Enhancing Traffic Management in Cyber Physical Systems – A Gradient Based Fuzzy Controller Approach

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Article Info
Journal of Machine and Computing (http://anapub.co.ke/journals/jmc/jmc.html)
Doi : https://doi.org/10.53759/7669/jmc202404082
Received 28 April 2024; Revised from 30 May 2024; Accepted 16 July 2024.
Available online 05 October 2024.

Abstract – Traffic forecast is a critical aspect of effective traffic management and planning in cyber-physical systems (CPS). In this study, we present a novel approach to traffic prediction and regulation within cyber-physical systems (CPS), introducing the Gradient Rule based Fuzzy Controller. This innovative methodology utilizes dynamic fuzzy logic control enhanced with gradient-based rules to adapt signal timings in real-time, effectively addressing the variable nature of traffic. Our results demonstrate significant improvements in reducing total queue length and delay at intersections, with reductions of up to 91.23%. Furthermore, extensive simulations and evaluations underscore the superiority of our approach compared to state-of-the-art models, highlighting its flexibility and adaptability to diverse traffic scenarios. This research emphasizes the novelty of integrating gradient-based rules into fuzzy control techniques, offering a promising avenue for advancing traffic management systems in CPS environments.

Keywords – Gradient Rule Fuzzy Controller, Cyber Physical Systems (CPS), Fuzzy Logic Controller, Queue Length.

I. INTRODUCTION

A CPS is an integrated network of computers and physical equipment that can perform varied high-level tasks. Many physical systems such as enterprises, cities, or Intelligent Transportation System (ITS) are getting increasingly connected with cyberspace. The complexity of CPS is increasing as it becomes more commonplace in everyday life. The CPS has several potential applications, but not limited to firefighting and deep-sea studies. It can also be employed in hazardous or inaccessible areas, such as firefighting, deep-sea research, and search-and-rescue missions. Interventions, such as preventing collisions, might benefit from this. Nanotechnology assembly and surgical robotics are two areas where this might be useful. Zero-net-energy construction is one area where this might be useful. It could be useful for coordinating things like traffic and military operations [1]. Transportation CPS and apps can better interact with and use the real world (people, roads, and cars) thanks to control, transmission, and computation advancements. Systemic (the control group and connection to reporting), Cyber (networking, computation, and connectivity), and Physical (including, but not limited to human/drivers, roads, waterways, airways, and vehicles) are the three main parts of a transportation CPS. Feedback control methods, powerful processing, and data sharing are essential components of any intelligent CPS [2].

Vehicles have long been seen as an extension of the human ambulatory system, subservient to the will of their drivers. This approach has been altered by recent developments in CPS development, design, and deployment, making way for Vehicular V-CPS [3]. However, as the social economy and urbanization progress, the number of cars on the road and people using them continue to rise, dramatically increasing urban congestion. Congestion, accidents, contamination, and energy scarcity are just some of the concerns that have become universal. There have been several initiatives over the last few years to address these issues. The ratio between demand and supply is unbalanced due to the sluggish rate at which urban traffic infrastructure can be built and constraints on traffic volume and urban area. These concerns necessitated the development of VCPS, which uses cutting-edge technology to address traffic congestion [4]. In general, short-term traffic status prediction is the basis for traffic-related service, traffic management, navigation, and the central component of Intelligent Transport Systems (ITS). Once the traffic status has been accurately determined, the information will be sent to an advanced traffic management system to relay to drivers in real-time.

Better-informed passengers can make more informed decisions about their routes, get route assistance, spend less time in transit, lessen their impact on the urban environment, increase transportation efficiency, and lessen their risk of injury or death. Therefore, it is critical to make reliable real-time traffic predictions to guarantee the smooth functioning of transportation networks [5]. CPS gathers environmental data from sensors and relays it to computers through a network; the computers then evaluate the information, make snap judgments, and direct the actuator to perform the desired actions. The real-time feedback loop binds the virtual and physical worlds together in complex ways. Timeliness, reliability, security, variety, and autonomy are all hallmarks of a CPS. The integration of CPS with Cloud is a contemporary trend, with a few significant efforts currently under way. But the present cloud-based CPS relies too much on Cloud, thus the system's reliability is entirely dependent on the reliability of the Cloud; this is the same as putting the reliability of the system in the hands of the Cloud providers [6].

