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Integrating Fuzzy Logic and Machine Learning To Improve Traffic Signal System

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DECLARATION

I hereby affirm that I acquired all the information presented in this thesis in adherence to academic standards and ethical principles. In addition, I certify, as required by these codes of conduct, that all non-original materials and findings have been appropriately cited and referenced in this work.

ABDULLAHI AHMED BASHI

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ABBREVIATIONS

FLC	Fuzzy Logic Controller
SUMO	Simulation of Urban Mobility
GPS	Global Positioning System
TSS	Traffic Signal Scheduling
TLSP	Traffic Light Scheduling Problem
CTM	Cell Transmission Model
ATSAC	Adaptive Traffic Signal Control
FRI	Fuzzy rule interpolation
ITS	Intelligent Transportation Systems QC queue count
WT	Waiting Time
MTM	Manual Traffic Management
RF	Random Forest
MOEA	Multi-Objective Evolutionary Algorithm
SCATS	Sydney Coordinated Adaptive System
T-FRI	Transformation-Based Fuzzy Rule Interpolation
SPSTLS	Static Phase Scheduling Traffic Light System

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ABSTRACT

Since their invention in 1868, traffic signal systems have significantly influenced how contemporary cities manage their traffic. Enhanced traffic management promotes the ease of daily commutes and has implications for environmental sustainability. Although their primary objective is to mitigate accidents and control the movement of pedestrians and vehicles, conventional traffic signal systems frequently need help adjusting to urban expansion's ever-changing characteristics. Throughout history, fixed traffic signal systems have regulated and established order in urban traffic. Nevertheless, these systems need to address the current traffic requirements adequately. Emerging technologies like sensors and detectors are tackling this issue by dynamically altering the timing of traffic signals based on real-time traffic conditions—fuzzy logic presents viable opportunities for improving traffic signal control within this framework.

Due to its capacity to process imprecise or dubious data, fuzzy logic enables traffic control to make more nuanced decisions. The incorporation of fuzzy logic methods into traffic signal systems facilitates advanced decision-making by leveraging expert knowledge and real-time data. This empowers the implementation of traffic management strategies that are not only more responsive but also highly adaptable, providing reassurance about the flexibility of the proposed system.

This research centers on examining fuzzy logic and machine learning methodologies in traffic signal systems to develop intelligent solutions for traffic management. We aim to successfully simulate traffic flow at individual intersections using the Simulation of Urban Mobility (SUMO) setup. Our objective is to create adaptive traffic control systems incorporating fuzzy logic and machine learning algorithms capable of dynamically changing signal timings in response to fluctuations in traffic conditions.

The potential benefits of fuzzy logic and machine learning in urban environments are significant. These technologies have the power to optimize traffic flow, reduce congestion, and minimize fuel consumption. However, their potential to enhance safety in urban transportation systems is their most important feature. Our objective is to make a positive contribution to the enhancement of safety, efficiency, and sustainability in contemporary urban transportation systems through the utilization of these technologies. This focus on safety should instill a sense of security and confidence in the proposed system.

Keyword: Adaptive Traffic control, Fuzzy Logic, Sumo, Machine Learning

ÖZET

Trafik Sinyal Sistemini İyileştirmek İçin Bulanık Mantık ve Makine Öğrenmesinin Entegrasyonu

1868 yılında icat edildiklerinden bu yana trafik sinyal sistemleri, çağdaş şehirlerin trafik yönetiminde önemli bir rol oynamıştır. Gelişmiş trafik yönetimi, günlük yolculukların kolaylığını sağlamakla kalmaz, aynı zamanda çevresel sürdürülebilirlik açısından da önem taşır. Trafik sinyal sistemlerinin birincil amacı kazaları azaltmak ve yaya ve araç hareketlerini yönetmek olsa da, geleneksel trafik sinyal sistemleri, kentsel genişlemenin değişken karakteristiklerine uyum sağlamakta sıklıkla zorlanmaktadır. Tarih boyunca, sabit trafik sinyal sistemleri, kentsel trafiğin düzenlenmesi ve düzenin sağlanması için hizmet etmiştir. Ancak, bu sistemleri mevcut trafik gereksinimlerini yeterince karşılayamamaktadır. Sensörler ve dedektörler gibi yeni teknolojiler, gerçek zamanlı trafik koşullarına dayalı olarak trafik sinyallerinin zamanlamasını dinamik olarak değiştirerek bu sorunu çözmektedir. Bulanık mantık, bu bağlamda trafik sinyal kontrolünü iyileştirmek için uygun fırsatlar sunmaktadır. Belirsiz veya şüpheli verileri işleme yeteneği sayesinde bulanık mantık, trafik kontrolünün daha incelikli kararlar almasına olanak tanır. Bulanık mantık algoritmalarının trafik sinyal sistemlerine entegrasyonu, uzman bilgisi ve gerçek zamanlı verileri kullanarak gelişmiş karar alma süreçlerini kolaylaştırır. Bu, daha duyarlı ve uyumlu trafik yönetim stratejilerinin uygulanmasını sağlar. Araştırmamız, trafik yönetimi için zeki çözümler geliştirmek amacıyla bulanık mantık ve makine öğrenmesi metodolojilerini trafik sinyal sistemlerine entegre etmeyi hedeflemektedir. Hedefimiz, Şehir İçi Hareketlilik Simülasyonu (SUMO) kurulumu kullanarak bireysel kavşaklarda trafik akışını başarıyla simüle etmektir. Amacımız, trafik koşullarındaki dalgalanmalara yanıt olarak sinyal zamanlamasını dinamik olarak değiştirme yeteneğine sahip makine öğrenmesi algoritmaları ve bulanık mantık içeren uyarlanabilir trafik kontrol sistemleri oluşturmaktır. Bulanık mantık ve makine öğrenmesinin kentsel ortamlardaki potansiyel faydaları arasında trafik akışının optimize edilmesi, tıkanıklığın azaltılması ve yakıt tüketiminin minimize edilmesi yer almaktadır. Amacımız, bu teknolojileri kullanarak çağdaş kentsel ulaşım sistemlerinde güvenlik, verimlilik ve sürdürülebilirliğin artırılmasına olumlu katkılarda bulunmaktır.

Anahtar Kelimeler: Uyarlanabilir Trafik Kontrolü, Bulanık Mantık, Sumo, Makine Öğrenmesi

PREFACE

I would like to express my sincere gratitude to all those who have supported me throughout the journey of conducting this research and completing this thesis.

First and foremost, I am deeply thankful to my supervisor Prof. Dr Abdurazzag Ali A Aburas, whose guidance, insights, and unwavering support have been instrumental in shaping the direction of this study. Their expertise and dedication have challenged me to think critically and strive for excellence.

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Lastly, I am indebted to all the researchers, authors, and contributors whose work has been referenced in this thesis. Your scholarship has provided a solid foundation upon which this research was built.

In conclusion, this thesis stands as a testament to the collective efforts of those who have guided, inspired, and supported me. Thank you for being part of this journey and for contributing to the realization of this endeavor.

1. Introduction

Traffic jam is a recognized impediment to economic and productivity work in many cities around the globe. It has profound consequences on living costs, commuting costs, and hourly worth of time we spend waiting. That highlights that people always attribute traffic jams to different causes, such as increased vehicles, poor infrastructure, and installing old traffic lights. Out of all those options, the traffic light contingency emerges as the most effective one for deterring traffic and causing congestion in traffic jams. Traditional traffic lights' tasks, which are decreasing delays, improving safety, and smartly ensuring the possible capacity of the intersection, are sometimes done by adhering to fixed schedules that do not react to dramatically changed traffic flow.

Fuzzy logic controllers (FLCs) could provide an attractive solution for overcoming this problem. Fuzzy Logic Controllers (FLCs), on their part, are making it easier to process data like human languages but present a more intricate set for the complex traffic data that is now moving at a much faster phase. As a result, the signal timings are now better responding to the climactic situations set at various locations. Machine learning algorithms can find helpful information balancing large datasets by detecting patterns and trends, which can strengthen adaptive and intelligent traffic control solutions.

Our proposed intelligent traffic signal system, which leverages the power of fuzzy logic and machine learning, is a unique feature of our project. This technology uses the fuzzy concept, a key operator in the decision-making process, to dynamically reprogram signals based on the current traffic conditions, thereby ensuring a smooth traffic flow through the junctions. The adaptive mechanism of machine learning algorithms, which learn from traffic patterns and adjust their approach to control, further enhances the system's capabilities, making it a compelling solution for traffic management.

The study covers some limitations of modern traffic signal systems by indicating the steps to create intelligent traffic management solutions and how this can maintain the traffic flow in metropolitan areas. The examination of fuzzy logic and machine learning specifically aims to develop a traffic management system that reduces congestion as much as possible while significantly improving the safety and efficiency of the entire

Traffic system.

Lotfi Zadeh pioneered the fuzzy logic idea in 1965, laying the groundwork for addressing these issues. Fuzzy logic addresses the challenges of imprecise and uncertain data; it introduced a new control system, significantly contributing to controlling complex systems like traffic lights. The first attempt by Pappis and Mamdani (1977) to use fuzzy logic to manage easy intersections was promising, prompting the research into more complex applications.

Many researchers have successfully applied fuzzy logic and machine learning to traffic management, paving the way for our proposed system. Kelsey and Bisset (1993) and Nakatsuyama et al. (1984) have extended the application of fuzzy logic to more complex transportation patterns with multiple entries and exits, demonstrating its versatility. In 1992, Chiu's work further advanced the field by automatically regulating signal timings on local traffic. These successful applications provide reassurance about the effectiveness of our proposed system.

Fuzzy logic controllers (FLCs) and machine learning systems are likely potent techniques for compensating for these constraints. Furthermore, FLCs (Flexible Logic Controllers) help handle rough traffic data that includes many unclear languages by improving the level of detail in signal timing settings. Machine learning algorithms can also review enormous amounts of data, allowing for the detection of patterns and trends that provide very insightful insights for adaptive and intelligent traffic control strategies.

This study recommends an intelligent traffic light system that applies fuzzy logic and artificial intelligence solicitation. The system uses fuzzy logic, which modifies the signals according to the conditioning traffic pattern. This maximizes efficiency throughout the crossing. Continuous learning from traffic patterns enhances machine learning algorithms' learning capacity, and feedback assimilation leads to control approach adaptation.

1.1 Motivation

The serious problem of urban traffic congestion leads to economic damage, environmental decline, and reduced quality of life for people in cities. Due to the limitations of fixed schedules represented by primitive algorithms, traditional signal control systems struggle to accommodate the highly dynamic nature of traffic flow. More and more cities are building up, which drives the need for advanced traffic management technologies to respond to emerging challenges. Because of its high efficiency, fuzzy logic is a significant metropolitan vehicle traffic control tool. Indeed, unlike the earlier binary logic that operated in precise logic,

Fuzzy logic is versatile and can easily handle the multiplicity and uncertainty of data that people cannot precisely describe. Plugging fuzzy logic into the automobile signal system makes it possible to develop adaptive systems that respond to the current state and challenges in the real world. Thus, the coupling enhances the thoroughness of traffic flow and alleviates traffic congestion. This thesis focuses on formulating an adaptive network-based traffic control line that employs a fuzzy logic method for relieving congestion. The system automatically assesses traffic violations without human involvement and employs intricate decision-making processes to overcome congestion. It aims to define the implications of fuzzy logic-based control systems in reducing traffic jams and commuting times by looking at them from the comprehensive perspective of transportation efficiency. To achieve this, we will conduct an in-depth study of relevant literature and use SUMO to reproduce multiple traffic projections.

1.2 Objective of the study

The study aims to achieve the following goals:

I. The goal of this research is to develop an advanced smart traffic signal scheme that is successful in decreasing delays in the intersections by presenting fuzzy logic method.

II. Evaluate the effectiveness of the proposed system by conducting comprehensive mockup tests and using traditional traffic control methods as the local reference.

III. By evaluating pros and cons of intelligent traffic management systems which rely on fuzzy logic, among other approaches, including scalability and workability as facilitating factors.

1.3 OUTLINE

Chapter 1 takes a closer look at what causes a road network jamb-up and how fuzzy logic and machine learning could be employed to tackle traffic control issues. The charter document consisting of the provisions, motives, and a short review of the fuzzy logic early days is presented down below. These enable the process that follows to involve a more deliberate and cautious discussion involving a smart traffic signal system.

Chapter 2 introduces literature review as a primary element, specifically fuzzy logic and machine learning techniques that I shall apply in the context of traffic light control system. It looks into the employment of fuzzy logic and the results of several studies which apply it in the traffic matters for traffic lights control with the performance adjustments and system limitations. The chapter also shows a way that machine learning algorithms can be employed in traffic forecasting and the design of intelligent transportation systems and which will help to improve traffic efficiency.

Chapter 3 Methodology outlines the systematic approach for experiments and analysis. It starts with research objectives and the rationale for chosen methods. Details include experimental setup, data collection methods, test case design, performance evaluation criteria, statistical analyses, and strategies for mitigating biases.

Chapter 4 Design Architecture and Analysis elucidates the structural framework and implementation specifics of two advanced traffic control systems: fuzzy logic and machine learning. It delineates the architectural layout of both systems, emphasizing the roles of components like the SUMO Simulation Environment, fuzzy traffic controller, Python interface, and data layer. The chapter also examines the objectives, rules, and integration of these systems.

Chapter 5 investigates using fuzzy logic and random forest to manage traffic with corresponding experimental results. The evaluation concentrates a indicating measure, including an estimated time of vehicles waiting and the driving behavior and reaction time of emergency vehicles. The competition between random forest algorithm and fuzzy logic turns out that the former achieves higher efficiency; however the latter is suitable for use in regulating emergency vehicle waiting time. The pros and cons of all approaches can be seen through visualizations, and on the applicability on real life city situations.

1.4 PROBLEM DESCRIPTION

Urban traffic jams are approaching cities with negative economic, circulatory, and everyday life consequences, primarily because of the growing number of vehicles and insufficient infrastructure. Conventional traffic signal systems are designed to optimize traffic capacity and safety through one-time schedules, which cannot intensify traffic flow due to their inability to adapt to dynamic traffic scenarios. Fuzzy logic had a significant impact on control systems in the 1970s, particularly for essential intersections. Recent improvements have given rise to using fuzzy logic to deal with complex traffic arrangements, integrating different techniques, and including turn actions. Nevertheless, the current traffic management system could suit many high-demand situations. Fuzzy logic controllers (FLCs) and machine learning are powerful ways to advance traffic light control systems. FLCs provide an opportunity to interact intelligently with the road user through imprecise input (signal phases) since they may communicate in different languages. Machine-learning methods can discern patterns of jamming and congestion indicators, enabling prompt and appropriate incorporation of efficient countermeasures.

Nevertheless, intelligent traffic lights with advanced technology proved helpful in urban traffic planning because they can speed up, improve traffic flow, and provide more safety. However, the widespread adoption of intelligent traffic control systems remains a distant goal. Most recent systems need to consider the use of both fuzzy logic and machine learning approaches, so they cannot respond well to the specially built urban traffic, which is becoming more complex day by day. Therefore, this research aims to design an intelligent traffic signal system that utilizes fuzzy logic and machine learning to adjust signal times to the current traffic situation dynamically. The proposed system derives its function from examining these approaches to reduce congestion, improve traffic flow, and promote urban area safety.

1.5 BENEFIT OF RESEARCH RELATED TO THE INDUSTRY

Despite the inherent uncertainty, individuals continue to relocate for employment or other desirable opportunities. Fuzzy logic has emerged as a highly beneficial system for developing more intelligent traffic signal systems as industries and urban infrastructure progress. This system operates by opportunistically adapting the timing signals in response to the continually changing traffic conditions. It can be accomplished by building dedicated lanes and infrastructure, facilitating smooth and efficient movement for vehicles, reducing congestion, minimizing the number of cars competing for space, and enhancing the overall travel experience. Furthermore, fuzzy logic and machine learning algorithms can increase resource economization by enabling the system to adjust to traffic patterns and use reinforcement learning of the path, resulting in reaching the optimum state. This transport network enables the optimum choices while leaving the most minor expenses. In addition to eliminating emissions from cars parked in the downtown area, these systems ensure that fuel use and emission levels of the vehicles also decrease, which is an eco-friendly initiative that aligns with the broader objective of launching eco-friendly public transport vehicles. Also, advanced traffic signals can prevent accidents. From an economic standpoint, they incentivize implementing effective traffic management systems to reduce transportation expenses, enhance productivity, and create a competitive corporate environment. Decentralized systems provide the advantage of rapid expansion and effective adaptation, allowing for creating systems tailored to the unique features of many towns and areas. Streaming data and urban changes are highly effective since they continuously update with evolving traffic patterns and urban growth for long-lasting and sustainable guidance. When considering the research outcomes in this field, the primary paradox is that the changes will extend beyond just the transportation industry sectors. Improving urban mobility, the environmental situation, safety, and economic performance will be a significant step towards a new technological revolution. Superior measures ensure safety at the crossing for both motorists and pedestrians.

