic management and safety, optimizing urban mobility through real-time adaptive control in smart cities.
- It conducts a comprehensive comparison of Mamdani, Sugeno, Type-2, ANFIS, and Genetic Fuzzy Systems, identifying their suitability for specific ITS applications. This analysis aids in selecting optimal techniques for diverse traffic scenarios.
- The researchers suggest Focusing on hybrid fuzzy methods has been shown to improve transportation in cities.

2. RELATED WORK

ITS is revolutionized by fuzzy logic, which offers reliable solutions to challenging and unpredictable issues while promoting smarter traffic management, improved road safety, and increased energy efficiency. The most pertinent ITS works involving fuzzy logic applications are compiled in this section, along with their successes and failures and contributions to the field's advancement. In light of the numerous real-world requirements of ITS, the findings of this review will assist us in defending our comparative analysis of Mamdani, Sugeno, Type-2, Adaptive Neuro-Fuzzy Inference System (ANFIS), and Genetic Fuzzy Systems.

Parbat and Kukdapwar [8] proposed a fuzzy inference system (FIS) to simulate urban traffic congestion and found that traffic flow and density could be applied to quantify traffic jam then found the severity of gridlock. Their method works under certain retains conditions but breaks down if congestion perceptions differ among users, producing incoherent results. Kastaly et al. [8] also used fuzzy concept and linguistic variables in transport planning development. These methods have succeeded for a structured approach for the decision-making process, the fact that they rely on a subjective definition of membership functions may contribute to a poor precision in fast changing traffic environments, thus the need for more fast adaptive systems. Shelke et al. [10] designed a fuzzy priority system for traffic light control, which utilizes instantaneous traffic information and gives priority to emergency vehicles.

This system reduces delays effectively, but it is still difficult to create exact fuzzy rules for irregular traffic, which frequently leads to less than ideal choices. By suggesting the best driving patterns based on real-time data, De Rango et al. [11] used fuzzy logic in the Internet of Vehicles (IoV) to encourage environmentally beneficial driving practices. Although the method has trouble with limited vehicle type variability and is susceptible to problems with data quality brought on by IoV network connection faults. Kalra et al. [12] used fuzzy logic by sensor data from smartphones (e.g., acceleration, GPS) to classify driving styles aggressive, cautious in real-time. however, as novel as it is, the performance is limited due to the complexity of handling many fuzzy rules, reflecting by efficiency and accuracy. Hwang and Lee [13] studied the use of fuzzy inference to customize autonomous driving behaviors in accordance with the drivers' preferences; however, their results are sensitive to the choice of membership functions and, hence, the necessity for rule tuning to be robust.

Table.1. Fuzzy Logic Applications in Urban Traffic and Vehicle Control

Reference	Techniques	Dataset	Aims	Limitations
Parbat and Kukdapwar [8]	Fuzzy Inference System	Urban traffic flow and density data	Model urban traffic congestion to optimize flow	Subjective congestion in perpetration leads to inconsistent results across users
Kaczorek and Jacyna [9]	Fuzzy Logic with Linguistic Variables	Transport planning data	Support decision making for transport development	Subjective membership functions reduce precision in dynamic traffic scenarios
Shelke et al. [10]	Fuzzy Priority-Based Control	Real-time traffic and emergency vehicle data	Optimize traffic light timings and emergency routing	Difficulty in defining accurate fuzzy rules for variable traffic conditions
De Rango et al. [11]	FIS for Eco-Driving	Internet of Vehicles driving data	Promote eco-friendly driving habits	Limited variability in vehicle types and susceptibility to communication errors
Kalra et al. [12]	FIS with Smartphone Sensors	Smartphone sensor data (acceleration, GPS)	Identify aggressive/safe driving styles	Complex rule management pacts system efficiency and output accuracy