To effectively optimize traffic control at junctions, a complex technique is required that combines Fuzzy Logic with a gradient controller. The main goal is to improve the efficiency of traffic movement, reduce congestion, and minimize delays [7]. An essential aspect is creating a mathematical model that accurately captures the dynamic characteristics of traffic, considering factors such as the number of vehicles, their speed, and past traffic trends. Apart from these linguistic variables, rule-based development of a FLC should also be considered [8]. This challenge includes real-time processing, model reliability as well as the system's robustness in general. The dynamic environment requires that there should always be continuous reviews being carried out on it for effectiveness purposes. The following are the research contributions made in the current study:

Development of a Hybrid Controller

Uniquely merging a sequential processing model with Fuzzy Logic results into creation of a controller which is able to combine strengths from the two models bringing about improved adaptability and efficacy in handling traffic conditions within Cyber Physical Systems (CPS).

Fuzzy Logic-Based Traffic Forecasting Model

A fuzzy logic-based traffic forecasting model for CPS that can predict traffic parameters such as queue length and delay can be added to the existing body of knowledge on transport systems.

Verification of Traffic Controller Efficiency

The study verifies the efficiency of the suggested traffic controller in improving road safety and traffic direction. It provides further evidence for the application of this developed controller, demonstrating how it could impact real-world situations within CPS.

Comparison with Previous Approaches

This research paper seeks to compare the proposed controller with similar ones done in previous times. Comparative studies provide answers on whether the created controller is better than others in terms of performance, effectiveness, and other aspects.

The organization of subsequent sections is represented as follows. Section II presents a brief review of current literature on traffic management. Part III gives a detailed step-by-step explanation of the recommended procedures and methodologies. Section 4 offers an inclusive analysis on simulated outcomes. Finally, the report ends with a summary of major findings and ideas for future research.

II. LITERATURE REVIEW

This section presents a brief overview about utilization of fuzzy logic in different models for traffic prediction in CPS by various researchers.

Regarding Cyber Physical Systems (CPS), Nandhini R. et al., (2022) [9] have developed an extremely efficient and extensive data-driven model, which can be used to forecast accurately the volume of traffic. The paper therefore proposes a Quantum Convolutional Neural Network with Bayesian optimization (QCNN BaOpt). In order to see how well the proposed model can work, metrics were calculated. Results indicate that this model is 99.3% accurate.

In recent years, CPSs have been implemented across critical infrastructures to enable execution of essential societal roles (Gupta et al., 2023) [10]. In a smart factory case study, Industrial Control Systems (ICSs) act as CPSs that independently control production processes through sensors and actuators. One possible approach to deal with this problem is presented in this article which supports Fuzzy Controller Autoencoder Framework (FCAF). Thus, authors argue for instance that such an architecture would identify cyber threats within smart manufacturing environment. The model could detect sudden changes from normal behavior or unusual behaviors after an attack starts which is shown by results. Besides, inclusion of fuzzy controller into the model further reduces inherent biasness in machine learning methods.

The novel hybrid approach was introduced by Ibor et al., (2022) [11] for predicting attacks on CPS communication networks. Key hyperparameters are used with bio-inspired hyperparameter search strategy to build better deep neural network structure based on NNs key hyper parameters. The prediction model is built around these datasets to test an improved neural network architecture. Over a considerable period of time, the model has proven superior in terms of accuracy, error and false positive rates compared to other existing methods.

Kure et al., (2022) [12] believe that the use of asset criticality; risk category prediction; and assessment of existing measures through their relevance for effective CSRM is crucial. The relevance or importance of an asset can be determined by applying fuzzy set theory. Machine learning classifiers predict possible risks while the effectiveness of current controls analyzed by a Comprehensive Assessment Model (CAM). This approach stems from mapping properties of VERIS community dataset (VCDB) into essential CSRM categories. In other words, based on this experiment's findings, stakeholders can now evaluate the criticality of their assets more effectively by using fuzzy set theory in this evaluation.

For instance, Guzman et al., (2021) [13] urban area cooperative traffic management was designed as a CPS plan. Namely, flexible cyber-physical entity abstraction and timed petri nets are presented within a three-layer framework for handling intersection management problems. Traffic management using the proposed technique has been shown to outperform timed, Webster, and coordinated control methods in pilot-scale implementations, while also being able to handle the communication and processing demands of a more realistic situation.