1.6 BACKGROUND OF RELATED PROJECTS

The rapid expansion of urban areas has led to a significant increase in the volume of vehicles on the road, causing extensive traffic congestion, extended journey durations, and environmental deterioration. Conventional traffic management methods, which depend on predetermined signal timings and pre-established strategies, have difficulties efficiently navigating the ever-changing dynamics of urban traffic patterns. Congestion not only results in time wastage and increased fuel consumption but also leads to elevated levels of air pollution and contributes to the release of greenhouse gas emissions.

In light of this, researchers and urban planners are investigating novel approaches to enhance the efficiency of traffic movement and mitigate congestion. These approaches incorporate fuzzy logic and machine learning techniques within traffic control systems. Fuzzy logic offers a versatile structure for representing uncertain and imprecise data. At the same time, machine learning methods enable the analysis of large datasets and the identification of trends to guide adaptive traffic control systems.

Fuzzy logic in traffic control systems demonstrates the potential for building adaptive and intelligent solutions that can dynamically modify traffic signal timings in response to changing traffic patterns. Traffic management systems' capacity to adapt allows them to acquire knowledge from real-time data inputs and adjust signal timings in response to variations in traffic demand, weather conditions, and special events.

Traffic control systems can strengthen their decision-making processes and optimize signal timings to meet objectives such as congestion reduction, Travel time minimization, and fuel efficiency enhancement by utilizing fuzzy logic and machine learning algorithms iteratively. The growing accessibility of real-time traffic data obtained from sensors, cameras, and GPS devices enables more knowledgeable and data-oriented traffic management approaches.

Scientists have investigated different control systems based on fuzzy logic and machine learning, showing encouraging outcomes in both simulated environments and real-world tests. Implementing these solutions presents distinct benefits in optimizing traffic flow and reducing congestion, with the potential to improve urban mobility and reduce traffic congestion.

Nevertheless, ongoing issues need to be addressed, such as the ability to guarantee safety, scalability, and the smooth integration of intelligent systems into preexisting traffic infrastructures. The primary consideration in traffic control systems is to compromise the adaptability of fuzzy logic and machine learning-based control systems and the reliability of older methods.

In summary, the use of fuzzy logic and machine learning in adaptive traffic control aims to tackle urban traffic congestion by providing intelligent and dynamic solutions. This field of study has the potential to create more efficient and pleasant urban environments. In such environments, traffic management systems may learn and adapt to the changing needs of transportation networks.

1.6.1 Traffic light Scheduling Problem

The traffic signal scheduling problem is critical in transportation engineering and urban planning. The challenge is to find optimal timing and control of intersections traffic light to improve traffic flow, minimize congestion, reduce vehicle waiting times, and improve overall Road network efficiency. This problem is especially relevant in urban areas, where traffic congestion is a frequent problem,

In 1923, the first mechanical electricity traffic light was installed in Paris at Boulevard de Strasbourg and Grand's Boulevards. (Inclusive City Maker. (n.d.). 1868-2019) Most of Europe's largest cities soon followed suit: Berlin in 1924, Milan in 1925, Rome in

1926, London in 1927, and Prague in 1928, Barcelona in 1930. The system was exported to Tokyo in 1931.

The first Convention for the Unification of Road Signs was signed in Geneva on 30 March 1931. Its objective was to enhance road safety and facilitate international travel by road. Through a unified road sign system. Most of the signs we recognize today were determined by this treaty. Traffic lights (red, yellow, green) have become the standard. Several years later in 1950, road traffic increased (Lighting Equipment Sales. (n.d.). 2021) significantly along with an increase in automobiles vehicle production and use. In 1975, the number of cars worldwide reached 300 million. The increasing number of vehicles makes it necessary to use traffic lights almost everywhere. Almost every city in the world uses traffic lights to manage traffic.

Traffic congestion costs Americans $124 billion each year direct and indirect losses and this would amount to $186 billion USD by 2030 (INR, 2014). This assertion is supported by data [INR, 2014; Christidis and Rivas, 2012]; predictor that costs accumulate from 2013 to 2030 in four countries – the UK, France, Germany and the US – will have a total 4.4 trillion USD. This cost represents the value of fuel, indirect costs, and the value of wasted time. As [INR, 2014] points out, the most important of the three is certainly the opportunity cost of lost time late in congested traffic.

With the increasing number of vehicles on the roads, conventional traffic control systems have encountered limitations in efficiently managing congestion, ensuring smooth traffic flow, and minimizing environmental impacts. In response to these challenges, there is a growing interest in harnessing the power of advanced technologies, to develop more adaptive and intelligent traffic control strategies. This thesis focusing on the application of fuzzy logic techniques to optimize traffic control in urban environments. Fuzzy logic, a mathematical framework can be applied to adaptive traffic light control systems to enhance their ability to respond to dynamic traffic conditions in a more flexible and adaptive manner compared to traditional fixed-time traffic light systems.

1.6.1.1 Utilization of Meta-heuristics for Traffic Light Scheduling

The authors of this study examines the utilization of meta-heuristics for addressing traffic signal scheduling (TSS) challenges in a heterogeneous traffic network that includes intersections that are both signalized and non-signalized. The authors (Gao, K., Zhang, Y., Su, R., Yang, F., & Suganthan, P. N. 2018) present an innovative framework for describing the traffic network and execute five meta-heuristics to optimize traffic signals: the genetic algorithm, artificial bee colony, harmony search, Jaya algorithm, and water cycle algorithm. Furthermore, an ensemble of local search operators is presented in the paper as a means to improve the efficacy of the meta-heuristics. Experiments are performed utilizing authentic traffic data from the Jurong region of Singapore in order to validate the efficacy of the suggested model and meta-heuristics. In addition, a comparison of the performance of the meta-heuristics is presented in the document, which also showcases the efficacy of the proposed ensemble in enhancing the overall performance.

This research introduces a methodical framework for tackling traffic signal scheduling challenges in a heterogeneous traffic network. It provides significant contributions to the field of traffic signal optimization through the utilization of meta-heuristics. On the basis of empirical traffic data, the proposed model and meta-heuristics are assessed in order to illustrate their efficacy and competitiveness. By juxtaposing the five meta-heuristics with a collection of local search operators, a thorough comprehension of their respective efficacy can be attained. Furthermore, the document emphasizes the importance of the suggested ensemble in enhancing the meta-heuristics' convergence and overall performance. The results emphasize the capability of the suggested methodology to enhance the scheduling of traffic signals in intricate traffic networks. This establishes a foundation for additional investigation and feasible implementations in the realm of traffic management and control.

By evaluating the proposed model and meta-heuristics using actual traffic data from the Jurong region of Singapore, their efficacy and competitiveness are demonstrated. By juxtaposing the five meta-heuristics with a collection of local search operators, a thorough comprehension of their respective efficacy can be attained. Potential future research avenues are also addressed in the paper, including the incorporation of pedestrians into the proposed model and the examination of diverse transportation networks situated in densely populated regions.

On the other hand, additional validation and testing in a variety of urban traffic environments may be required, and potential real-world implementation and scalability issues should be taken into account. Furthermore, the potential ramifications of unanticipated incidents, such as road closures or accidents, on the suggested traffic signal scheduling strategies might not be adequately considered in the paper. In addition, the computational complexity and resource demands associated with the implementation of the suggested meta-heuristics in real-time traffic management systems might not be comprehensively addressed in the paper.

In general, the research offers significant contributions to the field of traffic signal scheduling through the utilization of meta-heuristics. However, additional attention could be paid to practical implementation obstacles and the resilience of the suggested approaches across various traffic conditions.

1.6.1.2 Shortest Processing Time Scheduling to Reduce Traffic Congestion

The study titled "Shortest Processing Time Scheduling to Mitigate Traffic Congestion in High-Population Urban Areas" provides an extensive examination of existing scholarly works pertaining to the phenomenon of traffic congestion and the application of intelligent scheduling algorithms as a means to tackle this problem. This study underscores the substantial influence of traffic congestion on both commuters and the economy, emphasizing the inefficient utilization of fuel and time due to prolonged waiting periods. The study concludes that conventional methods such as expanding roads are unproductive and expensive, leading to the suggestion of intelligent transportation systems (ITS) as a more efficient strategy for managing traffic.

This paper presents an introduction to intelligent scheduling algorithms, including the Minimum Destination Distance First (MDDF) and Minimum Average Destination

Distance First (MADDF) algorithms, as viable strategies for mitigating congestion at intersections. The simulation results demonstrate the higher performance of these algorithms when compared to existing scheduling techniques. The study also examines the utilization of adaptive traffic signals and the incorporation of real-time data from diverse sensors for the purpose of enhancing the efficiency of traffic queue management.

The literature analysis offers a comprehensive examination of pertinent traffic light control techniques and models utilized in the estimation of intersection capacity. This paper examines the constraints associated with pre-timed traffic lights and emphasizes the necessity for traffic control systems that are more adaptable and flexible. The study additionally incorporates a sensitivity analysis of the roadside architecture of the wireless sensor network (WSN), emphasizing the influence of transmission power, data rate, and vehicle density on the viability of the model.

Furthermore, the literature review provides an overview of the researchers who participated in the study, namely Ahmad, F., Mahmud, S. A., and Yousaf, F. Z. (2015), along with their respective affiliations and areas of research focus. The research is grateful for the help and financial assistance provided by the National ICT Research and Development Fund of Pakistan.

1.6.1.3 Utilization of Machine Learning Techniques in Traffic Light Scheduling

This study examines the utilization of machine learning techniques to create a real-time traffic light scheduling system with the aim of mitigating the growing issue of traffic congestion in both urban and rural regions. The current traffic light system functions based on predetermined schedules, resulting in inefficiencies in the movement of vehicles and heightened levels of congestion. The objective of the proposed system is to adaptively modify signal timing in response to the current traffic intensity at the junction. The system will employ sensors to quantify the density of vehicles and subsequently modify signal timing in order to enhance the efficiency of traffic flow. The investigation additionally incorporates the utilization of image processing techniques to ascertain the vehicle densities present on each route, thereby enabling the system to give precedence to roadways exhibiting higher vehicle densities. The implementation procedure encompasses the acquisition of real-time images via web cameras, the utilization of image processing techniques, and the application of object detection algorithms to quantify the quantity of cars present at the junction, hence facilitating the optimization of traffic signal timing.

The study underscores the necessity of implementing a real-time traffic signal scheduling system, emphasizing its potential advantages such as the mitigation of average vehicle waiting time, reduction in emissions of detrimental pollutants, and enhancement of traffic efficiency. The suggested system is comprised of two primary components: a web service designed for operations linked to traffic signals and a traffic signal scheduling system that takes into account the density of vehicles. The implementation entails the acquisition of real-time vehicle counts for each lane, followed by the adjustment of traffic light schedules in accordance with vehicle densities, with the aim of efficiently mitigating congestion. The report also explores the approach, providing a comprehensive explanation of how image processing techniques, object detection algorithms, and convolutional neural networks are employed to identify and quantify cars for the purpose of optimizing traffic signal timing.

Moreover, the research provides an overview of the authors' (Nichat, O., Kulkarni, S., Mane, A., Naik, S., & Bhandari, S. 2023) profiles, highlighting their academic qualifications, areas of interest, and work histories. The individuals in question are currently pursuing their undergraduate degrees in computer engineering, with a focus on machine learning, data science, web development, and artificial intelligence. In addition, they have successfully undertaken internships in web development and data analysis, showcasing a strong inclination towards acquiring knowledge and advancing their careers. Moreover, the document includes a disclaimer from the publisher, ensuring a clear distinction between the publisher and the perspectives and claims presented in the publication. In summary, the article offers a thorough examination of the creation and execution of a real-time traffic signal scheduling system utilizing machine learning. It gives valuable information about the system's approach, advantages, and possible influence on traffic control.

1.6.2 Traditional Traffic Light Methods

According to US Department of Transportation Traditional methods of traffic signal control are either vehicle-actuated or fixed-timed. Fixed time control employs predetermined green and cycle times with a consistent duration, irrespective of diurnal fluctuations in traffic volumes. Based on historical data, this form of control allocates the majority of the green time to the busiest traffic flow. Certain fixed-time systems designate distinct predetermined time intervals to accommodate periods of high demand, such as the morning and evening prime hours. As a result, this methodology is incapable of accommodating an unforeseen fluctuation in traffic requirements. Vehicle-actuated traffic signals are implemented to rectify this situation. In theory, conventional vehicle-actuated signals function with green-demand and green-extension functions by detecting vehicles, provided that the headways in the traffic flow are brief enough to permit precise measurement, and all within predetermined limits. Due to the variable cycle duration, coordination of adjacent signalized intersections is only possible in exceptional circumstances.

1.6.3 Adaptive Traffic Light

Effective traffic management has emerged as a significant concern due to the rapid growth in the number of people utilizing roadways and the insufficiency of existing traffic control mechanisms. Ineffective in resolving this matter. Currently, there is growing recognition of the paramount importance of implementing an efficient approach to mitigate traffic congestion, save petroleum resources, and achieve cost savings for all individuals utilizing roadways.

The conventional method of signal timing is characterized by its time-consuming nature and the need for a significant quantity of manually gathered traffic data. Adaptive Signal Control Technologies (ASCT) operate by receiving and processing data from strategically positioned sensors, enabling them to ascertain the appropriate lighting conditions and distinguish between red and green signals. The Transportation

Department of Los Angeles has deployed an adaptive traffic signal system known as ATSAC (Adaptive Traffic Signal Control). Sydney, a city known for its high traffic volume, benefits from the ATSAC system's ability to modify signal timings in response to prevailing traffic circumstances. Additionally, Sydney employs another traffic system called SCATS (Sydney Coordinated Adaptive Traffic System). SCATS dynamically modifies signal timing in response to traffic demand to improve traffic flow.
Several authors have outlined the constraints of conventional traffic signal control systems and suggested various remedies to tackle these issues. Below, we provide numerous examples of this contribution.

1.6.3.1 Agent Based Modeling System for Traffic signal Regulation

Ach. Maulana Habibi Yusuf and Rahadian suggested in this research that implementing an agent-based modeling system for traffic signal regulation in accordance with the vehicle density at various road segments. A fuzzy logic controller and the Unity3D platform are utilized in this study to simulate and model traffic signal management. The performance of the system is assessed in conditions of moderate to smooth traffic, crowded conditions. Various parameters are measured, including average vehicle speed, average waiting time, and the number of vehicles that halt. Adaptive traffic light control can effectively reduce waiting time, decrease the number of halted vehicles at intersections, and increase vehicle speed in comparison to fixed time traffic light control, according to the simulation results. In addition, the experimental configuration, simulation conditions, operation of the traffic light controller, simulation analysis, and a comparison of the outcomes of adaptive and fixed traffic signal systems are detailed in the study.

The study introduces adaptive traffic signal regulation as a viable remedy for the challenges posed by the increasing number of cars in densely populated areas. This statement underscores the importance of implementing more efficient traffic flow control systems and highlights the constraints associated with fixed-time traffic signals.