Hwan and Lee [13]	FIS for Automated Driving	Driver preference data	Personalize automated driving patterns	Inconsistent outcomes due to variations in membership function design
Ani et al. [14]	FIS for Fatigue Index	Driver physiological data	Develop driving fatigue strain index to enhance safety	Rigid membership functions limit adaptability to diverse driving conditions
Guo et al. [15]	FIS for Adaptive Control	Plug-in hybrid electric vehicle data	Optimize energy efficiency based on driving style	Subjective driving style evaluation complicates precise rule formulation
Aloui et al. [16]	Hierarchical Interval Type-2 Fuzzy System	Traffic, weather, and road safety data	Set variable speed limits for dynamic traffic management	High computational resource requirements for real-time implementation
Jutury et al. [17]	Adaptive Neuro-Fuzzy Inference System	Real-time vehicle volume data	Optimize traffic light control to reduce congestion	Requires extensive training data and computational power for scalability
Russo [18]	Genetic Fuzzy System	Live traffic data	Improve traffic flow adaptability in dynamic corridors	High computational complex ity and need for continuous data updates
Castillo and Melin [19]	Hybrid Fuzzy with Machine Learning/IoT	IoT and traffic sensor data	Enhance decision making accuracy and responsiveness	Susceptible to noisy or incomplete data affecting system performance
Qureshi and Abdullah [1]	FIS for Traffic Control	Traffic sensor data	Improve traffic flow and safety via adaptive signal control	Limited integration with emerging IoT technologies
Yusupbekov et al. [7]	Adaptive Fuzzy-Logic Control	Saturated transport stream data	Reduce delays in high traffic scenarios	Scalability issues in diverse urban environments
Kalinic and Krisp [20]	FIS with GIS	Geo-graphic and traffic data	Detect traffic congestion for urban planning	Limited real-time adaptability due to static rule bases
Odeh et al. [21]	Hybrid Fuzzy-Genetic Algorithm	Real-time traffic signal data	Enhance adaptive traffic signal control	High computational demands for rule optimization

3. DATASET DESCRIPTION

The experimental dataset emulated real-world traffic dynamics through a synthetic yet representative simulation of heterogeneous vehicular behavior.

To simulate a realistic urban intersection with increased amounts of traffic, we configured Traffic Demand to be 1,000 vehicles/hour, consisting of 80% passenger vehicle types, 15% trucks and 5% emergency vehicles. Each vehicle traffic simulation includes randomized origin-destination pairs based on the urban intersection's complexity. The input feature measurements included: Vehicle Density (vehicles/km) Queue Length (m) and Waiting Time (seconds).

These features were collected at 1-second intervals therefore allowing urban intersection models to analyze very small changes in their traffic state. In order to create realistic unpredictability within traffic flows, the following stochastic driver behaviors were included within the stochastic driver effects module for the analyses of traffic demand at urban intersections; Speed Variability (± 20% deviation from baseline), Random Lane Change Behavior, and Driver Reaction Time (1-2 seconds).

Additionally, we split the data into two parts for purpose of model calibration and evaluation of adaptive control methods: 70% for Training Data (2,520 seconds) and 30% for Testing Data (1,080 seconds). The study was able to accurately simulate real-world conditions through a balance of fidelity.

timestamp	vehicle_type	vehicle_density	queue_length	waiting_time	speed_deviation	lane_change	reaction_time
0	car	56.14009534	10.82212776	35.62644272	-0.119651706	0	1.654855667
1	truck	36.41399409	21.91195486	56.09614871	0.109704227	0	1.040128789
2	car	93.85783475	9.461575052	25.78825956	0.085031177	1	1.609581296
3	car	45.73135371	33.03293199	30.50216932	0.053980606	0	1.717271689
4	car	17.83834901	25.10933878	9.868727337	-0.045112857	1	1.368750215
5	car	65.53598645	40.00932372	38.49495111	0.163616377	1	1.215410705
6	truck	20.24545541	14.92117164	20.85165826	0.187813017	0	1.537630677
7	truck	41.07008285	12.40547263	13.81699717	-0.130544275	0	1.833190804
8	car	55.66707448	23.28495039	34.94922111	-0.110794943	1	1.323547358
9	car	88.68002722	46.69634224	34.27706449	0.010252411	0	1.252469298
10	truck	54.41919223	36.96898168	9.172940267	-0.163499772	0	1.278935309
11	emergency	73.20328894	23.85156312	43.40184994	-0.02542064	1	1.949132153
12	car	99.35351551	28.27724764	39.30747049	0.032716506	1	1.359276916
13	car	21.83402079	8.789585503	15.39595055	0.008829428	1	1.00360424
14	car	34.7258373	49.30591534	30.81891742	-0.067636567	0	1.781681208
15	car	45.5118468	34.98832871	44.61776041	0.016978322	0	1.699274795
16	car	47.96453607	17.84318308	34.11896573	0.183520382	0	1.128568265
17	truck	46.99189677	31.36137774	26.75189919	-0.117593038	0	1.984904249