Tang et al., (2021) [14] proposed a hybrid model, named genetic approach with attention-based long short-term memory (GA-LSTM), that combines spatial-temporal correlation analysis to predict traffic volume on urban highways. The experimental results demonstrate that the GA-LSTM framework effectively captures the spatial and temporal correlation and obtains the least forecast errors.

Jafari et al., (2021) [15] introduced a novel and reliable Takagi-Sugeno (TS) fuzzy controller designed specifically for urban traffic management. After developing a fuzzy smart controller to adjust the light based on the queue length, the Lyapunov theorem is used to show that the system is stable. Based on the simulation findings, the suggested approach outperforms the fixed time controller and the typical fuzzy traffic controllers in terms of efficiency.

Bethge et al., (2020) [16] suggested a customized strategy that offers assurances in the face of uncertainty by combining trained models with model predictive control. A single autonomous vehicle is governed by the predictive controller through adjustments in acceleration and steering angle, without relying on a centralized controller. The results demonstrate the ability to create a model of human driving behavior using actual recorded trajectory data.

Padmajothi et al., (2020) [17] suggested a fuzzy logic controller built on a powerful scheduler. The suggested dynamic scheduler uses a trio of scheduling algorithms, one of which will be chosen by a fuzzy controller according to the changing needs of a CPS. An Adaptive Neural Fuzzy Inference System (ANFIS) is created by fusing a neural network with the fuzzy controller to boost the system's innate intelligence. The simulation results validate the superiority of the proposed method. Considering three distinct time limitations, the percentage of deadlines met ranges from 92% to 95% to 98.3%. **Table 1** describes the summary of the literature review revised by different authors.

Table 1. Summary of Literature Review

Authors	Techniques	Outcomes
Nandhini R. et al., (2022) [9]	QCNN_BaOpt	The suggested QCNN_BaOpt model achieved an accuracy of 0.993 when compared to both state-of-the-art machine learning techniques and CNN.
Gupta et al., (2023) [10]	Fuzzy Controller-enabled Autoencoder Framework	The suggested method has a maximum reported specificity of 93% and a sensitivity of 49.9%.
Kure et al., (2022) [11]	CSRM Approach	According to the outcomes, machine learning classifiers perform admirably at predicting various forms of risk, such as DoS attacks, cyber espionage, and malicious software.
Ibor et al., (2022) [12]	Deep Neural Network	Extensive testing shows that when predicting assaults on CPSs' communication networks, the provided model performs better than competing state-of-the-art models.
Guzman et al., (2021) [13]	Simulation of Urban Mobility (SUMO)	Fuzzy techniques were used in the implementation of the suggested architecture to aid in the modeling of congestion and the determination of splits.
Tang et al., (2021) [14]	GA-LSTM	The GA-LSTM model successfully captures the spatio-temporal correlation and achieves the lowest prediction errors.
Jafari et al., (2021) [15]	TS fuzzy controller	The simulation results indicate that the recommended solution is superior in efficiency compared to both the standard fuzzy traffic controllers and the fixed time controller.
Bethge et al., (2020) [16]	Model predictive control	Results show how human driving behavior can be modeled based on real recorded trajectory data.
Padmajothi et al., (2020) [17]	ANFIS model	The anticipated outcomes are used to distribute task sets over a network of computers efficiently. Results validate predictive scheduling's efficacy.

III. MATERIAL AND METHODS

This section discussed the methods used in the designing of a gradient rule fuzzy controller for double intersection as well as the mathematical model of the controlled system.

Fuzzier Approach

Fuzzier translates inputs into potential outcomes in this suggested method by assigning numbers between 1 and 7 to each characteristic. Fuzzy Values are used to determine how much emphasis should be placed on each aspect, and from that, Fuzzy Rules are generated for each text. Fuzzy rules are established here to account for the importance of feature value while evaluating sentences. A characteristic gives the phrase its least weight with a VERY LOW score. Values like LOW, MEDIUM, HIGH, and VERY HIGH are used to determine how significant a certain statement is. Therefore, if the fuzzy rule gives a phrase the least importance for its summary, it should have all seven feature values set to 1, and vice versa. These guidelines are based on comparing source sentences and summarizing phrases from many texts.