The paper suggests a multi-agent approach with fuzzy decision-making to enhance the effectiveness of traffic control by managing traffic lights in real-time road conditions. The document provides a comprehensive overview of the design of simulations in Unity 3D, encompassing various aspects such as map layout, vehicle attributes, sensor setups, and traffic light parameters. The present study focuses on the application of Navmesh for vehicle mobility and the integration of fuzzy logic configuration into the control system. The research utilizes simulations in various traffic scenarios to demonstrate the enhanced efficacy of adaptive traffic light management as compared to fixed-time traffic light control. In terms of reducing waiting time, minimizing stopped vehicles at junctions, and increasing average vehicle speed, adaptive traffic light management demonstrates higher performance when compared to fixed-time control. The study report presents an analysis of the efficacy of adaptive traffic signal control in improving traffic management and providing more efficient strategies for regulating traffic flow. The study makes substantial contributions to the comprehension of the appropriate use of agent-based modeling and fuzzy logic control for the regulation of traffic lights. The implications of these discoveries are promising for the development of effective traffic management systems. Furthermore, it suggests possible directions for future investigation, such as integrating real-life circumstances into the modeling procedure and broadening the simulations to incorporate various crossings. The advancements above would enhance the feasibility and effectiveness of the proposed system. The study primarily uses a Unity 3D platform and fuzzy logic control framework to simulate and model the management of traffic lights. Nevertheless, it is crucial to acknowledge that these methodologies may not fully capture the complexities and nuances of real-world traffic circumstances. Moreover, this study solely focuses on three specific traffic conditions: congested, moderate, and uncongested. It is important to note that these conditions may not fully capture the diverse traffic situations commonly seen in urban environments. Furthermore, the study does not address various challenges or restrictions that could arise during the real implementation of the proposed adaptive traffic signal control system. These include infrastructural requirements, cost implications, and potential technical constraints. Ultimately, the analysis neglects to analyze the potential consequences of external factors, such as adverse weather conditions, pedestrian movement, or crucial situations, on the operational effectiveness of the adaptive traffic light system.

1.6.3.2 A self-Adaptive Approach to Traffic Signal Control

(Cano, M. D., Sanchez-Iborra, R., Freire-Viteri, B., Garcia-Sanchez, A. J., Garcia-Sanchez, F., & Garcia-Haro, J. 2017). Have proposed a self-adaptive approach to traffic signal control in an urban network, with the intention of addressing the difficulties associated with adaptive control in urban environments resulting from stochastic and non-linear events. The proposed methodology makes proactive traffic control decisions at each intersection by utilizing both current and historical traffic data. Through simulations, the study contrasts the performance of this self-adaptive method to that of a system with predetermined offsets between intersections and fixed cycle durations. The findings indicate that the REDV method, which is self-adaptive, can adjust to traffic conditions without requiring explicit coordination between intersections. In spite of this, the fixed-cycle approach outperforms it in the majority of situations. Conversely, when confronted with asymmetric fluxes in a practical setting, the performance metrics of the two approaches approach parity, suggesting the possibility of autonomous coordination. In its conclusion, the study examines the self-adaptive method's potential in intricate urban networks and emphasizes the necessity for additional research in this area. The introduction underscores the growing significance of traffic management within the context of smart cities, placing particular emphasis on the aspiration for autonomous, self-organizing, adaptive, and learning solutions to regulate urban traffic. The text also addresses the difficulties associated with the practical implementation and intricacy of these algorithms. The segment on related work offers an exhaustive examination of self-organizing algorithms utilized in traffic vehicle intersection regulation. It delves into a range of proposals and evaluates their effectiveness in maximizing traffic flow. The implementation and testing of the REDV algorithm are described in the materials and methods section. This includes the evaluation of various traffic patterns and the utilization of the microscopic traffic simulator SUMO. The results section provides an analysis of the simulations' outcomes, contrasting the fixed-cycle approach and REDV with respect to average transit time and waiting time. Additionally, the self-coordination capability of REDV in urban environments is examined. The significance of the REDV algorithm in adaptive traffic management is underscored in the conclusion, which also stresses the necessity for additional research to comprehend its operation in intricate urban networks.

1.6.3.3 Adaptive Quasi-Dynamic Traffic Light Control

Fleck, J. L., Cassandras, C. G., & Geng, Y. (2015) introduced the research that examines the issue of traffic light control within a stochastic hybrid system framework, specifically focusing on a single intersection. The research centers on a quasi-dynamic policy that relies on partial state information. Online gradient estimators of a cost metric pertaining to controllable light cycles and threshold parameters are derived via infinitesimal perturbation analysis. The article emphasizes the necessity of adaptive control strategies capable of dynamically modifying signal settings in response to real-time traffic data in order to optimize the overall performance of the system across a range of traffic conditions. Additionally, the paper examines the difficulties and constraints associated with current control methodologies, including deterministic and heuristic strategies. To overcome these, it suggests a data-driven approach that enables stochastic control in the absence of explicit traffic flow models.

A mathematical model for a highly nonlinear and stochastic traffic system is introduced, along with a comprehensive formulation of the traffic signal control problem specifically for a single intersection. In order to capture the inherent hybrid character of the system, it additionally constructs a stochastic hybrid automaton model and establishes a viable control set for the traffic light controller. Furthermore, the article explores the crucial function of perturbation analysis methods in furnishing impartial assessments of system performance metrics pertaining to controllable parameters. This, in turn, enables the deployment of a streamlined adaptive traffic signal control system that makes use of real-time data. In its entirety, the research makes a valuable contribution to the field of adaptive traffic signal control through the development of an all-encompassing structure for online gradient-based optimization. This framework enables the concurrent optimization of queue content threshold values and phase times within a quasi-dynamic control environment. The methodology that has been proposed demonstrates significant progress compared to previous findings and offers valuable perspectives for the advancement of traffic control systems in urban environments that are more adaptive and efficient. It tackles the difficulties that arise from real-time traffic fluctuations and optimizes system performance.

This study might not comprehensively encompass the intricacies inherent in traffic systems in the actual world. Furthermore, the research predominantly focuses on the enhancement of traffic signal control through the utilization of quasi-dynamic policies and partial state information. Consequently, the difficulties linked to the application of these approaches in tangible, real-life traffic conditions may be disregarded. In addition, the potential effects of external factors such as road maintenance, weather conditions, and unforeseen events on the efficacy of the proposed adaptive traffic signal control system are not thoroughly examined in the paper. Finally, a thorough comparison with other established adaptive traffic signal control strategies is absent from the study, potentially constraining the comprehension of the comparative merits and demerits of the suggested methodology. The article "Adaptive Quasi-Dynamic Traffic Light Control" examines the issue of traffic light control within a stochastic hybrid system framework, specifically focusing on a single intersection. The research centers on a quasi-dynamic policy that relies on partial state information. Online gradient estimators of a cost metric about controllable light cycles and threshold parameters are derived via infinitesimal perturbation analysis. The article emphasizes the necessity of adaptive control strategies capable of dynamically modifying signal settings in response to real-time traffic data to optimize the overall performance of the system across a range of traffic conditions. Additionally, the paper examines the difficulties and constraints associated with current control methodologies, including deterministic and heuristic strategies. To overcome these, it suggests a data-driven approach that enables stochastic control in the absence of explicit traffic flow models.

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1.7 SCOPE AND LIMITATIONS

1. Scope

This research aims to develop a cutting-edge traffic management system using fuzzy logic to alleviate congestion and enhance safety in megacities. By constantly modifying traffic signals in response to current traffic conditions, this novel method aims to get beyond the drawbacks of conventional traffic signal systems. Fuzzy logic, a system that yields findings that mimic human reasoning, allows the program to analyze traffic data sophisticatedly. This sophisticated analysis allows for more complex and adaptable responses to changes in traffic, instilling confidence in the system's capabilities. Additionally, this study compares the effectiveness of fuzzy logic with the Random Forest algorithm. By comparing the performance of both strategies, we aim to find the most effective traffic control strategy. This research aims to produce a flexible and efficient traffic management solution that can seamlessly adapt to urban traffic dynamics, drawing on Lotfi Zadeh's pioneering work and recent advances in fuzzy logic and traffic control.

2. Limitation

While the proposed system has the potential for better traffic handling, many challenges make it more complicated. The system's success hinges on the data it receives and the quality of the sensors it uses to monitor traffic conditions. Additionally, implementing it may cost per intersection estimated between $46,000 and $65,000 according to the United States Department of Transportation, which may limit its viability in some places. Furthermore Regulations cannot control external factors such as weather, accidents, and road construction, which can also have negative effects. Along with the aforementioned points, there is also the issue of whether or to what extent the public will accept using these technologies and whether or not privacy concerns will emerge when collecting traffic information. Finally, the study solely focuses on capital expenditure for the traffic system without exploring other domains like urban planning or policy implications.

1.8 Software

The project includes the Python programming language, as well as the SUMO (Simulation of Urban Mobility), to meet the requirements and to perform the traffic control system operation. Python was chosen for its high level of versatility, and numerous libraries, as well as grants for implementing data science operations. Along with the advancements in the adoption of digital technology in our society, automated cars will inevitably make use of Python for data processing, analysis, and fuzzy logic control. SUMO, which stands for public transportation software suite, is traffic simulation software that models urban traffic scenarios and consequently simulates traffic flow. The platform is used to study the system's operations in a variety of situations, involving peak hours; some weekend voyages, or if there is an emergency. An integration of Python with SUMO gives a pathway that the trajectory control algorithms can utilize to link with the simulation environment. The linkage comes with clear and smooth communication, which is the basis of intelligent programming. It also provides more realistic usage and testing of outcomes

2 LITERATURE REVIEW

2.1 Fuzzy logic

Fuzzy logic methodology in traffic light systems involves using fuzzy logic to manage and control traffic signals based on dynamic conditions. It utilizes if-then rules to evaluate inputs such as traffic flow, waiting time, and pedestrian presence to determine the optimal timing for light changes.

2.1.1 Verification of a Traffic Signal Management System Using Fuzzy Logic

The study investigates the creation and validation of a traffic light management system that utilizes intelligent fuzzy logic for the Owerri Metropolitan Area in Nigeria. Isdore Onyema Akwukwaegbu, Eleazar Mfonobong, Jude Obichere, and Paulinus Nwammuo Francis Chiedozie presented the paper in 2023. This research focuses on traffic congestion problems which are defined as ways of maximizing potential and minimizing environmental degradation and wasting of energy. This project deals with the creation of traffic control application with the help of Arduino microcontroller as a medium. The program is tested and validated by modeling with proteus circuit model, Matlab software, and simulated urban mobility simulation, SUMO, environment. The modern traffic light system integrates novel ultrasound sensors for detection of ferries and fuzzy logic for computation of optimum green interval at each intersection. In addition to that initial module, it also measures the traffic urgency and allows for an extended period.

The simulations demonstrate that the suggested smart fuzzy logic traffic light controller outperforms the conventional fixed-time controller. The significant reductions in waiting and travel times further confirm the controller's suitability for traffic management at Owerri City's various intersections. The study highlights the necessity of implementing an intelligent traffic light control system to address the inefficiencies of the current system. This study highlights the utilization of artificial intelligence and fuzzy logic technologies in creating a traffic signal management system capable of emulating human intellect for traffic control purposes. The system works on a fuzzy logic program to self-adjust making traffic signal intervals depending on the level of traffic along the route while using ultrasonic sensors to know traffic density. The study results indicate that the fuzzy logic traffic light controller, which the authors of this study suggest, operates in a much better way compared to the fixed-time controller. Efficient and reduced waiting times, with the improvement of the traffic flow, potential benefits in fuel economy, lowering of air and noise pollution, and overall management of congestion in the city of Owerri are the driving factors. This study fails to come up with a clear system of implementation which has the potential to bring about difficulties during the process of actually implementing such a system. In addition, the research does not discuss the problems with future upgrades or as well the repairing of the system in a real urban scenario. Also, a comprehensive review of the economic feasibility as well as the cost implication of the implementation of the latest intelligent fuzzy logic traffic signal controller in Owerri Metropolis is missing in the study. However, comprehensive research and experimentation may be needed to evaluate the viability and effectiveness of the proposed techniques in Owerri city through the reduction of traffic chaos and regulation of traffic flow, the limitations in this regard should be kept in mind.

2.1.2 A Combination of Fuzzy Logic and Multiple Network Architectures

The authors of this research article (Arena, F., Severino, A., Pau, G., Ralescu, A., & You, I. 2022). Entitled "A Novel Framework for Dynamic Traffic Lights Management: A Combination of Fuzzy Logic and Multiple Network Architectures" describes an inventive method for dynamically regulating the phases and cycles of traffic lights at isolated intersections. This study examines the necessity for contemporary traffic signal management systems to evolve in response to the escalating urban population and traffic complexities. The significance of Intelligent Transportation Systems (ITS) and the incorporation of information technologies to provide novel services and enhance user experiences in smart cities are underscored by the authors. The study exposes the shortcomings of static traffic signal management systems and investigates a dynamic control methodology that minimizes congestion and optimizes traffic flow through the use of vehicular communications and fuzzy logic controllers. The authors conduct an exhaustive examination of various network architectures, including IEEE 802.11p and LTE-V2V, and assess their efficacy in the management of vehicle movements and traffic light cycles.

The research paper describes the construction of a traffic generator that emulates the fluctuating volume of traffic over some time, taking into account high hours and various traffic patterns. The assessment scenarios comprise a comparison of three construction hypotheses, namely the deployment of LTE-V2V vehicular communications, IEEE 802.11p, and static traffic lighting.

The technique for performance evaluation is to find the mean and maximum values of signalization delays for the vehicles at the intersection under different network structures. The network architecture of lanes can be considered with different mean waiting periods per car, which depends on lane simulation results and has consequences for traffic management systems. In a general sense, the studies in question yield vital conclusions about the adaptive nature of traffic signals by employing intricate network system architectures and intelligent fuzzy logic controllers. The results of this research have a great role in creating traffic management systems that adapt to circumstances, aiming for smart cities and urban traffic that keeps growing in complexity. This approach to scrutinizing the network's performance and traffic flow serves as the cornerstone for future research, as well as a working baseline for possible deployment within traffic management systems. The research confirms that the method may fail to provide a perfect level of service under specific traffic conditions, such as when heavy congestion occurs only on one road while the others remain empty. This would imply longer wait times for cars on major waterways with more traffic. Besides that, the study pinpoints that the presented methodology could not take full account of the growing proliferation of intelligent vehicles and vehicular communications. Further research and development is required to address the constraints and improve the effectiveness of the proposed method.

2.1.3 Image Processing with Fuzzy Logic

Chabchoub, A., Hamouda, A., Al-Ahmadi, S., and Cherif, A. (2021) designed the 'Intelligent Traffic Light Controller', which uses image processing and fuzzy logic to address the traffic congestion problem in urban areas. The system engineers regulate traffic flow in two distinct ways: through a hybrid system that utilizes fuzzy logic and MATLAB image processing, as well as through a combination of cameras and auto sensors.

Based on the number of vehicles on each road, the fuzzy logic controller receiver changes the period of red, green, and yellow lights. The aim is to reduce vehicle congestion and improve traffic flow by utilizing adaptive signaling that synchronizes with varying traffic conditions.

The proposed traffic flow management system's primary goal is to reduce traffic congestion on the main road networks in major cities or smart cities. In Al Medina, Saudi Arabia, it is critical to prioritize the removal of traffic bottlenecks, particularly during the holy months of Haj and Umrah. The schedule demonstrates the effectiveness of the system by highlighting the "smart" and efficient traffic signal timing of the fuzzy logic controller, as opposed to the conventional fixed-time controller.

Moreover, the paper provides an in-depth analysis of the design and execution of the suggested system. It specifies how photographs of automobiles are captured by a variety of sensors and cameras, and how those images are subsequently processed to determine the precise quantity of automobiles within particular zones. The operational framework of the system is established upon a fuzzy logic controller that receives inputs procured from roadside fixed cameras' images. The emphasis is placed on the adaptability of fuzzy logic when dealing with stochastic systems, and simulations of the system indicate promising results. The comprehensive elucidation of the fuzzy rule base, membership functions, design criteria, and constraints of the traffic light controller highlights the proposed system's resilience and flexibility. Furthermore, the document emphasizes the potential ramifications of the system in optimizing traffic circulation in urban centers such as Medina and Makah. Furthermore, it suggests that future expansion and validation efforts could leverage datasets from additional nations to further bolster the system's efficacy.