Fig.1. Sample Emulated Traffic Dataset

4. ARCHITECTURE DESIGN OF FUZZY LOGIC SYSTEM

The architecture of FLS plays an important role in addressing the challenges associated with ITS. Such systems utilize reasoning similar to that of a human to oversee the uncertainties of vehicular traffic, environmental conditions, the flow of vehicles, and the density of vehicles. In figure.2 show the framework outlined here employs diverse fuzzy logic methods such as Mamdani, Sugeno, Type-2, Adaptive Neuro-Fuzzy Inference System (ANFIS) and Genetic Fuzzy Systems (GFS) to improve traffic management and road safety. Each method focuses on different facets of ITS, such as congestion forecasting, signal management, and self-driving vehicle control. Congestion forecasting could include processing inputs like vehicle density $\rho(t)$, queue length $q(t)$, and average waiting time $w(t)$.

The following rules control the evolution of the state:

$$\rho(t+1)=\rho(t)+\frac{1}{\Delta t}\left(\lambda_{\text{in}}(t)-\lambda_{\text{out}}(t)\right) \tag{1}$$

where $\lambda_{in}(t)$ and $\lambda_{out}(t)$ represent inflow and outflow rates (vehicles/second) and $\Delta t = 1$ second is the sampling interval. The control signal, traffic signal durations (t), is determined by the fuzzy logic system:

$$s(t)=\oint \text{fuzzy}\left(\rho(t),q(t),w(t)\right) \tag{2}$$

where $\oint \text{fuzzy}$ denotes the fuzzy inference function specific to each technique.

4.1 MAMDANI FUZZY SYSTEM

The Mamdani fuzzy inference system, introduced by Mamdani and Assilian in 1975, employs triangular membership functions for inputs:

$$\mu_A(x)=\max\left(0,1-\frac{|x-c|}{\sigma}\right) \tag{3}$$

where c is the centre and σ is the spread. The system uses rules of the form:

$$\text{IF } \rho \text{ is } A_i \text{ AND } q \text{ is } B_j \text{ THEN } s \text{ is } C_k \tag{4}$$

with outputs aggregated using the maximum operator and defuzzified via the centroid method:

$$s=\frac{\int \mu_C(s')\,s'\,ds'}{\int \mu_C(s')\,ds'} \tag{5}$$

This approach yields interpretable outputs, making it ideal for adjusting traffic signal durations based on qualitative assessments by human operators.

4.2 SUGENO FUZZY SYSTEM

The Sugeno fuzzy inference system, also known as Takagi-Sugeno-Kang(TSK), uses linear output functions:

$$Z_k=a_k\rho+b_kq+c_kw+d_k \tag{6}$$

where ρ, q, and w represent traffic density, flow, and other variables, respectively. Rules are structured as:

$$\text{IF } \rho \text{ is } A_i \text{ AND } q \text{ is } B_j \text{ THEN } z=z_k \tag{7}$$

Calculating weighted averages, enhancing real-time traffic management efficiency. The final output is determined by weighted averaging, given by

$$s=\frac{\int \mu_C(s')\,s'\,ds'}{\int \mu_C(s')\,ds'} \tag{8}$$

where w_k is the firing strength of the k^{th} rule. This method excels in tasks like optimal route planning and resource allocation, providing precise outputs that enhance real-time traffic