De-Fuzzier Approach

The fuzzy score for each phrase is determined when the de-fuzzier applies the selected rules from the rule picker. Input for the deep learning method is then prepared using de-fuzzier. To calculate the fuzzy logic score, de-fuzzier first evaluates the feature values and then modifies the feature matrix depending on the rule's assigned feature values. Separating the rules into their constituent phrases yields a new feature, a matrix that can be fed into the deep learning algorithm [18-20]. The encrypted data in fuzzier and De-fuzzier flow diagram architecture is shown below in **Fig 1**.

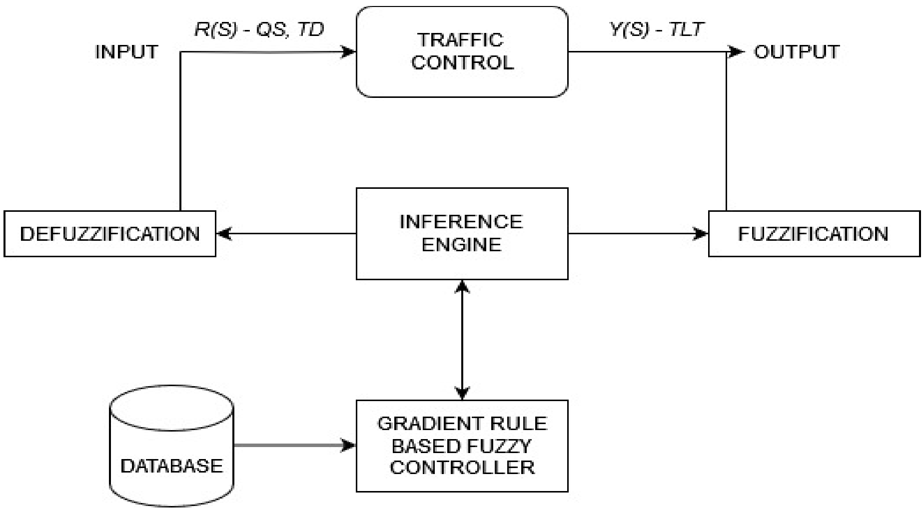

Fig 1. Architecture of Gradient Based Fuzzy Controller (GBFC).

Designing A Gradient Rule Fuzzy Controller for Intersection

Controlling the timing of the traffic lights at each junction to maximize traffic flow is the aim when dealing with a intersection that has traffic lights. Two variables enter the system: Queue Length (QL) and Traffic Density (TD), and one variable exits the system: Traffic Light Timing (TLT).

Membership Function

For every linguistic phrase, define the membership functions that are trapezoidal or triangular. As an illustration:

$\mu_{TD_L}, \mu_{TD_M}, \mu_{TD_H},$ For TD

$\mu_{QL_S}, \mu_{QL_M}, \mu_{QL_L},$ for QL

Gradient Based Rule

Provide a set of rules based on gradient:

Rule 1: If TD is TD_L and QL is QL_S then TLT is TLT_S.

Rule 2: If TD is TD_M and QL is QL_M then TLT is TLT_M.

Rule 3: If TD is TD_H and QL is QL_L then TLT is TLT_L.

Inference

Apply the minimal operator to each rule to get the degree of membership:

$$\alpha_1 = min(\mu_{TD_L}, \mu_{QL_S}) \quad (1)$$

$$\alpha_2 = min(\mu_{TD_M}, \mu_{QL_M}) \tag{2}$$

$$\alpha_3 = min(\mu_{TD_H}, \mu_{QL_L}) \tag{3}$$

Aggregation
Create a single fuzzy set from each rule's output to reflect the overall output membership distribution:

$$TL = \alpha_1 \cdot TLT_S + \alpha_2 \cdot TLT_M + \alpha_3 \cdot TLT_L \tag{4}$$

Where, TLT_S is short traffic light time, TLT_M is medium traffic light time, TLT_L is long traffic light time.

Defuzzification
Transform the combined fuzzy output TL into a precise value, usually by utilizing the centroid approach:

$$TLT_{Crisp} = \frac{\int TL.xdx}{\int TLdx} \tag{5}$$

A gradient rule fuzzy controller for a double intersection is described theoretically in this way.