The efficacy of the intelligent traffic control system in alleviating traffic congestion in the designated metropolitan area of Al Medina, Saudi Arabia, especially during high-demand periods like Hajj and Umrah, has been confirmed through simulation. The report does not thoroughly investigate the system's efficiency in various traffic conditions or diverse metropolitan locations. However, this is an important topic that requires additional research.

In addition to that, the article disregards the issue of possible limitations or restrictions connected with fuzzy logic and image processing technologies in traffic control systems. The confirmation of the system’s effectiveness and versatility outside this particular scenario would require more investigations and experimentations conducted in various urban settings and when traffic conditions change.

2.1.4 Optimizing Traffic Flow at Isolated Intersections with Fuzzy Logic

The research primarily examines a distinct traffic congestion issue in Islamabad, Pakistan, and may not comprehensively tackle the wide array of traffic management difficulties encountered in other metropolitan regions. Furthermore, the research uses fuzzy logic to conduct a simulation-based assessment of the efficacy of the proposed traffic light control system, which may require real-world experimentation to validate its performance in realistic scenarios.

Furthermore, the research fails to provide an exhaustive analysis of the possible drawbacks and difficulties the scheme might encounter, such as the costs associated with installation and maintenance, technical complications that could arise, and the need for restructuring or adding services to the infrastructure. The study's authors are as follows: Firdous, M., Iqbal, F. U. D., Ghafoor, N., and Qureshi, N. K. 2019. The authors designed a traffic signal controller that processes the fuzzy logic to bring more cars onto the streets through the isolated intersections. The study's primary goal is to address the traffic issues in cities that arise from the increasing number of vehicles in towns. In turn, these issues contribute to traffic congestion, lengthen pedestrian travel times, and increase fuel consumption rates. We will develop the system based on two fuzzy controllers, which will manage traffic until we update the driveway signal program for either the primary or secondary driveway. The research paper uses as an example the implemented traffic light control program based on fuzzy decision rules, which contrasts the signal program for a fixed time with several traffic demand situations.

The study delineates the present challenges faced by urban networks due to the escalating volume of vehicles, which has led to a decline in capacity and deterioration in road service quality.

This clearly shows the absolute necessity for new ways to control transport, especially in the intelligent transport systems (ITS) area of knowledge. The research critically examines the current state of traffic signal optimization, emphasizing the application of various approaches such as fuzzy logic for effective traffic management. This research investigates the application of fuzzy logic to adaptive traffic light control at separate signalized intersections using fuzzy sets. It does this by creating fuzzy rules that make use of resource exploitation with such factors as queue length, arrival flow, and exit flow as factors.

The paper also discusses simulation results and fuzzy traffic signal controller evaluations in three distinct traffic scenarios. The results imply that various traffic indicators—including mean and maximum queue durations, number of vehicles stopped, and emissions—have improved.

The research paper examines the impact of imprecise traffic light controllers on pollution reduction in comparison to fixed signal programs, as well as the adjustment of cycle lengths.

The conclusion highlights fuzzy logic in the smart traffic signal system because of its efficiency in reducing congestion and increasing traffic parameters. In the same way, it emphasizes the fact that the area remains quite interesting for further research into cooperative control and optimization of the system by genetic algorithms. It could be that the proposed fuzzy logic traffic light controller will be better than the main driveway because, in some circumstances, performance may be a bit less. Furthermore, it's important to note that the investigation focused solely on a single traffic signal intersection, which obstructs the monitoring of the fuzzy logic controller's performance across complex traffic networks that may include multiple signal phases and intersections. In brief, the paper considered only the implementation of fuzzy logic and excluded the probabilities of the forthcoming advantages in combination with other AI techniques in traffic regulation.

2.2 Machine Learning

Machine learning is a subfield of artificial intelligence that uses algorithms trained on data sets to create models that enable machines to perform tasks that would otherwise only be possible for humans, such as categorizing images, analyzing data, or predicting price fluctuations.

2.2.1 Random Forest

Random forest is a popular machine-learning method created by Leo Breiman and Adele Cutler. It takes the output of several decision trees and combines it into a single result. It has become very popular because it is simple to use and can be used for both classification and regression situations. Decision trees.

Algorithm 1: Traffic Light Simulation and Control Using Random Forest
1. Start 2. Setup SUMO Check if SUMO_HOME environment variable is set. If not set, exit with a message to declare SUMO_HOME. Append SUMO tools path to the system path. Define SUMO binary and command. Start SUMO using the defined command. 3. Initialize Variables Define lanes for G2H1 and D1B2 directions. Initialize counters and lists for: Total vehicle waiting time. Emergency vehicle waiting time. Total feedback. Total emergency vehicles. Number of stopped and moving vehicles. Combine all lanes. 4. Train Random Forest Model Create training data (X_train and y_train). Train the Random Forest model with the training data. 5. Simulation Loop 6. Close SUMO Simulation

The algorithm establishes the SUMO environment, initializes variables to monitor vehicle data, and then trains a random forest model. The method tracks the number of vehicles and the duration of waiting periods in various lanes using a simulated loop. Emergency vehicle data is meticulously monitored. The algorithm periodically utilizes the trained model to forecast and modify traffic signal phases. Upon finishing the simulation, it generates and stores data regarding the duration of vehicle waiting times and movements. The method optimizes traffic flow by constantly adapting signals using real-time vehicle data and machine learning predictions, ultimately concluding the simulation smoothly.

To evaluate we used metrics from the sci-kit-learn library, such as mean absolute error (MAE), root mean squared error (RMSE), and R-squared (R2), to rate the success of machine learning algorithms. These are the following Equations: (1)–(3)

$(y,\hat{y}) = 1n\Sigma|yi-\hat{y}i|n-1i=0$ (1)

$R2\ (y,\hat{}) = 1-\Sigma(yi-y\hat{i})2ni=1\Sigma(yi-\bar{y})2$ (2)

$(y,\hat{y}) = [1n\Sigma(yi-\hat{y}i)2n-1i=0]1/2$ (3)

2.2.2 Machine Learning Algorithms for Traffic Flow Prediction in Smart Traffic Lights

To enable adaptive traffic control, the researcher’s presents in this paper "Using Machine Learning Algorithms for Traffic Flow Prediction in Smart Traffic Lights" that explores the use of machine learning (ML) and deep learning (DL) algorithms in the context of predicting traffic flow at junctions. The authors emphasize the growing utilization of neural networks and machine learning methodologies to tackle issues such as traffic congestion, pollution, and stress in urban areas. This study centers on the utilization of machine learning (ML) and deep learning (DL) algorithms to forecast traffic flow at intersections. The objective is to establish a foundation for adaptive traffic control using remote control of traffic lights or algorithmic adjustment of timing, which is contingent upon the expected flow. The authors (Navarro-Espinoza, A., López-Bonilla, O.R., García-Guerrero, E.E., Tlelo-Cuautle, E., López-Mancilla, D., Hernández-Mejía, C., & Inzunza-González, E. 2022) train, validates, and test the suggested models using two publicly available datasets. This demonstrates the practicality of integrating machine learning (ML) and deep learning (DL) models on smart traffic light controllers. The Multilayer Perceptron Neural Network (MLP-NN) demonstrated superior performance, with Gradient Boosting and Recurrent Neural Networks (RNNs) closely trailing behind. While RNNs exhibited favorable metrics and outcomes, they required longer training durations. The study additionally provides a comparative analysis of performance metrics utilizing two distinct datasets, demonstrating the resilience of the suggested models in predicting traffic flow.

Additionally, the study offers valuable insights into the cost-benefit analysis associated with the implementation of the models, shedding light on the average duration required for training each method. The study demonstrates the potential application of the suggested models in an intelligent traffic light controller, simplifying the programming of traffic light timings through traffic flow predictions. The suggested utilization scenario entails the establishment of wireless communication channels between traffic lights and a central station or controller, enabling the instantaneous modification of traffic light states. In summary, the study determines that the suggested machine learning (ML) and deep learning (DL) models exhibit satisfactory performance in forecasting traffic flow at intersections. This implies that smart traffic signal controllers could potentially implement these models.

The scope of this research is limited, as it solely focuses on predicting traffic flow at intersections using machine learning and deep learning methods. Although the study showcases the practicality of incorporating these models into intelligent traffic light controllers, it fails to consider other facets of intelligent transportation systems or more comprehensive traffic management techniques. Moreover, the study's conclusions stem from the analysis of specific datasets, which might not fully capture the complexities involved in traffic flow forecasting in different urban environments. Moreover, the research needs to explore the possible obstacles or constraints associated with the application of these prognostic models in practical traffic management systems.

2.2.3 Traffic Prediction for Intelligent Transportation

In an article, Meena, Sharma, and Maharishi (2020) investigated the evolution of a predicting tool for traffic flow in the Intelligent Transportation System (ITS) using machine learning and big data principles. Accurate traffic flow data is important because it helps to make informed travel decisions, reduces congestion, ensures traffic efficiency, and allows for the possibility of self-driving vehicles. The inability of current traffic models, which use vast amounts of traffic data and rely on shallow models, to accurately predict traffic flow raises issues that this research work centers around. The main focus of this article is the use of machine learning, genetic algorithms, soft computing methods, and deep learning algorithms with large-scale data on transportation systems. The goal is to simplify the process. Furthermore, we investigate the use of imaging processing technology for detecting traffic signs, which is a training module for self-driving cars. Moreover, it deals with different complex learning algorithms, including but not limited to the decision tree, support vector machines (SVM), and random forest, that are utilized to reveal traffic issues and achieve more efficiency and precise outcomes.

The objective of the proposed method is to detect and categorize congested situations by analyzing the gathered traffic data, including location, speed, and junctions. The document closes by providing an evaluation matrix that presents the accuracy, precision, recall, and time taken for predicting traffic congestion for several machine learning methods. Additionally, it explores the possibility of incorporating web servers and applications, together with the forthcoming enhancement of traffic algorithms to achieve greater precision.

The article primarily centers on the creation of a traffic prediction tool that utilizes machine learning and big data principles.

The objective of the research is to develop a method for making precise flow predictions in the Intelligent Transportation System (ITS). This expression emphasizes the role of precise travel data in making reasonable travel options, reducing traffic congestion, improving traffic efficiency, and seeing the benefits of autonomous vehicles. The study utilizes a range of machine learning methods, such as Decision Tree, Support Vector Machine (SVM), and Random Forest, to forecast traffic congestion and improve operational effectiveness. The objective of the proposed method is to detect and categorize instances of congestion by utilizing gathered traffic data and geographical information. Moreover, the publication provides a comprehensive assessment framework for various machine learning algorithms, showcasing their levels of accuracy, precision, recall, and prediction time about traffic congestion. The publication moreover explores prospective endeavors to combine web servers and apps, as well as to improve traffic algorithms to attain heightened precision.

Furthermore this study employed the Random Forest algorithm because of its resilience and capacity to handle datasets with a large number of variables, providing an efficient solution for intricate traffic management situations. Random forest is an ensemble learning technique that constructs numerous decision trees and merges their predictions, resulting in a versatile and precise approach for both classification and regression tasks. The capacity to adapt is essential for effectively managing a variety of traffic circumstances and accurately predicting the most appropriate traffic light phases in real-time. The method's high efficiency in processing massive volumes of data enables it to effectively handle and evaluate the extensive datasets produced by traffic simulations, hence supporting enhanced decision-making processes. Random Forest outperforms fuzzy logic in terms of feedback accumulation and overall traffic flow management, especially in situations with high traffic volumes, while having longer total vehicle waiting times. The practical application of this system is demonstrated by its integration with the SUMO simulation environment, which allows for the dynamic adjustment of traffic signals based on real-time data. This highlights its potential to significantly improve traffic control systems.

3 METHODOLOGY

3.1 Introduction

This chapter provides a comprehensive overview of the key elements involved in the proposed research. The initial segment of the chapter will outline the previous research. Subsequently, it provides valuable information regarding the techniques employed in data analysis.

Utilizing collected data. The chapter closes by explaining the mathematical representation of the proposed system.

3.2 Current System

The study employed a research technique that specifically concentrated on gathering and examining data about traffic congestion in Mogadishu City, Somalia Presented by Osman, A. A. (2022). The methodology included a blend of qualitative and quantitative descriptive research designs to precisely understand the data. The methods used to collect the data included first-hand assessments of traffic jams in certain parts of the city and manual counts of traffic flow every 15 minutes during peak and off-peak times. The study also used the travel time method to look at traffic jams by contrasting measurements like total segment delay and delay ratio with other signs of traffic jams.
In addition, the methodology utilized congestion indicator factors such as level of service (LOS), trip times, and speeds to ascertain the presence of traffic congestion at certain intersections or road segments. They developed a research approach to address fundamental traffic congestion questions, providing a comprehensive understanding of traffic flow patterns and the economic impact of congestion in the designated study region. In summary, we designed the technique to align the outcomes with the study objectives and inquiries.

Table 1. Amount of traffic in all directions

Date	Talex approach	Adiqasin approach	Sobe approach	Aden-Cade approach
13/12/2021	9308	.4705	11078	7428

The table's gives a full picture of how much traffic in Mogadishu was at two important crossings on certain dates: the KM4 Roundabout and the Dabka Intersection. In Table 1, which provides information about the KM4 Roundabout, each row shows a different date of observation. The next four columns show the number of cars coming from Taleex, Abdiqasin, Sobe, and Adan Ade. For instance, on December 13, 2021, the Taleex Approach recorded 9308 vehicles, while the Abdiqasin Approach recorded 4705. Of these, 11078 vehicles came from the Sobe direction, and 7428 vehicles came from the Adan Ade direction.

Table 1. (Continue)

Date	Bakaraha Approach	Sayidka Approach	Km4 Approach	Buundada Approach
20/12/2021	4133	.5748	7701	6257

In table 1 shows same format with different result of number of traffic flow from four different directions: KM4, Sayidka, Bakaraha, and Buundada. In 2021 researchers observed 4133 vehicles on the Bakaraha Approach and 5748 vehicles on the Sayidka Approach. Also there were 7701 and 6257 vehicles coming from KM4 and Buundada.

3.3 Existing System

Analyzing the gathered data, we have effectively identified pivotal components within the current system. The subsequent part will present the results obtained from the data analysis (Muzamil et al.., 2021). This study introduces a flexible method for regulating traffic signals that combines fuzzy logic with the Webster and modified Webster formulas—the SUMO traffic simulator utilized to achieve the objective. The primary aim of the proposed methodology is to ascertain the optimal cycle time and phase green timings, taking into account the current traffic conditions. This study aims to assess the efficacy of the proposed adaptive control strategies for fixed-time Webster and modified Webster-based traffic control systems—the assessment performed with real-world field data and simulated traffic requirements. The results indicate that the suggested approaches outperform the fixed-time and fuzzy logic-based traffic control strategies regarding average vehicle delay, speed, and trip time. This work presents an overview of the utilization of fuzzy logic and optimal cycle formulas in developing an adaptive traffic signal control system. This study thoroughly examines the process of determining the most efficient cycle duration and effective green times. It utilizes crucial lane flows and employs inductive loop detectors to evaluate traffic flow. The study report also offers a comparative examination of the proposed adaptive strategies and various traffic control technologies based on fixed-time and fuzzy logic. The present study employs empirical field data and simulated traffic demands for analysis. Combined with Webster's formula, it exhibited exceptional performance regarding average waiting time, journey time, and speed, particularly in situations with heavy traffic congestion. Overall, the research offers valuable insights into the efficacy of the suggested adaptive traffic signal control technologies and their capacity to enhance traffic flow and minimize delays at crossings.

The cost of transitioning at the five-phase intersection impedes the mean speed at the five-approach intersection, which is a study limitation. Moreover, the suggested approaches may perform less effectively in average velocity in specific traffic demand scenarios. The study acknowledges the need for further improvements to the proposed approaches, recommending the refinement of fuzzy logic memberships through either a neural network or a genetic algorithm. The highlighted constraints offer promising avenues for additional research and enhancement.