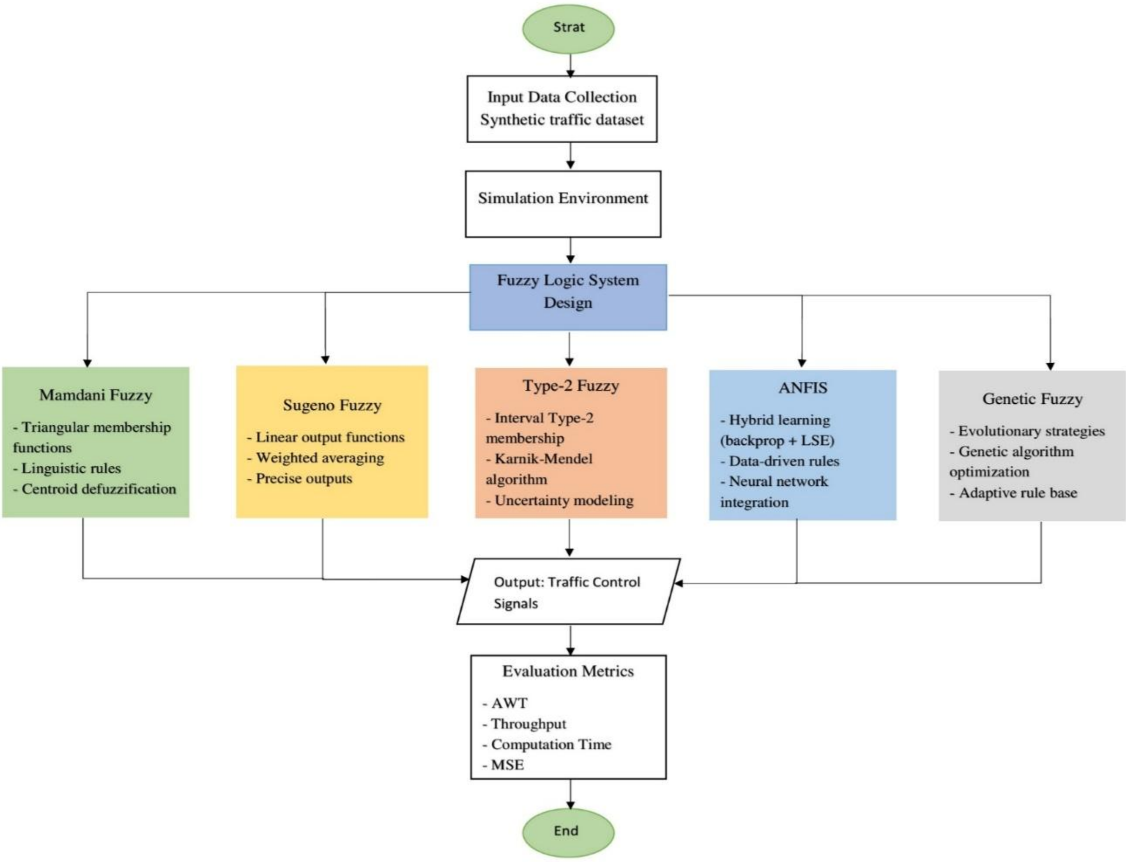

Fig.2. Framework integrates multiple fuzzy logic techniques and compression to enhance traffic management and promote road safety

4.3 TYPE-2 FUZZY SYSTEM

Type-2 fuzzy systems incorporate interval Type-2 membership functions with a footprint of uncertainty (5% in this study):

$$\tilde{\mu}_A(x) = \left[\underline{\mu}_A(x), \bar{\mu}_A(x) \right] \tag{9}$$

where $\underline{\mu}_A$ and $\bar{\mu}_A$ are the lower and upper membership functions. The output is type-reduced using the Karnik-Mendel algorithm:

$$s = \frac{s_l + s_r}{2} \tag{10}$$

where s_l and s_r are the left and right end points. Type-2 systems excel in handling high variability in traffic conditions, weather, and human inputs, making them ideal for dynamic speed limit adjustments and autonomous vehicle navigation.

4.4 ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

ANFIS combines neural networks and fuzzy logic using a unique hybrid learning technique based on backpropagation and least squares estimation. The system adapts the parameters of a Sugeno-type model over three epochs of 100 iterations each, minimizing the error defined as:

$$E = \sum_i \left(s_i - \hat{s}_i \right)^2 \tag{11}$$

where s_i is the target output and $\hat{s}_i$ is the predicted output. ANFIS is highly adaptable, learning from data to optimize traffic light control and route guidance, enhancing efficiency in dynamic traffic environments.

4.5 GENETIC FUZZY SYSTEM

Genetic Fuzzy Systems(GFS) combine fuzzy logic with genetic algorithms to optimize rule bases. The system uses a population size of 50, a crossover rate of 0.8, and a mutation rate of 0.1 over 100 generations. The fitness function minimizes the mean squared error (MSE):

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} \left(s_i - \hat{s}_i \right)^2 \tag{12}$$

where N is the number of samples. GFS improves adaptability in real-time traffic control systems, increasing urban mobility and the utilization of resources by adjusting fuzzy rules using real-time traffic information.