Mathematical Model of The Gradient Rule Fuzzy Controlled System
Let us examine a universal system that is depicted by a transfer function. A regulated system often consists of a plant, which refers to the system being controlled, and a controller. The closed-loop transfer function provides a comprehensive description of the total system. Let us assign labels to the following variables:
$G(s)$: The transfer function represents the dynamic characteristics of the plant, which is the system being regulated.
$H(s)$: Controller's transfer function.
$E(s)$: The error signal refers to the discrepancy between the desired output and the actual output.
$U(s)$: Regulate the input to the plant.
$Y(s)$: Output.
The defined system can be shown in the following manner:

$$E(s) = R(s) - Y(s) \tag{6}$$

$$U(s) = H(s).E(s) \tag{7}$$

$$Y(s) = G(s).U(s) \tag{8}$$

Replace the given expression for U(s) in the equation for Y(s):

$$Y(s) = G(s).H(s).E(s) \tag{9}$$

Now, replace the formula for E(s) by the corresponding equation:

$$Y(s) = G(s).H(s).[R(s) - Y(s)] \tag{10}$$

Rearrange the terms to obtain the expression for the output Y(s) in relation to the reference input R(s):

$$Y(s) = \frac{G(s).H(s)}{1+G(s).H(s)}.R(s) \tag{11}$$

This equation is a representation of the closed-loop transfer function that the controlled system possesses. It is the characteristic equation of the closed-loop system that the denominator 1+G(s)·H(s) is.
When referring to the entire closed-loop transfer function, the notation T(s) is frequently used:

$$T(s) = \frac{Y(s)}{R(s)} = \frac{G(s).H(s)}{1+G(s).H(s)} \tag{12}$$

Within the context of a controlled system, this mathematical model provides a description of the relationship that exists between the reference input R(s) and the output Y(s).

IV. SIMULATION RESULTS

This section provides a comprehensive discussion of the outcomes that were achieved following the implementation of the plan. The gradient rule fuzzy controller that has been provided is utilized to optimize the length of the queue as well as the delay of the cars that are available in the traffic. **Table 2** shows the hardware and software configurations of the system used for implementation.

Table 2. System Specifications

Model	Specifications
Software	Matlab
Computer	Windows 10 pro
Processor	Intel core i5 2.70GHz
RAM	8+8 GB
Type	X64 based processor

Dataset Description

The dataset employed in this research is generated through primary sources, a real time data which is collected through real world traffic sensors. These sensors recorded the vehicle count, queue length and traffic signal timings. Further this data is organized into a table format using traffic analysis software. In this research this dataset is used to evaluate the traffic control strategies. **Table 3** shows a detailed description of important attributes and their values.

Table 3. Dataset Description

Timestamp	Intersection ID	Approach	Vehicle count	Queue length	Traffic signal phase	Signal timings (s)
2024-01-01 13:45:00	100	Northbound	12	55	Green	45
2024-01-01 13:46:00	101	Eastbound	10	35	Red	60
2024-01-01 13:47:00	102	Southbound	5	40	Yellow	5
2024-01-01 13:48:00	103	Westbound	9	28	Green	45
2024-01-01 13:49:00	104	Northbound	17	12	Red	60
2024-01-01 13:50:00	105	Southbound	2	325	Yellow	5

V. RESULTS DISCUSSION

Fig 2 and **3** depict the number of automobiles in the queue length at a double intersection in urban traffic control. **Fig 2** represents the scenario when a gradient rule fuzzy controller is used, while **Fig 3** represents the scenario without employing the controller. The utilization of a gradient fuzzy controller results in a decrease in the length of the vehicle queue, as seen in **Fig 3**.