3.4 Proposed System

In figure 1 the flowchart shows the process of simulating a traffic light. The simulation begins by acquiring traffic data. The system checks for emergency vehicles, and if any are present, handles them accordingly. If no emergency vehicles are detected, it evaluates the vehicle count on red lanes and, if needed, extends the green light for these lanes. It also assesses the vehicle count on green lanes and, if necessary, shortens the green light duration. If neither condition is met, it assesses the waiting times and determines whether to maintain the existing length of the traffic signal. Upon implementing the decisions, the program verifies whether the simulation has executed for a total of 5000 steps. If it has, the program terminates. If not, the process continues. In summary the system offers a comprehensive method for controlling traffic in a continuous cycle. Simulation data informs control decisions, subsequently influencing the simulation environment. This process entails a perpetual loop of observing, evaluating, and implementing modifications to enhance the movement of vehicles and mitigate traffic congestion.

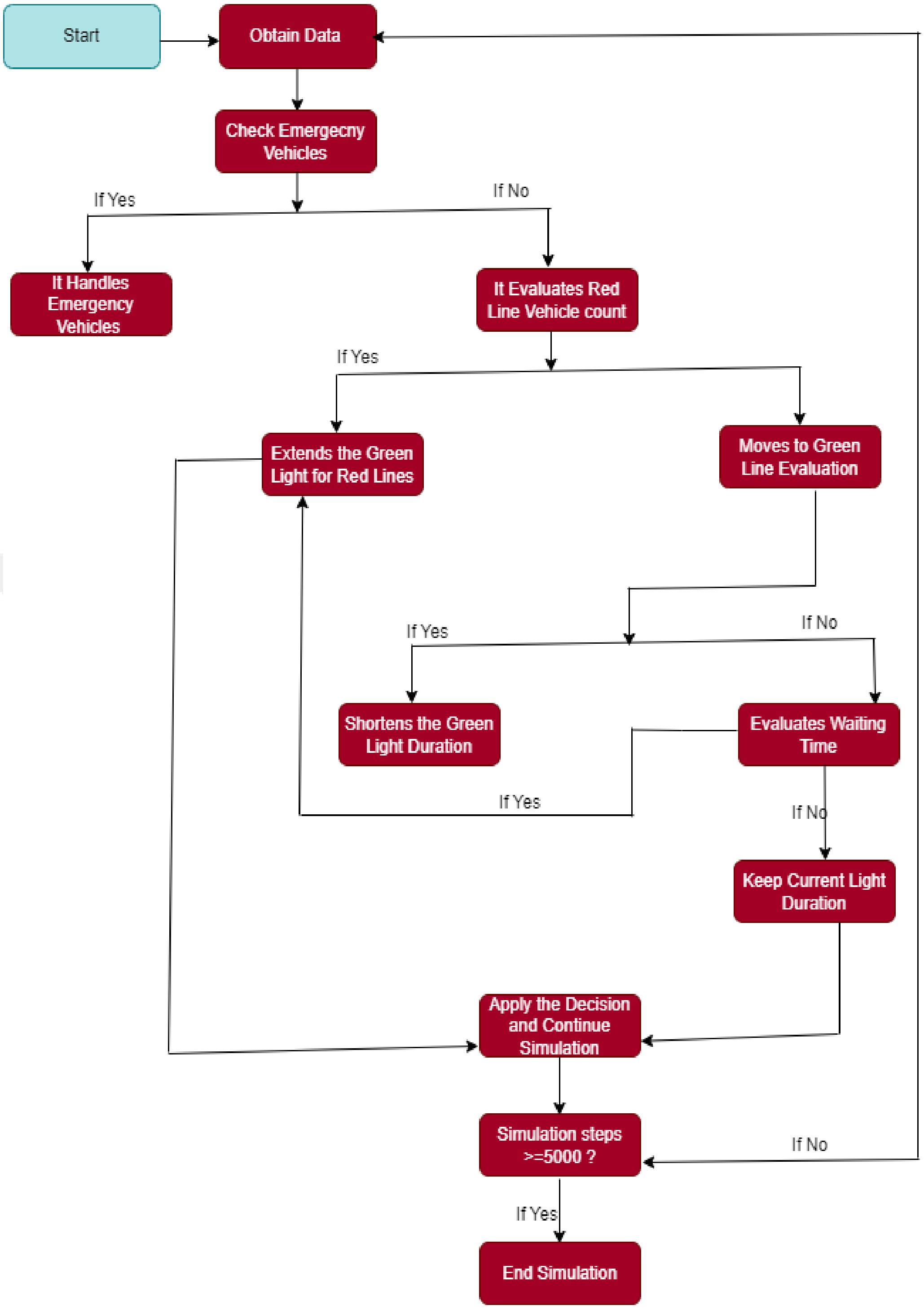


Figure 1. Proposed System Flowchart

Figure 1 flowchart delineates the decision-making process of the adaptive traffic signal control system. Initially, the system acquires traffic data and assesses the presence of emergency vehicles. If emergency vehicles are detected, the system prioritizes their passage. In the absence of emergency vehicles, the system evaluates the vehicle count on red lines. Based on this evaluation, the system either extends the green light duration for heavily congested red lines or proceeds to assess green line conditions. For green lines, the system determines whether to shorten the green light duration based on the traffic flow. Additionally, the system evaluates waiting times and may adjust or maintain the current light duration accordingly. The process iterates, applying decisions and continuing the simulation until a predefined threshold of simulation steps (5000 steps) is reached, at which point the simulation concludes.

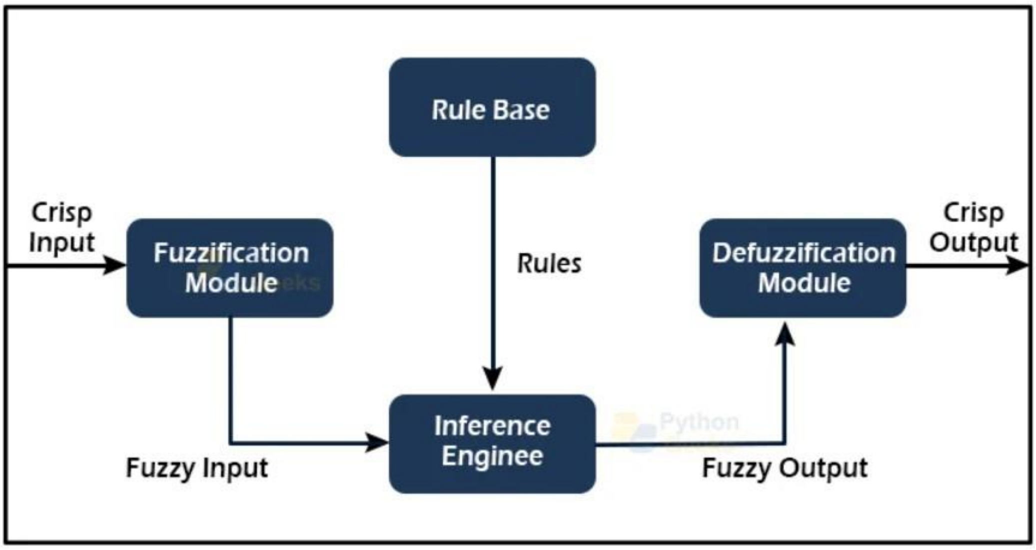


Figure 2. Fuzzy Logic System Diagram

Figure 2 show the component of FLSs consists of four parts:

1. Fuzzification Module: This module uses membership functions to transform crisp input data into fuzzy sets. This step is necessary for dealing with vague knowledge in the real world.

2. Rule Base: This part stores a group of fuzzy rules that come from expert knowledge or real-world data. These rules are usually in the form of "if-then" sentences. In a fuzzy way, these rules describe how input variables link to output variables.
3. Inference Engine: The inference engine acts on fuzzy data using rules from the rule

base. It is the main part of the FLS. It uses these rules to come up with fuzzy results or conclusions.

4. Defuzzification Module: Finally, this module takes the fuzzy output that the inference engine makes and turns it back into a clear output that can be used. This step is very important for understanding the data and using them in the real world.

Moreover, the system utilizes machine learning methods, notably a Random Forest classifier, to improve traffic light control decisions. While simulating, the system gathers a variety of traffic-related data, such as the duration of cars waiting, the length of queues, and the occurrence of emergency vehicles. The Random Forest model then uses this data to train and forecast the most effective ways to switch traffic lights. By utilizing data gathered from previous simulation runs, the model can confidently recognize trends and make well-informed decisions to improve traffic flow efficiency.

Furthermore, the system provides sophisticated control mechanisms and powerful capabilities for data collection and analysis. During the simulation process, the system consistently collects and assesses traffic data, providing valuable insights into traffic behavior and performance. This technique uses data to allow transportation authorities to make judgments based on factual facts and perform targeted interventions to improve traffic management strategies.

The system's intuitive and user-friendly interface allows users to observe the traffic simulation in real-time and interact with it during simulation runs. Users can modify simulation settings, examine simulation outcomes, and investigate different traffic management scenarios. This enables them to get a more profound understanding of traffic dynamics and assess the efficiency of different control systems.

In summary, the suggested system is a major improvement in managing urban traffic. It takes a comprehensive approach by integrating advanced control techniques, machine learning algorithms, and data-driven analysis. The system utilizes fuzzy logic and machine learning to optimize traffic flow, minimize congestion, and enhance the efficiency and sustainability of urban transportation networks.

3.5 Mathematical Approach in Fuzzy Logic

In the field of traffic management, the application of fuzzy logic-grounded traffic control sets has gained traction due to their ability to create complex decision rules that effectively address arising uncertainties and inaccurate data. In that regard, defuzzification is an integral part of these systems because it transforms fuzzy output sets into precise values that are traffic signals' control directives.

This study seeks to provide a mathematical representation of defuzzification in the context of traffic control, employing the centroid technique. To get a more accurate mathematical representation of the given inputs and outputs, it is important to create precise fuzzy sets, membership functions, fuzzy rules, and a defuzzification technique. Triangular membership functions will be implemented.

The fuzzy output set will be denoted as Y, with fuzzy sets "change" and "maintain" represented by μY change(y) and μY maintain(y), respectively.

The centroid C is calculated using equation (4) as follows:

$$C = \frac{\sum y \cdot \mu_{Y_{change}}(y) + \sum y \cdot \mu_{Y_{maintain}}(y)}{\sum \mu_{Y_{change}}(y) + \sum \mu_{Y_{maintain}}(y)}$$

(4)

Where:

Y is the crisp value.

μY change(y) and μY maintain(y) are the degrees of membership of Y in the fuzzy sets "change" and "maintain," respectively.

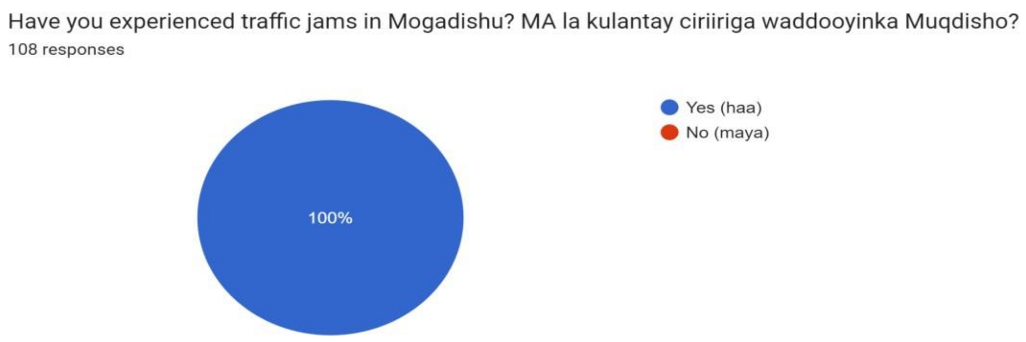
The centroid value obtained indicates a single representative value for the traffic light phase, indicating the optimal timing for switching between "change" and "maintain" actions. This value is then used to determine the duration of each phase in the traffic light cycle, ensuring efficient traffic flow and minimizing congestion.

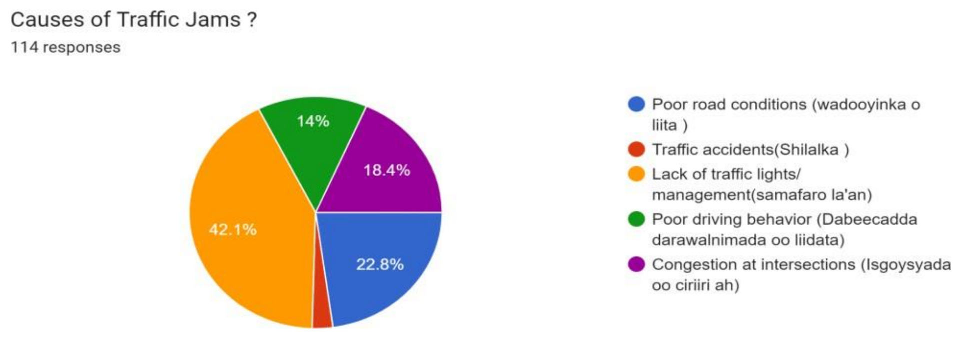
3.6 Survey

We conducted a survey in Mogadishu that sheds the light on the prevalent issue of traffic congestion plaguing the city. With a unanimous response of 100% among participants having experienced traffic jams, it underscores the widespread nature of the problem. The primary culprit, identified by 42.1% of respondents, is the lack of traffic lights or management systems. This finding emphasizes a critical need for infrastructure development and investment in traffic management technologies to regulate flow effectively.

Moreover, the survey reveals other significant contributing factors to the congestion. Poor road conditions, cited by 22.8% of participants, highlight the necessity for ongoing maintenance and improvement efforts. Potholes, uneven surfaces, or inadequate signage can significantly impede traffic flow and contribute to bottlenecks.

Additionally, the survey highlights behavioral issues as a notable cause of congestion, with 14% attributing it to poor driving behavior. This underscores the importance of educational initiatives and enforcement measures to promote safer and more responsible driving practices among motorists.





Furthermore, the prevalence of congestion at intersections (18.4%) underscores the importance of implementing efficient traffic flow strategies and potentially enhancing infrastructure to alleviate traffic bottlenecks at critical junctions.

Only 2.7% of respondents mentioned traffic accidents, despite their substantial impact on road safety and congestion. By guaranteeing a continuous flow of traffic, initiatives to reduce accident rates through improved road design, rigorous enforcement of traffic laws, and public awareness campaigns can indirectly alleviate congestion.

In general, the survey emphasizes the multifaceted and intricate components of traffic congestion in Mogadishu.

A comprehensive strategy focusing on infrastructure improvement, encouraging responsible driving, optimizing traffic flow at intersections, and enhancing overall road safety measures is necessary to effectively tackle this issue.

In conclusion, the methods described in this chapter are in line with our research goals and set the stage for the next parts of the study. This chapter sets the stage for the empirical analysis and evaluation of our proposed system. It does this by combining previous research results, proposing a new system design, conducting survey research, and giving a mathematical representation of traffic control.

4 DESIGN ARCHITECTURE AND ANALYSIS

4.1 Introduction

This chapter expounds on the design architecture and implementation specifics of two sophisticated traffic control systems: fuzzy logic and machine learning. The objective of these systems is to adaptively modify the duration of traffic signal cycles according to current traffic circumstances to maximize the movement of vehicles and minimize traffic congestion.

4.2 Fuzzy Logic System Architecture

Figure 3 depicts the architectural framework of a fuzzy logic-based traffic control system. The primary component is the SUMO Simulation Environment, which simulates various traffic scenarios and supplies real-time information on vehicle quantities and traffic flow. This data is essential for providing information to the fuzzy traffic controller, which is the decision-making component of the system. The Fuzzy Traffic Controller uses fuzzy logic, a computational method that imitates human decision-making in situations of uncertainty, to modify traffic signal durations according to the traffic data it receives. By dynamically adjusting traffic light signals, the controller's goal is to increase traffic flow efficiency and reduce congestion. The Python Interface serves as a means to enable communication between the SUMO environment and the Fuzzy Traffic Controller. Its purpose is to facilitate the smooth and immediate interchange of data and control commands. By enabling the system to adjust and respond according to traffic conditions, this architectural layout enhances the efficiency and efficacy of managing traffic. Its primary objective is to boost vehicle mobility, minimize congestion on roads, and optimize transportation performance in a simulated environment.