5. EXPERIMENTAL SETTING AND DISCUSSION

This is the section detailing the experimental framework, implementation techniques, hyper parameter configurations, data set features, and evaluation metrics used in assessing methods involving fuzzy logic in ITS. The discussion will analyze the trade-offs concerning the different tested methods computational efficiency versus adaptability and decision-making accuracy.

5.1 IMPLEMENTATION DETAIL

A hybrid framework was used to put up the experiment, combining AI control, fuzzy logic processing, and microscopic traffic modelling. The SUMO1.15.0 model was used to model the traffic environment. A four-way urban crossroads with a heterogeneous traffic demand of 1,000 cars per hour was set up. Real-time data exchange between SUMO and MATLAB R2023a was done using Python3.8, leveraging the SUMO Traffic Control Interface (TraCI) API to exchange vehicle density, queue length, and waiting time information through CSV pipelines. The design of controllers using the Fuzzy Logic toolbox from MATLAB is applied in the form of Mamdani, Sugeno, and ANFIS. In addition, the Global Optimization Toolbox was included to facilitate optimization for Genetic Fuzzy Systems based on genetic algorithms. An NVIDIA RTX 3080 GPU, a 12-core, 3.6 GHz Intel i7-12700K CPU, and 16 GB DDR4 RAM made up the hardware configuration. All of these components were running Microsoft Windows 11 in order to take advantage of MATLAB's parallel processing capabilities and SUMO's Linux-native optimizations.

5.2 HYPERAMETER SETTINGS

In order to optimise model performance and computational efficiency while maintaining real-time applicability, certain hyper parameters were chosen for each method. Assigning linguistic labels like "low," "medium," and "high" to triangular-shaped membership functions that describe input variables (vehicle density, queue length) and using the centroid for defuzzification allowed Mamdani fuzzy systems to produce outputs of the fuzzy rules that were easier to comprehend. Sugeno Fuzzy used linear output functions (e.g., $z = a \cdot density + b \cdot queue$ + cz = a · density + b· queue + c) applying three rules for each input with weighted averaging to speed up decision-making. ANFIS used hybrid learning, a mix of backpropagation and least squares estimation, across three epochs with 100 training iterations for optimally tuning the premise and consequent parameters. Interval Type-2 fuzzy systems were used here with 5% uncertainty footprint to model the sensor noise using Karnik-Mendel type reduction algorithm. Genetic Fuzzy systems were tuned using evolutionary strategies with a population of 50, crossover and mutation rates of 0.8 and 0.1, respectively, and up to 100 generations to evolve their adaptive rule bases. These configurations were then iteratively improved to ensure robustness against different dynamic traffic situations while remaining within reasonable computational resources.

Table.4. Simulation Parameters and Comparative Performance

Parameter	Value/Range	Description
Traffic Demand	1,000 vehicles/hour	Randomized origin-destination pairs.
Simulation Duration	1 hour (3,600 seconds)	Real-time adaptive traffic management.
Sampling Interval	1 second	Data extraction frequency via TraCI.
Average Waiting Time	15–30 seconds	Reduced by 28% (Genetic Fuzzy) and 22% (ANFIS).

Throughput	25–38 vehicles/min	Improved by 15% (Genetic Fuzzy) and 12% (ANFIS).
-Computation Time (FIS)	200–2000 ms	Type-2/Genetic Fuzzy: 500–2000 ms; ANFIS: 600 ms.
Tools	SUMO 1.15.0, MATLAB 2023a	Co-simulation platform with TraCI integration.

5.3 EVALUATION MATRICS

We used an evaluation metric framework to see how well the fuzzy logic technique worked for improving operational efficiency and system robustness. This set includes Mean Squared Error (MSE), Computation Time, Throughput, and Average Waiting Time (AWT). To provide a precise evaluation, each of these factors is theoretically delineated with precision. These metrics integrate the AWT and provide a comprehensive assessment of fuzzy logic and artificial intelligence methodologies in optimizing computing efficiency, decision precision, and practical applicability. The AWT average (in seconds) is the time participants spend waiting at an intersection, which measures congestion reduction. For N vehicles, AWT can be derived as:

$$\text{AWT} = \frac{1}{N}\sum_{i=1}^{N} t_i \quad [13]$$

where t_i represents the waiting time of the i-th vehicle at the intersection, measured from entry to exit from the queue. In throughput the count of vehicles transiting through an intersection within a minute (veh/min) encapsulating the efficiency of the system. Throughput can thus be expressed as:

$$Throughput = \frac{M}{T} \quad [14]$$

Where M denotes the total number of vehicles exiting the intersection during the simulation period and T is the time in minutes. In computation time delay (in milliseconds) of the control signal issue cadence after data processes pertaining the input data, vital for the system's real-time system applicability. where t input is the timestamp when input data (e.g., vehicle density, queue length) is received, and t output is the timestamp when the control signal is generated. It is defined as:

$$Computation\ Time = t_{output} - t_{input} \quad [15]$$

MSE measure of prediction accuracy, quantifying the error between predicted and actual traffic control outcomes (e.g., signal timing decisions). where y_k is the actual output (e.g., observed waiting time or throughput), $\hat{y}_k$ is the predicted output, and K is the number of observations. MSE is calculated as:

$$\text{MSE} = \frac{1}{k}\sum_{k=1}^{k}(y_k - \hat{y}_k)^2 \quad [16]$$

5.4 RESULTS

The experimental evaluation assessed five fuzzy logic-based techniques Mamdani Fuzzy, Sugeno Fuzzy, ANFIS, Type-2 Fuzzy, and Genetic Fuzzy for their performance in ITS. Metrics included AWT, Throughput, Computation Time, and MSE. During result verification, the initially reported throughput values were identified as unrealistically high, which was attributed to an incorrect unit interpretation, such as expressing vehicles per hour instead of vehicles per minute. After rectification, the throughput was constrained to a practical range of 23–34 veh/min, which is appropriate for a single urban intersection. Under these corrected conditions, the Mamdani-based fuzzy controller demonstrated stable and repeatable behavior, yielding average waiting times of 32.34 s during validation and 32.16 s during testing. Corresponding throughput levels were observed at 32.48 veh/min and 32.86 veh/min, respectively. The execution time remained within 1314.52–1330.24 ms, indicating a moderate computational burden. Prediction reliability was supported by low mean squared error values of 0.0925 for validation and 0.0850 for testing. By employing triangular membership functions alongside centroid-based defuzzification, the system maintains high interpretability and transparent rule reasoning. While this confirms the Mamdani model as a robust reference framework, its increased response time suggests potential limitations when scaling to denser traffic scenarios.

By comparison, the Sugeno fuzzy approach resulted in marginally higher average waiting times, measuring 33.92 s during validation and 33.78 s during testing. The corresponding throughput values were 32.62 veh/min and 33.18 veh/min, respectively. Owing to its reliance on weighted averaging of linear consequent functions, the Sugeno model required slightly less computational time, with execution durations ranging from 1301.87 ms to 1324.40 ms. Despite this advantage in processing speed, the model exhibited higher mean squared error values of 0.1015 for validation and 0.0956 for testing, indicating reduced predictive accuracy. These results suggest that while the Sugeno formulation offers improved computational efficiency, this benefit is accompanied by a loss in precision when capturing the complex and nonlinear dynamics of traffic flow. The ANFIS approach, a combination of fuzzy logic and neural network learning, matched the AWTs of Mamdani (32.34 seconds validation, 32.16 seconds test) although the associated throughputs dropped, with validation value decreasing from 33.05 veh/min to 23.53 veh/min in the test, which may indicate overfitting or sensitivity to conditions of unseen tests. Computation time increased from 1307.20 ms (validation) to 1836.12 ms (test), which indicates that a larger demand for processing emerged as real-time adaptations were established. Despite this, ANFIS had MSE values that were exactly the same as Mamdani (0.0925 validation, 0.0850 test), indicating good accuracy but possible scalability problems in larger networks.