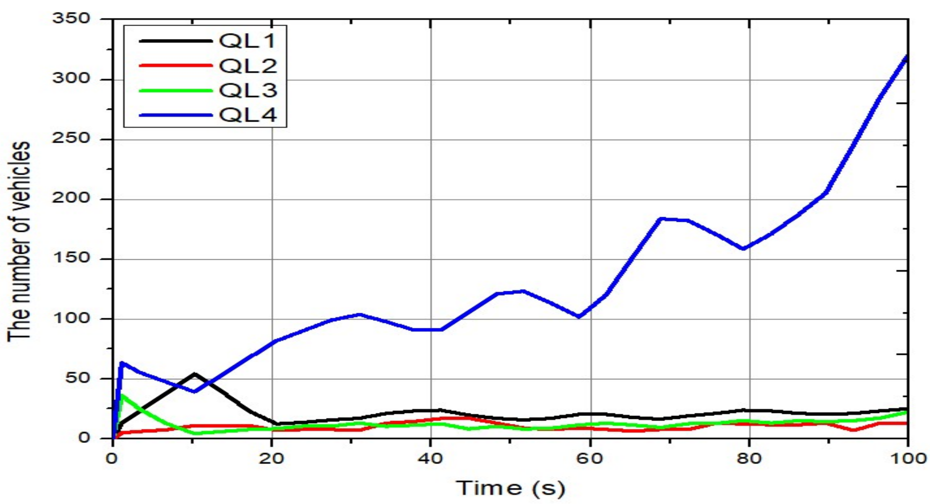

Fig 2. Vehicle Queues at Intersections Without Gradient Rule Fuzzy Controller.

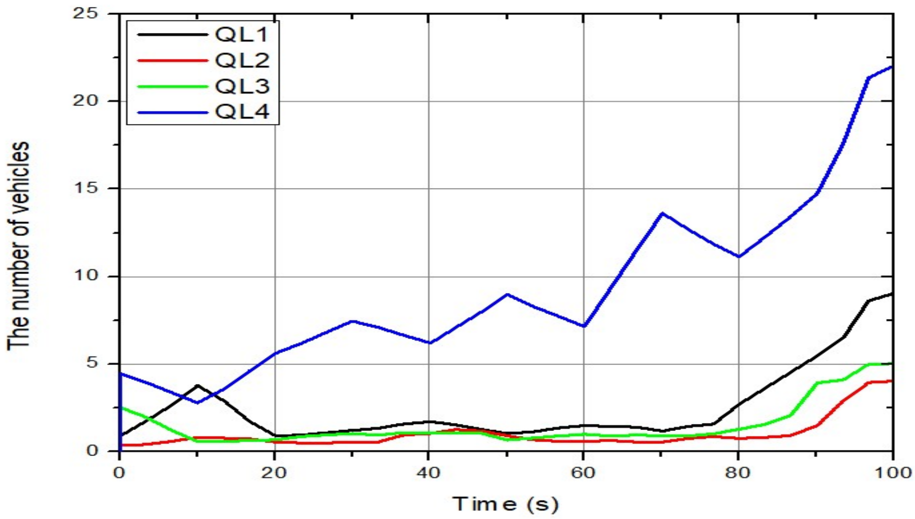

Fig 3. Vehicle Queues at Intersections with Gradient Rule Fuzzy Controller.

Following the implementation of the suggested gradient rule fuzzy controller, the queue length that was optimized is displayed in **Table 4** and **Fig 4**. It is evident from **Table 4** and **Fig 4** that all of the Queue lengths, including QL1, QL2, QL3, and QL4, have been optimized, and the average improvement percentage is 91.23%. This indicates that the overall queue length and delay of the vehicles in traffic has been optimized as a result of the application of the proposed gradient fuzzy rule controller.

Table 4. Queue Length Improvement Percentage Before and After Using Gradient Rule Fuzzy Controller

Queue length	Before	After	Total improvement percentage
QL1	55	8	85.45
QL2	25	4	84.0
QL3	40	5	87.5
QL4	325	22	93.23
SUM	445	39	91.23