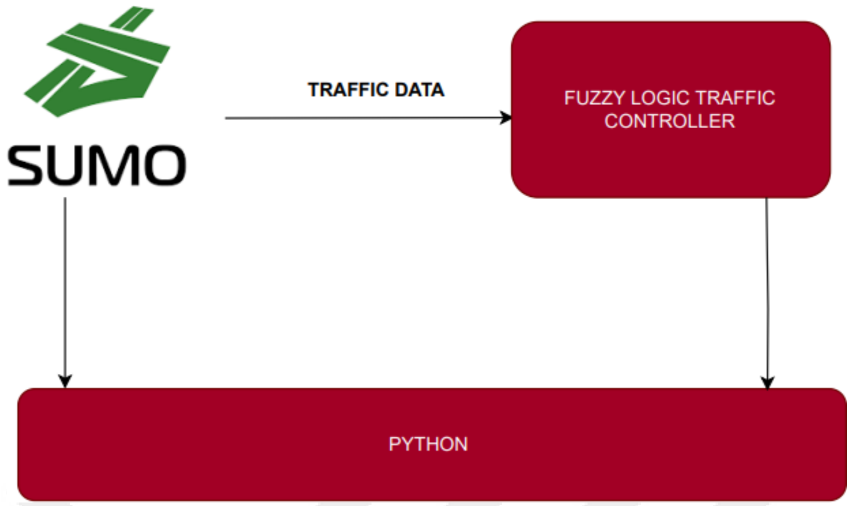


Figure 3. Fuzzy system architecture

Figure 3 suggest system architecture for the FTC system comprises four primary layers The descriptions are provided below.

1. Simulation

Simulation is the act of imitating or replicating a real-life scenario using computer software, physical models, or other tools and techniques.

The component embodied in the SUMO Simulation Environment bears responsibility for traffic scenario simulation and the real-time provision of traffic data. It incorporates software modules to account for vehicle behavior, road networks, traffic signals, and flow simulation. Through its simulation layer, crucial statistical information regarding vehicle counts, speeds, and waiting periods is generated; these outputs serve input purposes within the control layer.

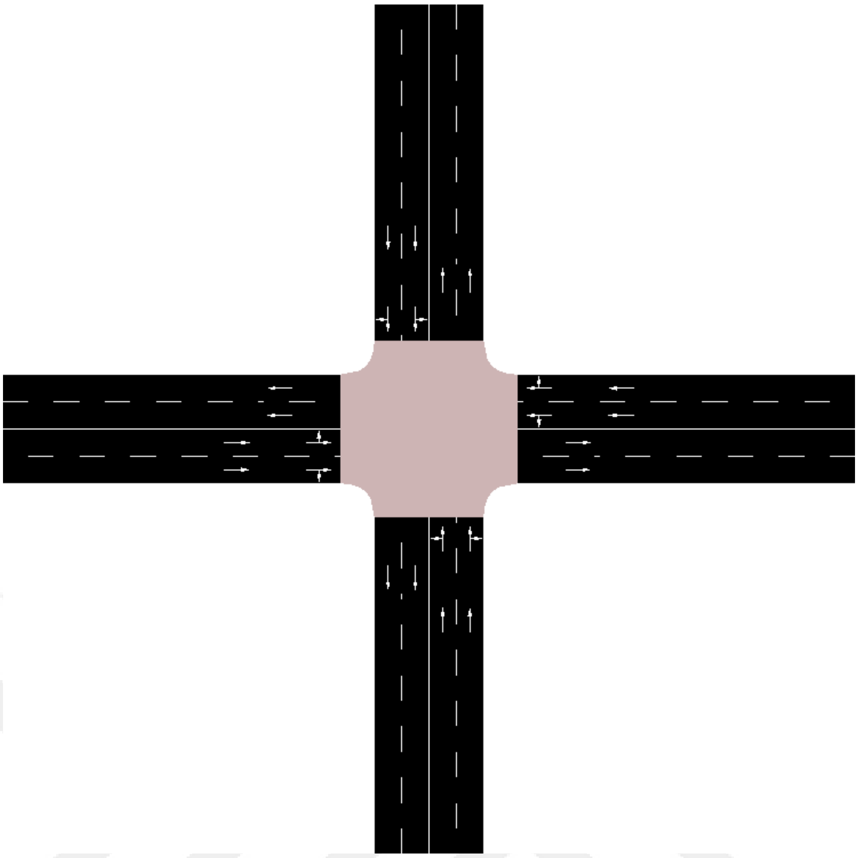


Figure 4. Simulation (SUMO)

Figure 4 depicts a four-way intersection within the simulation environment. This intersection model includes multiple lanes with directional arrows indicating the traffic flow for each lane. The complexity of this layout underscores the diverse traffic patterns that the proposed traffic control system must effectively manage, providing a realistic scenario for testing and evaluation.

2. Fuzzy Controller

The fuzzy intelligent controller employs fuzzy logic techniques to generate optimal traffic signal scheduling from large amounts of incoming traffic data. Constant modifications enable it to properly manage car movement and reduce traffic congestion, resulting in a smoother traffic flow. This layer's purpose is to improve automated traffic systems' decision-making abilities.

Rules:

Three rules are developed to map combinations of input variables into output commands:

Rule 1: If there are few vehicles in the red or green lanes, the traffic command is low.

Rule 2: If there are a medium number of vehicles in the red or green lanes, traffic command is medium.

Rule 3: If there are a lot of cars in the red or green lanes, the traffic command is high.

3. Interface

The interface layer facilitates the transfer of data between the simulation environment and the control layer. The Python interface serves as a channel for transmitting live data and controlling commands. The system facilitates efficient data exchange and decision-making by ensuring a smooth connection between the simulation environment and the fuzzy traffic controller.

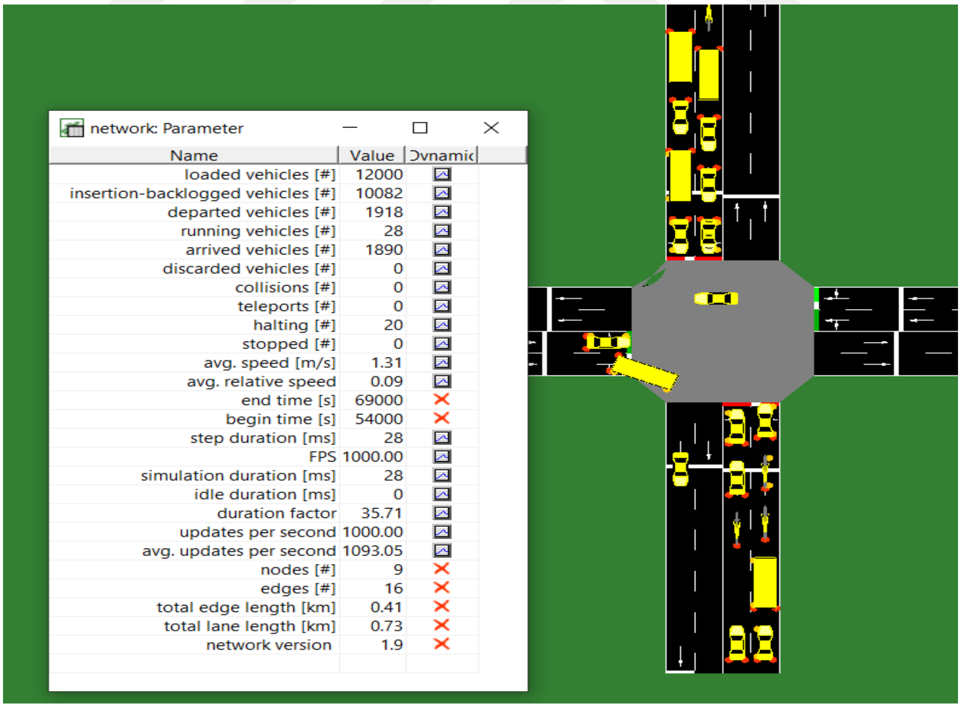


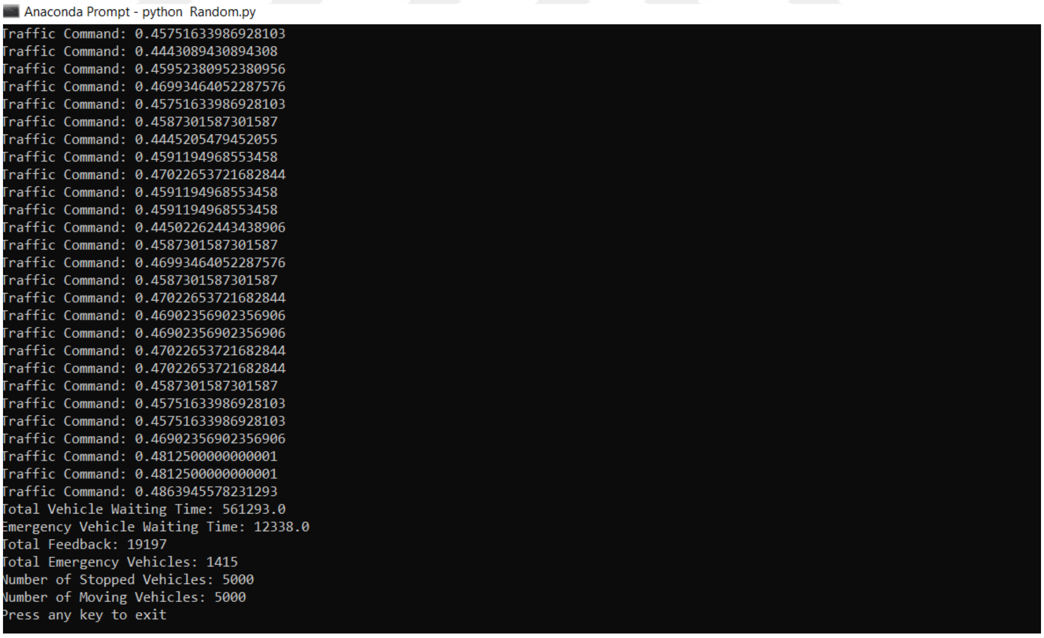
Figure 5. GUI Output

Figure 5 shows a graphical user interface (GUI) output from the SUMO simulation, displaying various real-time traffic metrics. These metrics include the number of loaded, departed, and running vehicles, average speed, and simulation duration. The visual representation of the intersection provides a dynamic overview of traffic flow and congestion, illustrating vehicle positions and movements within the intersection. This data is critical for assessing the performance and efficacy of the traffic control system in a simulated urban environment.

4. Traffic Data

The simulation environment generates the data layer, which provides traffic information. The dataset encompasses details such as vehicle count, velocity measurements, duration of inactive intervals, and directional movement within the traffic flow.

In the simulated environment, the traffic controller uses the input to make well-informed decisions regarding traffic signal adjustments and traffic flow management.



```
Anaconda Prompt - python Random.py
Traffic Command: 0.45751633986928103
Traffic Command: 0.4443089430894308
Traffic Command: 0.45952380952380956
Traffic Command: 0.46993464052287576
Traffic Command: 0.45751633986928103
Traffic Command: 0.4587301587301587
Traffic Command: 0.4445205479452055
Traffic Command: 0.4591194968553458
Traffic Command: 0.47022653721682844
Traffic Command: 0.4591194968553458
Traffic Command: 0.4591194968553458
Traffic Command: 0.44502262443438906
Traffic Command: 0.4587301587301587
Traffic Command: 0.46993464052287576
Traffic Command: 0.4587301587301587
Traffic Command: 0.47022653721682844
Traffic Command: 0.46902356902356906
Traffic Command: 0.46902356902356906
Traffic Command: 0.47022653721682844
Traffic Command: 0.47022653721682844
Traffic Command: 0.4587301587301587
Traffic Command: 0.45751633986928103
Traffic Command: 0.45751633986928103
Traffic Command: 0.46902356902356906
Traffic Command: 0.4812500000000001
Traffic Command: 0.4812500000000001
Traffic Command: 0.4863945578231293
Total Vehicle Waiting Time: 561293.0
Emergency Vehicle Waiting Time: 12338.0
Total Feedback: 19197
Total Emergency Vehicles: 1415
Number of Stopped Vehicles: 5000
Number of Moving Vehicles: 5000
Press any key to exit
```

Figure 6. Fuzzy Output

4.3 Machine Learning System Architecture

Figure 6 shows an architecture that includes a SUMO simulation environment that generates real-time traffic statistics. A data collection module is responsible for gathering the data, while a feature extraction module is responsible for analyzing the data to find and extract relevant characteristics. Next, we feed the collected features into a Random Forest Classifier, a machine-learning model that predicts the optimal timings for traffic lights. The simulation environment produces traffic data, which forms the data layer. The dataset includes data on vehicle quantities, velocities, waiting periods, and traffic flow rate. The traffic controller utilizes the given input to make informed decisions regarding modifications to traffic signals and management of traffic flow within the simulated environment.

The traffic controller, which utilizes machine learning, receives these forecasts and adjusts traffic signals accordingly. This architecture combines simulation, data processing, and machine learning to enhance traffic flow and reduce congestion in the simulated environment. The system can adjust in real-time to fluctuations in traffic conditions using machine learning methodologies, resulting in improved traffic management efficiency.

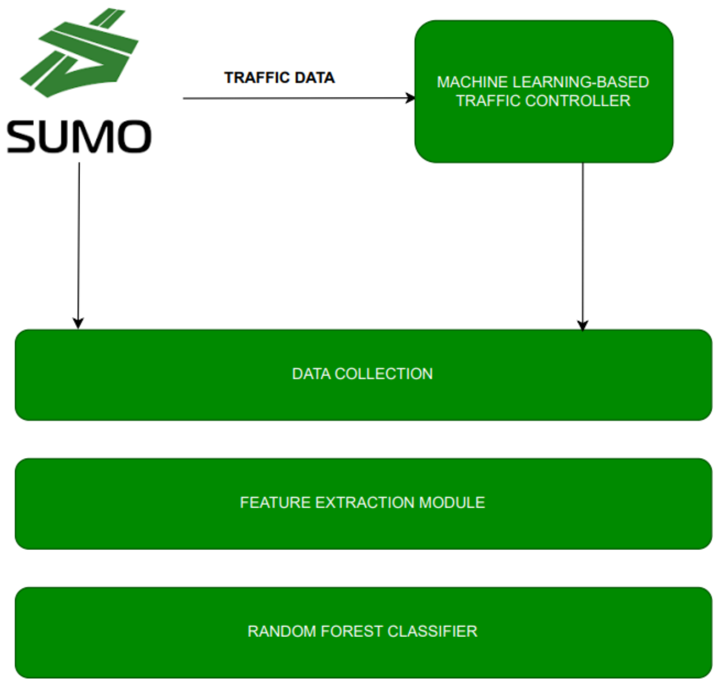


Figure 7. Machine Learning system architecture

1. SUMO Simulation Environment

This layer simulates traffic scenarios and generates traffic data in real-time. In figure 7 SUMO (Simulation of Urban Mobility) provides a platform for simulating vehicular traffic, including vehicles, roads, intersections, and traffic lights.

2. Data Collection Module

The Data Collection Module collects raw traffic data from the SUMO simulation environment in Figure 7. It gathers information such as vehicle counts, speeds, and waiting times.

3. Random Forest Classifier

The Random Forest classifier is essential for the dynamic regulation of traffic signal phases in this program. At the outset, it is trained on historical traffic data to identify patterns and relationships between a variety of traffic conditions and the most effective traffic signal transitions. The classifier employs these acquired patterns during simulation to forecast whether the current traffic signal phase should transition.

In particular, the classifier considers the number of vehicles in red and green lanes, the maximal waiting time in red lane, the waiting time of emergency vehicles in both red and green lane, and the count of emergency vehicles in each lane. Predictions are generated at predetermined intervals throughout the simulation cycle by employing these attributes. The traffic light is dynamically adjusted by the program if the classifier anticipates a transition to the green light phase based on the present conditions.