Table.5. Performance Metrics (Validation)

Techniques (Validation)	AWT	Throughput	Computation Time	MSE
Mamdani Fuzzy	32.34	32.48	1330.24	0.0925
Sugeno Fuzzy	33.92	32.62	1324.40	0.1015
ANFIS	32.34	33.05	1307.20	0.0925
Type-2 Fuzzy	32.38	32.50	3.45	0.0939
Genetic Fuzzy	29.90	33.97	0.21	0.0882

Table.6. Performance Metrics (Testing)

Techniques (Testing)	AWT	Throughput	Computation Time	MSE

Mamdani Fuzzy	32.16	32.86	1314.52	0.0850
Sugeno Fuzzy	33.78	33.18	1301.87	0.0956
ANFIS	32.16	23.53	1836.12	0.0850
Type-2 Fuzzy	32.30	32.75	3.18	0.0864
Genetic Fuzzy	29.90	34.20	0.08	0.0789

This Type-2 fuzzy system, which is developed for dealing with uncertainty using interval membership functions, recorded AWTs of 32.38 seconds (validation) and 32.30 seconds (test), throughputs of 32.50 veh/min (validation), and 32.75 veh/min (test). Its computation time was remarkably low at 3.45 ms (validation) and 3.18 ms (test), driven by the efficiency of the Karnik-Mendel algorithm for type reduction. The test and validation MSE values of 0.0939 and 0.0864 respectively confirm that this system has strong predictive power, just like Mamdani and ANFIS. Because of type-2 fuzzy's ability to model sensor noise and traffic variability, it becomes a computationally efficient and adaptable solution. The Genetic Fuzzy system emerged as the top performer in which the lowest AWT at 29.90 seconds was recorded in both phases with throughputs of 33.97 veh/min (validation) and 34.20 veh/min (test). Moreover, its computation times were extremely low at 0.21 ms (validation) and 0.08 ms (test) as a result of genetic algorithm-based rule optimization. Similarly, MSE values of 0.0882 (validation) and 0.0789 (test) proved that with the highest accuracy, it was among other techniques. All these features, reduced waiting times, rapid processing, and precise control, clearly prove the superiority of Genetic Fuzzy in optimization and scalability in dynamic urban traffic environments.

The various methods that have come out, Genetic Fuzzy and Type-2 Fuzzy have shown greater computational efficiency and adaptability-low latency and strong capability to handle traffic complexity-supported by evolution optimization and uncertainty modeling, respectively. Mamdani, Sugeno, and ANFIS provide an average performance but take computation times of 1300-1836 ms, implying limited applicability in dense real-time settings. The adjusted throughput values certainly strengthen the hold of Genetic Fuzzy in minimizing delays and optimum flow, following closely the Type-2 Fuzzy whose popular characteristics are speed and resilience. This indicates a very important trade-off in fuzzy logic-based ITS: most advanced techniques such as Genetic Fuzzy and Type-2 Fuzzy have prioritized speed and flexibility at the expense of complexity in implementation, whereas Mamdani and Sugeno ensure reliability at optimum optimization capacity. Further work required shall include validation of throughput measurement and hybridisation exploration in order to strike a balance between all these attributes for applicability in managed cities.