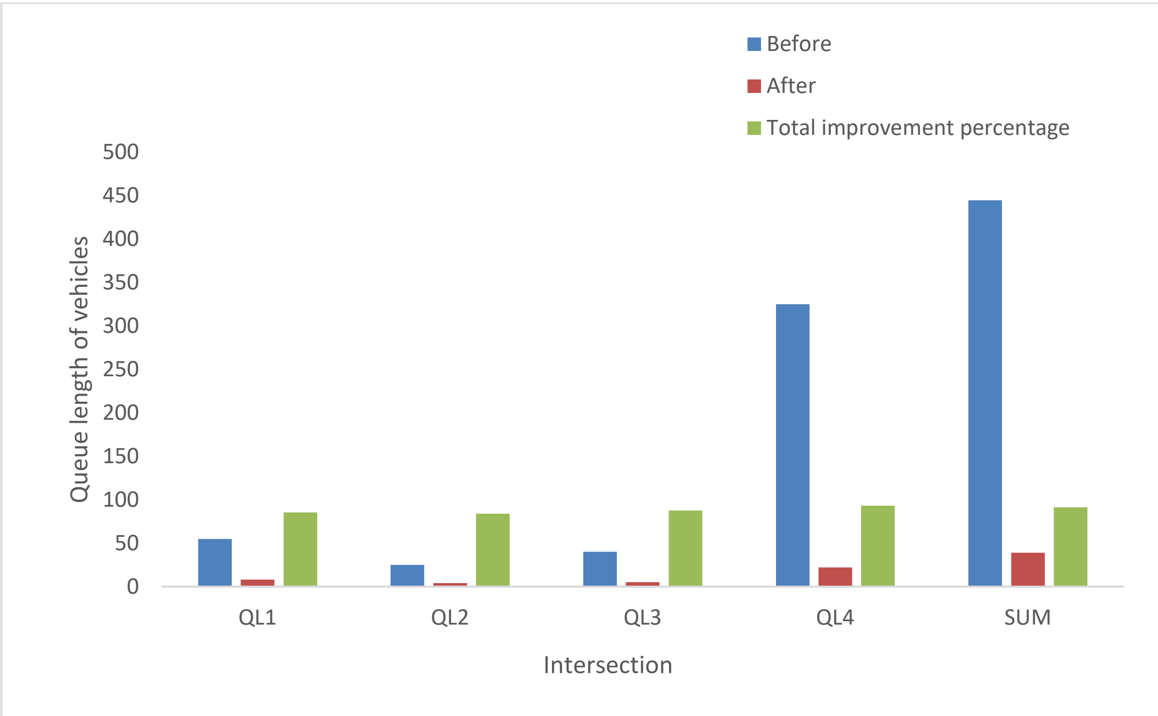

Fig 4. Optimization in Queue Length Using Gradient Rule Fuzzy Controller.

VI. COMPARATIVE ANALYSIS

A comparison is made between the suggested gradient rule fuzzy controller and other traditional techniques that are used in the same body of work in this section. A fuzzy intelligent controller achieves the least amount of optimization, which is 88.29%, as shown in **Table 5**. The suggested gradient rule fuzzy controller achieves the highest improvement in percentage, which is 91.23%, demonstrating that the proposed controller is superior to the other controllers.

Table 5. Comparison of Proposed Gradient Rule Fuzzy Controller with Earlier Studies

Author	Model	Problem	Solution	Advantage	Improvement
Bethge et al., (2020)	Model predictive control	Traffic at intersections	Predictive	Optimization	-
Tang et al., (2021)	GA-LSTM	Traffic low	Predictive	Optimize	91.12%
Jafari et al., (2021)	Fuzzy intelligent controller	Urban traffic	Reduce the length of the queue and average waiting time	Optimization and prediction	88.29%
Current study	Gradient rule fuzzy controller	Urban traffic and traffic at intersections	Reduce the length of the queue and average waiting time	Reduce traffic congestion and optimize transportation	91.23%

VII. CONCLUSION AND FUTURE SCOPE

To summarize, the incorporation of a Gradient Rule Fuzzy Controller into traffic control prediction has proven to be highly effective in improving the total queue length and delay at intersections. The inherent flexibility of the fuzzy logic controller, along with the adaptability offered by gradient-based rules, allows for real-time modifications that greatly enhance the efficiency of traffic flow. The attained optimization of up to 91.23% in the total length of queues and delay highlights the effectiveness of the suggested solution. This work enhances the progress of intelligent traffic control systems by demonstrating the capabilities of gradient fuzzy controllers in dealing with the intricate and ever-changing characteristics of urban traffic.

Overall, the future scope of the Traffic Prediction Model Design for CPS using Fuzzy Logic lies in integrating advanced techniques, expanding data sources, and addressing the challenges associated with dynamic and complex traffic environments. These advancements can lead to more accurate and reliable traffic predictions, ultimately facilitating efficient traffic management and improving transportation.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

No funding agency is associated with this research.

Competing Interests

There are no competing interests

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