5 EXPERIMENT & RESULT

5.1 Experiment

The proposed traffic control system utilizes a combination of SUMO simulation and fuzzy logic control to manage traffic flow efficiently. During the simulation, the system continuously monitors vehicle movements and traffic light states, calculating feedback based on waiting times and queue lengths. The fuzzy traffic controller receives this feedback and uses predefined rules to determine the timing of traffic lights. These rules consider factors such as the number of vehicles in red and green lanes to determine the appropriate traffic command (low, medium, or high). Through iterative simulation steps, the system dynamically adjusts traffic light signals to optimize traffic flow and minimize waiting times, particularly prioritizing emergency vehicles. For analysis, we gather data on vehicle movements and control decisions. Testing involves verifying the correctness of control logic, validating the system's effectiveness in improving traffic flow, and assessing its performance and robustness across various traffic scenarios. Ultimately,

The system aims to enhance overall traffic management by intelligently adapting traffic light control in real time based on observed traffic conditions.

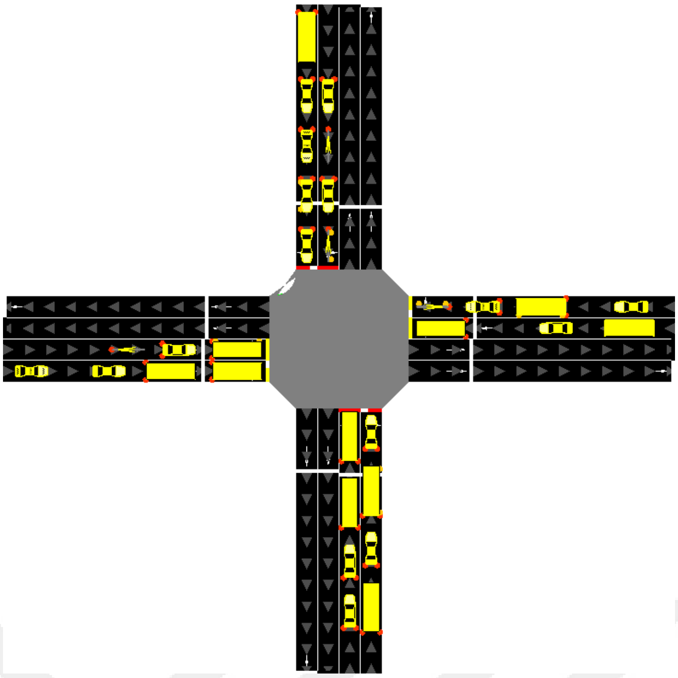


Figure 8. Simulation of 4 way intersection

Figure 8 the simulation of a four-way intersection entails the replication of the behavior and interactions of vehicles at a road junction where four roads intersect. Vehicles are simulated as they approach, navigate, and exit the intersection using mathematical models and algorithms. In order to accurately represent real-world conditions, factors such as traffic flow, vehicle velocities, signaling, and right-of-way rules are integrated.

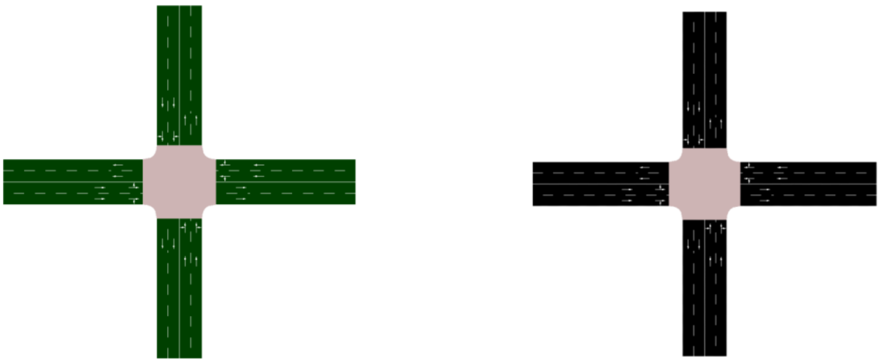


Figure 9. Network drawing process

In figure 9 the multi-step process of network design is facilitated by SUMO (Simulation of Urban Mobility), as illustrated in figure 9. Initially, a road network is generated by importing existing GIS data or utilizing a dedicated tool. Intersections are represented by nodes, while road segments are represented by edges. Subsequently, each road segment is designated attributes such as connectivity, lane numbers, and speed limits. The network configuration is inspected and refined by users through the use of visualization tools in SUMO, which guarantees realism and accuracy. In addition, SUMO offers traffic flow simulation capabilities, which facilitate the examination of the effects of infrastructure modifications, congestion patterns, and vehicle movements.

5.2 Results

The assessment of the traffic control system's performance is carried out by taking into account crucial indicators, such as the overall vehicle waiting time, the waiting time specifically for emergency vehicles, the total feedback received from vehicles, and the number of emergency vehicles managed. The effectiveness of the system in reducing congestion and improving traffic flow is assessed using these parameters.

Table 2 Fuzzy Logic Test Case

Test case	Total Vehicle Waiting Time	Emergency Vehicle Waiting Time	Total Feedback	Total Emergency Vehicles	Total Vehicles
1	561293.0	12338.0	19197	1415	5000
2	1122690.0	30355.0	38518	2425	10000
3	1667623.0	47003.0	57595	3736	15000
4	2754181.0	146599.0	92273	6439	50000

The test cases (1-4) in table 1 of Fuzzy Logic illustrate different degrees of performance in the management of traffic issues. Although the proposed approach suggests that

Fuzzy Logic excels at minimizing waiting times, a crucial factor in real-time systems where promptness is essential. Test Case 4 indicates that Fuzzy Logic's interpretability and rule-based nature render it appropriate for situations in which human-like reasoning and transparency are essential. This is evidenced by the accumulation of feedback and reduced waiting times. This feature is especially advantageous in situations where decisions must be readily comprehensible and substantiated.

Table 3 Random forest Test case

Test case	Total Vehicle Waiting Time	Emergency Vehicle Waiting Time	Total Feedback	Total Emergency Vehicles	Total Vehicles
1	2043376.0	30536.0	76225	1415	5000
2	4115188.0	52886.0	151399	2425	10000
3	6166601.0	80224.0	228268	3736	15000
4	10212957.0	146599.0	399124	6439	50000

The test scenarios (1-4) presented in Table 3 of the Random Forest technique exhibit substantial enhancements in handling feedback accumulation when compared to Fuzzy Logic. Nevertheless, it frequently leads to increased overall vehicle waiting times. In Test Case 4, the total vehicle waiting time was 10,212,957.0, far surpassing the waiting time of the Fuzzy Logic technique. This implies that although Random Forest is highly effective at managing intricate datasets and high volumes of traffic, it may not always be the most suitable option for decreasing waiting times in real-time situations.

The ability to make timely, transparent, and comprehensible decisions is crucial in real-time applications. Although Random Forest is known for its flexibility and resilience in dealing with high-dimensional data, Fuzzy Logic offers distinct benefits in terms of interpretability, focused priority of emergency vehicles, and transparency. Fuzzy Logic possesses qualities that make it highly suitable for real-time traffic management systems, where the utmost importance is placed on expeditious, dependable, and easily understandable decision-making procedures.

5.3 Analysis

5.3.1 Fuzzy Logic Approach

Fuzzy sets and linguistic rules are used by the Fuzzy Logic method to make decisions in uncertain situations. Fuzzy Logic routinely showed shorter waiting times for emergency vehicles and total vehicles in the test circumstances than the Random Forest model. For instance, in Test Case 1 the emergency vehicle waiting time was 12,338.0 and the overall vehicle waiting time was 561,293.0. This implies that Fuzzy Logic is very good at reducing waiting periods, which is an important aspect in real-time systems when speed is critical. However, the Random Forest model exhibited a tendency to accumulate a greater quantity of feedback in general, which implies that it may be adaptable and responsive to a diverse array of inputs. Fuzzy logic is suitable for situations that necessitate transparency and reasoning that is comparable to that of humans due to its rule-based nature and easy interpretability. This feature is especially advantageous in situations where decisions must be readily comprehensible and justified.

5.3.2 Random Forest Approach

Random Forest, on the other hand, uses ensemble learning to make several decision trees and then combines their results. Overall, the test cases show big improvements in how traffic is managed, especially when there is a lot of traffic. As a whole, vehicles had to wait 10,212,957.0 seconds in Test Case 4, and emergency vehicles had to wait 146,599.0 seconds.

This shows that Random Forest is able to effectively manage high traffic volumes. Although the total waiting periods are greater in comparison to Fuzzy Logic, the Random Forest model demonstrates substantial improvements in total feedback. Specifically, Test Case 4 shows a total of 399,124 instances of feedback. This demonstrates its versatility and effectiveness in handling various and intricate traffic situations. The model's capacity to handle datasets with a large number of dimensions without needing considerable knowledge in the field makes it a potential choice for practical implementation, especially in situations that demand strong and flexible traffic management solutions.

5.3.3 Comparison

In real-time systems where responsiveness and efficiency are paramount, the fuzzy logic model might be considered better suited based on the comparison. Its consistent ability to minimize waiting times for both total vehicles and emergency vehicles suggests a high degree of predictability and control, which aligns well with the demands of real-time operations.

Fuzzy logic is highly effective in capturing intricate, non-linear connections in data and making judgments based on imprecise or uncertain inputs. This makes it particularly suitable for the dynamic environments that are typical of real-time systems. The rule-based approach of this system enables rapid decision-making, which is vital in situations that require fast actions, such as traffic management or emergency response systems.

Although the random forest model has advantages such as adaptability and perhaps better feedback integration, in real-time systems, the fuzzy logic model's capacity to consistently decrease waiting times and assure effective resource allocation may outweigh these benefits.

Thus, for real-time systems that prioritize prompt and dependable decision-making to enhance resource allocation and reduce waiting times, the fuzzy logic model is emerges as the better option.

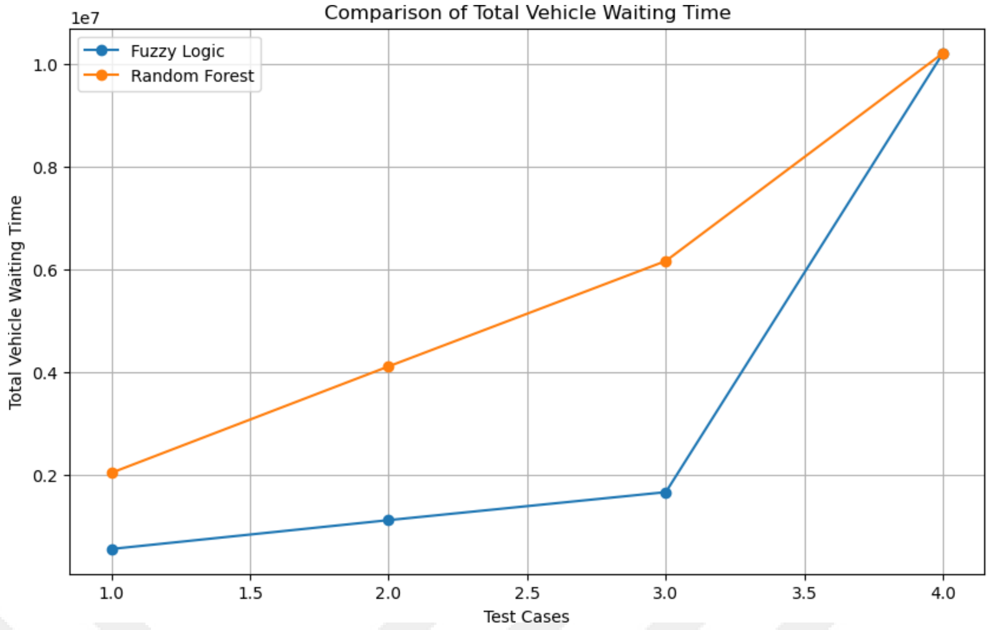


Figure 10. Comparison of Total Non-EMV Vehicle Waiting Time

In figure 10 the graph illustrates the total waiting time for vehicles in each test case using fuzzy logic and random forest methods. Across all scenarios, fuzzy logic consistently demonstrates lower waiting times compared to random forest, indicating its efficiency in minimizing overall vehicle wait times.

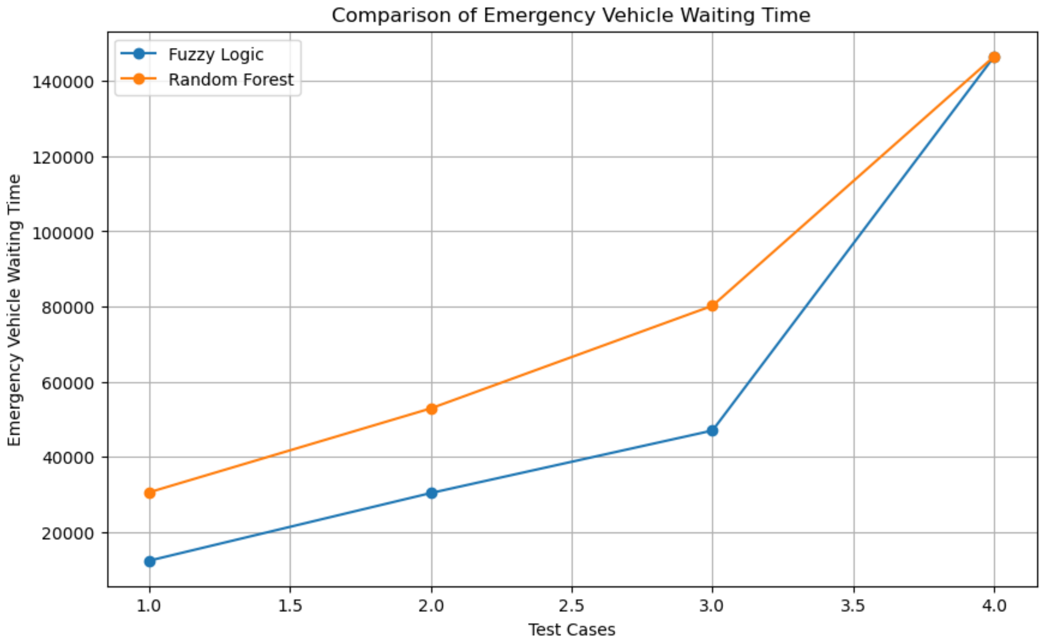


Figure 11. Comparison of Emergency Vehicle Waiting Time

Figure 11 shows the waiting time for emergency vehicles in each test case, comparing the fuzzy logic and random forest techniques. Fuzzy logic regularly outperforms random forest by constantly maintaining lower emergency vehicle waiting times in all cases, indicating its reliability in prioritizing urgent vehicle movements.

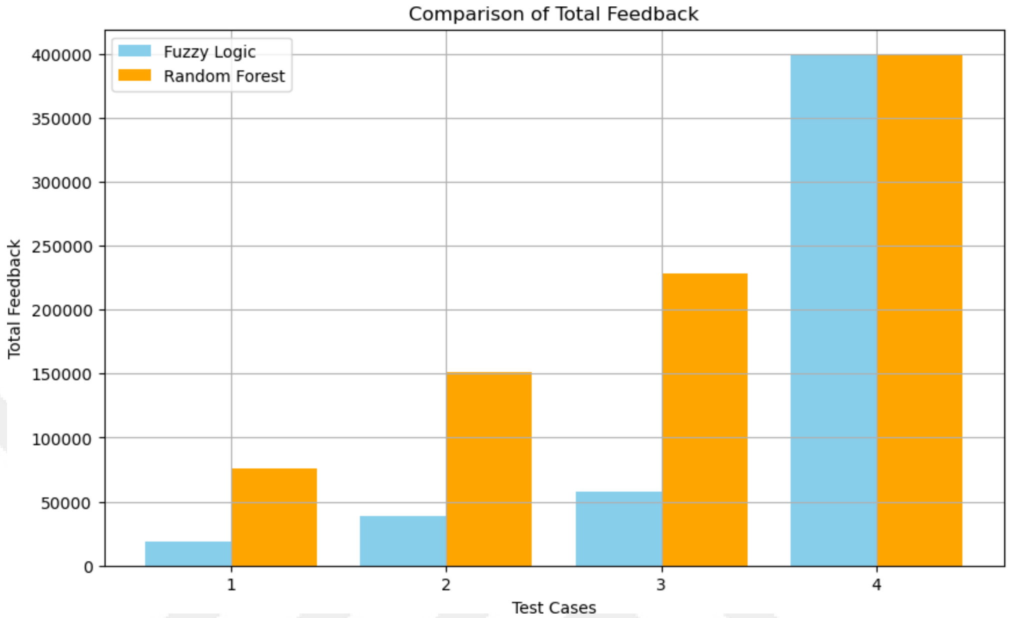


Figure 12. Comparison of Total Feedback

Figure 12 shows a bar graph illustrating the total feedback obtained in each test for both the fuzzy logic and random forest approaches. Random forest generally obtains higher feedback, whereas fuzzy logic also achieves significant feedback acquisition, although slightly lower than random forest in all situations.