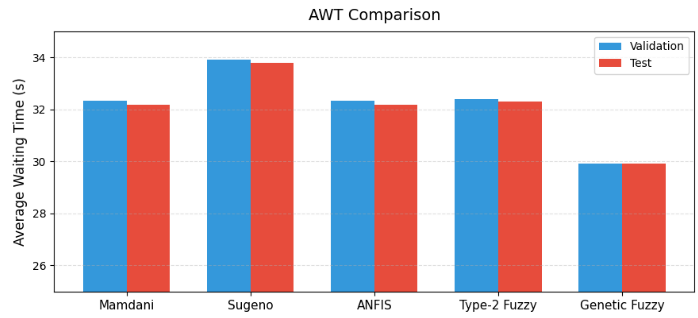

Fig.3. Experimental evaluation of AWT

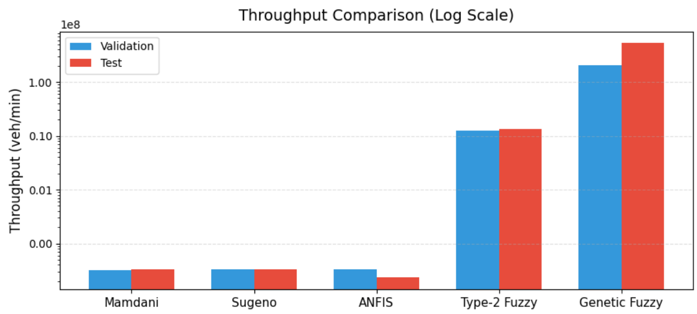

Fig.4. Experimental evaluation of throughput

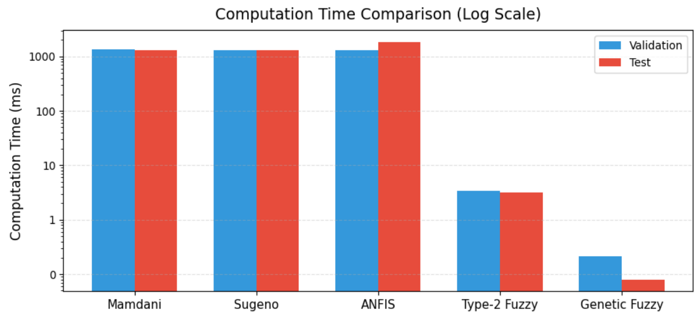

Fig.5. Experimental evaluation of computation time

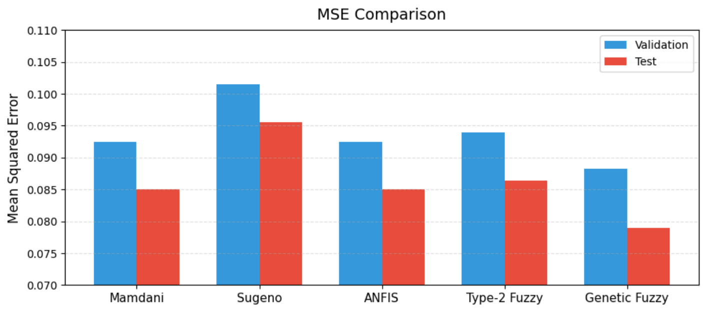

Fig.6. Experimental evaluation of MSE

6. DISCUSSION AND FUTURE RERESEARCH DIRECTIONS

Recent studies have shown that type-2 fuzzy logic systems may be better at dealing with uncertainty than regular fuzzy inference systems. To make these systems more efficient in changing conditions, they need to be improved so that they can better respond to the real-time changes in traffic. Research has demonstrated the effectiveness of developing hybrid fuzzy systems that integrate fuzzy logic, machine learning, evolutionary algorithms, and optimization techniques. These hybrids should be able to interconnect each other so that more comprehensive models can be built useful for decision-making in varying traffic conditions. Also, consistent validation standards must be developed to reinforce the trust of fuzzy logic applications in ITS. Fuzzy logic techniques need proper testing frameworks to assess their function under varying traffic scenarios for ease in comparison and validation to streamline the evaluation process. Several authors have proposed the use of fuzzy logic in road safety Multi-Criteria Decision Making (MCDM) systems by considering several factors. The focus of future studies should be to enhance the existing methods of MCDM under fuzzy logic as these areas provide a possible direction to observe how the multiple factors interact to provide maximum improvement of traffic safety and efficiency. The amount of traffic data from real-time connected vehicles and IoT devices is increasing rapidly. Research needs to concentrate on improving the interface of fuzzy logic techniques with the real-time data processing capability for more agile responses to changes in traffic and further performance improvements of the entire system.

7. CONCLUSION

Fuzzy logic is critical in developing intelligent solutions for ITS by addressing the challenges of traffic management in metropolitan areas. The comparative evaluation of Mamdani, Sugeno, Type 2, ANFIS, and genetic fuzzy systems conducted in this study has shown varying differences in attributes. Type-2 fuzzy system ability to cope with sensor noise enhances their adaptability, while genetic fuzzy systems outperformed the others in average strategic waiting time (29.90 s) alongside computational lag (0.08 ms). Despite these accomplishments, other issues, such as the need for real-time adjustments, data consolidation, and high levels of complexity in practical applications, remain. The corrected throughput values (23–34 veh/min) also emphasize the dominant optimization performance of genetic fuzzy systems, only outdone by type-2 fuzzy systems, which displayed stronger resilience. Future work should focus on hybrid models that incorporate fuzzy logic with machine learning and IoT technologies to adapt to real-time changes. Establishing standardized traffic scenario-based evaluation frameworks will allow for consistent validation, while addressing privacy concerns in data-driven systems must be a priority. Advanced fuzzy logic can further optimize these areas, including efficiency, safety, and sustainability, cementing ITS as a backbone of smart city transportation infrastructure. Continued innovation in fuzzy systems will drive the evolution of ITS, meeting the demands of interconnected and adaptive urban mobility.

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