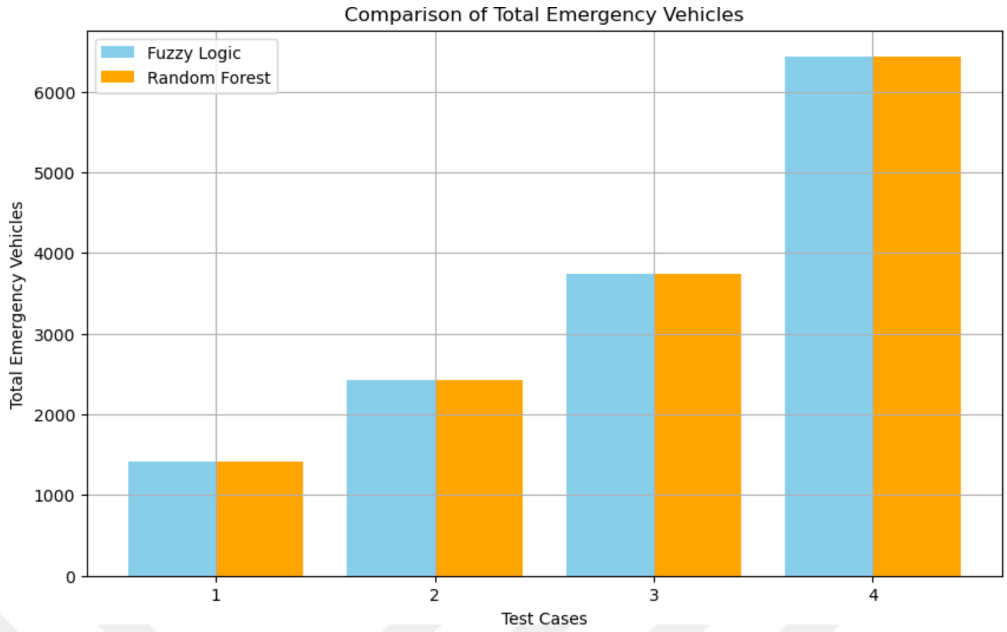


Figure 13. Comparison of Total Emergency Vehicles

The total number of emergency vehicles in each test case is compared between the fuzzy logic and random forest methods in this graph. Regardless of the methodology employed, both methods produce identical tallies of emergency vehicles in all scenarios, suggesting that emergency situations are managed consistently.

5.4 Discussion

The graphs and tables in this research give a valuable assessment of the fuzzy logic and random forest models' individual performance in real-time systems.

The tables revealed significant differences in critical parameters among the test instances. The fuzzy logic model consistently displayed reduced total vehicle and emergency vehicle waiting time than random forest model.

This implies that fuzzy logic is highly effective in reducing waiting times, which is a critical aspect in real-time systems where timeliness is vital. Nevertheless, the random forest model had a propensity to accumulate a greater amount of overall feedback, suggesting its capacity for flexibility and receptiveness to various inputs.

The graphical depictions further solidified these discoveries. The line graphs demonstrate the continuous advantage of fuzzy logic in minimizing waiting times for both overall car waiting time and emergency vehicle waiting time in many scenarios. In contrast, the bar graph representing the total feedback clearly showed that the random forest algorithm was capable of collecting a greater amount of feedback. However, this came with the drawback of slightly increased waiting times. Furthermore, the bar graph illustrating the total number of emergency vehicles demonstrated the uniformity of both models in managing emergency situations, as they had the same number of emergency vehicles in all circumstances.

This talk highlights the compromises between the two paradigms in real-time systems. Although fuzzy logic is highly effective in reducing waiting times, the random forest model provides advantages in terms of flexibility and the integration of feedback. Hence, the selection between the two models is contingent upon the particular priorities and specifications of the system. Fuzzy logic is the preferred choice for applications where reducing waiting times is of utmost importance, such as traffic management or emergency response systems. Nevertheless, the random forest model can offer a more appropriate solution in situations that favor flexibility and the incorporation of feedback. In order to choose the most suitable model for real-time operations, it is crucial to have a comprehensive comprehension of the system's goals and limitations.

6 CONCLUSION

This study encompassed a thorough examination of two approaches to traffic management: fuzzy logic and random forest. We employed the SUMO traffic simulator and the Python programming language to conduct simulations with the objective of evaluating the efficacy of these strategies in optimizing traffic flow and reducing waiting times for both non-emergency vehicles and emergency vehicles.

Our results indicate that fuzzy logic has the capacity to optimize traffic flow in scenarios with unpredictable traffic conditions and reduce waiting periods, particularly for emergency vehicles. In contrast, Random Forest offers consistency and stability across multiple iterations, rendering it a viable option for traffic management systems that prioritize dependability. The comparison between fuzzy logic and random forest underscores the necessity of considering the unique objectives and requirements of each individual when selecting an appropriate approach. Fuzzy logic is particularly adept at mitigating ambiguity and decreasing wait times, whereas Random Forest consistently produces accurate results, particularly in the presence of stable traffic conditions.

6.1 Future Prospect

Moving forward, there are various opportunities for further research and development. To begin, hybrid approaches that combine the strengths of Fuzzy Logic and Random Forest could be investigated in order to take use of the benefits provided by each methodology. This could include creating integrated decision-making frameworks that react dynamically to changing traffic conditions.

Furthermore, additional research into algorithmic fine-tuning and parameter optimization may lead to improved traffic management system performance. Techniques like neural networks or evolutionary algorithms could be used to optimize the settings of Fuzzy Logic controllers or Random Forest models, increasing their usefulness in real-world scenarios. Moreover, broadening the study's scope to cover more diverse traffic scenarios, as well as taking into account the incorporation of upcoming technologies like linked and autonomous vehicles, could provide useful insights into the future of traffic management systems. To summarize, while our research demonstrates the promise of Fuzzy Logic and Random Forest in traffic management, there is still much opportunity for discovery and innovation in this subject. By resolving limits and exploring future research paths, we can continue to progress the development of intelligent and efficient transportation systems.

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APPENDIX A Fuzzy logic

```
import os  # Importing the os module for operating system functionalities
import sys  # Importing the sys module for system-specific parameters and functions
import pickle  # Importing the pickle module for object serialization
import traci  # Importing the traci module for interacting with SUMO (Simulation of Urban MObility)
from fuzzy_traffic_controller import fuzzy_controller_function  # Importing a fuzzy traffic controller function
```

```
from helper_functions import *  # Importing custom helper functions

def setup_sumo():  # Defining a function to set up SUMO
    if 'SUMO_HOME' in os.environ:  # Checking if the SUMO_HOME environment variable is set
        tools = os.path.join(os.environ['SUMO_HOME'], 'tools')  # Creating path to SUMO tools
        sys.path.append(tools)  # Appending SUMO tools path to system path
    else:
        sys.exit("Please declare the environment variable 'SUMO_HOME'")  # Exiting if SUMO_HOME is not set

    sumo_binary = "sumo-gui"  # Setting SUMO binary
    sumo_cmd = [sumo_binary, "-c", "4-junction/4-junction.sumocfg", "--start"]  # SUMO command for simulation
    traci.start(sumo_cmd)  # Starting SUMO simulation using traci

def simulate_traffic_light(traffic_light_id, max_steps, cycle_length, waiting_time_threshold, queue_length_threshold):
    # Defining a function to simulate traffic light behavior
    lanes_in_G2H1 = ['F2_0', 'F2_1', 'G2_0', 'G2_1', 'H1_0', 'H1_1', 'I1_0', 'I1_1']  # Defining lanes in G2H1 direction
    lanes_in_D1B2 = ['A2_0', 'A2_1', 'B2_0', 'B2_1', 'D1_0', 'D1_1', 'E1_0', 'E1_1']  # Defining lanes in D1B2 direction

    total_vehicle_waiting_time = 0  # Initializing total vehicle waiting time
    emv_waiting_time = 0  # Initializing emergency vehicle waiting time
    total_feedback = 0  # Initializing total feedback
    total_emergency_vehicles = 0  # Initializing total emergency vehicles counter

    no_stopped = []  # Initializing list to store number of stopped vehicles
    no_moving = []  # Initializing list to store number of moving vehicles
```

```
    all_lanes = lanes_in_G2H1 + lanes_in_D1B2  # Combining all lanes

    step = 0  # Initializing simulation step counter
    max_steps = 32000  # Setting maximum simulation steps
    cycle_length = 7  # Setting traffic light cycle length
    while step < 5000:  # Running simulation loop for a certain number of steps
        lanes_currently_moving, lanes_stopped_by_light = get_lane_lists(lanes_in_D1B2,
lanes_in_G2H1, traffic_light_id)

        vehicles_in_red_lanes = get_vehicles_in_lane(lanes_stopped_by_light)
        vehicles_in_green_lanes = get_vehicles_in_lane(lanes_currently_moving)

        no_vehicles_in_red_lanes = len(vehicles_in_red_lanes)
        no_vehicles_in_green_lanes = len(vehicles_in_green_lanes)
        no_moving.append(no_vehicles_in_green_lanes)
        no_stopped.append(no_vehicles_in_red_lanes)

        # Calculate waiting times for all vehicles
        all_vehicles = traci.vehicle.getIDList()
        waiting_times = [traci.vehicle.getWaitingTime(vehicle) for vehicle in all_vehicles]

        # Calculate feedback for each vehicle based on waiting time
        vehicle_feedback = [calculate_feedback(waiting_time, 0, waiting_time_threshold,
queue_length_threshold) for waiting_time in waiting_times]

        # Accumulate total feedback for the current step
        total_feedback += sum(vehicle_feedback)

        vehicles_waiting_time = vehicle_waiting_time_in_lane(vehicles_in_red_lanes)
        if vehicles_waiting_time:
            max_waiting_time_in_red_lanes = max(vehicles_waiting_time)
```

```
    total_vehicle_waiting_time += sum(vehicles_waiting_time)

  emv_waiting_time_red_lane = get_emv_waiting_time(vehicles_in_red_lanes)
  emv_waiting_time_green_lane = get_emv_waiting_time(vehicles_in_green_lanes)

  emv_waiting_time += emv_waiting_time_red_lane
  emv_waiting_time += emv_waiting_time_green_lane

  emv_current_lane = get_emv(vehicles_in_green_lanes)
  emv_other_lane = get_emv(vehicles_in_red_lanes)

  no_emv_current_lane = len(emv_current_lane)
  no_emv_other_lane = len(emv_other_lane)

  # Calculate queue lengths for all lanes
  queue_lengths = [traci.lane.getLastStepHaltingNumber(lane) for lane in all_lanes]

  # Calculate total queue length for monitoring purposes
  total_queue_length = sum(queue_lengths)

  # Add the total queue length to the feedback calculation
      total_feedback += calculate_feedback(0, total_queue_length,
waiting_time_threshold, queue_length_threshold)

  # Count emergency vehicles
  for vehicle_id in all_vehicles:
    if traci.vehicle.getTypeID(vehicle_id) == "emergency":
      total_emergency_vehicles += 1

  if (step > 0) and (step % cycle_length) == 0:
    traffic_command = fuzzy_controller_function(
      no_vehicles_in_red_lanes, no_vehicles_in_green_lanes,
```

```
            max_waiting_time_in_red_lanes, emv_waiting_time_red_lane,
            emv_waiting_time_green_lane, no_emv_current_lane, no_emv_other_lane
        )

        if traffic_command >= 0.5:
            # Check if there are no vehicles in the green lanes, then switch the green light
            if no_vehicles_in_green_lanes == 0:
                current_phase = traci.trafficlight.getPhase(traffic_light_id)
                traci.trafficlight.setPhase(traffic_light_id, 4 if current_phase < 5 else 9)

    traci.simulationStep()
    step += 1

traci.close()  # Close the SUMO simulation
print("Total Vehicle Waiting Time:", total_vehicle_waiting_time)  # Print total vehicle waiting time
print("Emergency Vehicle Waiting Time:", emv_waiting_time)  # Print emergency vehicle waiting time
print("Total Feedback:", total_feedback)  # Print total feedback
print("Total Emergency Vehicles:", total_emergency_vehicles)    # Print total emergency vehicles

# Save data to files using pickle
with open("amount_stopped_vehicles.txt", "wb") as fp:
    pickle.dump(no_stopped, fp)

with open("amount_moving_vehicles.txt", "wb") as fp:
    pickle.dump(no_moving, fp)

print('Number of Stopped Vehicles:', len(no_stopped))  # Print number of stopped vehicles
```

```
    print('Number of Moving Vehicles:', len(no_moving))  # Print number of moving vehicles
    input('Press any key to exit')  # Wait for user input before exiting

def calculate_feedback(waiting_time, queue_length, waiting_time_threshold, queue_length_threshold):
    # Function to calculate feedback based on waiting time and queue length
    # Example: Penalize vehicles for exceeding waiting time or high queue lengths, reward otherwise
    if waiting_time > waiting_time_threshold or queue_length > queue_length_threshold:
        return -1  # Apply penalty
    else:
        return 1   # Apply reward

def run_simulation_cycle():
    # Function to run the simulation cycle
    setup_sumo()  # Set up SUMO
    traffic_light_id = traci.trafficlight.getIDList()[0]  # Get traffic light ID
    max_steps = 32000  # Set maximum simulation steps
    cycle_length = 7  # Set traffic light cycle length
    waiting_time_threshold = 30  # Set waiting time threshold
    queue_length_threshold = 50  # Set queue length threshold
    simulate_traffic_light(traffic_light_id, max_steps, cycle_length, waiting_time_threshold, queue_length_threshold)  # Simulate traffic light behavior

if __name__ == "__main__":
    run_simulation_cycle()  # Run the simulation cycle
```

APPENDIX B Random forest

```
import os  # Importing the os module for operating system functionalities
import sys  # Importing the sys module for system-specific parameters and functions
```

```
import pickle  # Importing the pickle module for object serialization
import traci  # Importing the traci module for interacting with SUMO (Simulation of Urban MObility)
from fuzzy_traffic_controller import fuzzy_controller_function  # Importing a fuzzy traffic controller function
from helper_functions import *  # Importing custom helper functions
from sklearn.ensemble import RandomForestClassifier  # Importing Random Forest classifier from scikit-learn
def setup_sumo():  # Defining a function to set up SUMO
    if 'SUMO_HOME' in os.environ:  # Checking if the SUMO_HOME environment variable is set
        tools = os.path.join(os.environ['SUMO_HOME'], 'tools')  # Creating path to SUMO tools
        sys.path.append(tools)  # Appending SUMO tools path to system path
    else:
        sys.exit("Please declare the environment variable 'SUMO_HOME'")  # Exiting if SUMO_HOME is not set

    sumo_binary = "sumo-gui"  # Setting SUMO binary
    sumo_cmd = [sumo_binary, "-c", "4-junction/4-junction.sumocfg", "--start"]  # SUMO command for simulation
    traci.start(sumo_cmd)  # Starting SUMO simulation using traci

def simulate_traffic_light(traffic_light_id, max_steps, cycle_length, waiting_time_threshold, queue_length_threshold):
    # Defining a function to simulate traffic light behavior
    lanes_in_G2H1 = ['F2_0', 'F2_1', 'G2_0', 'G2_1', 'H1_0', 'H1_1', 'I1_0', 'I1_1']  # Defining lanes in G2H1 direction
    lanes_in_D1B2 = ['A2_0', 'A2_1', 'B2_0', 'B2_1', 'D1_0', 'D1_1', 'E1_0', 'E1_1']  # Defining lanes in D1B2 direction

    total_vehicle_waiting_time = 0  # Initializing total vehicle waiting time
```

```
emv_waiting_time = 0  # Initializing emergency vehicle waiting time
total_feedback = 0  # Initializing total feedback
total_emergency_vehicles = 0  # Initializing total emergency vehicles counter

no_stopped = []  # Initializing list to store number of stopped vehicles
no_moving = []  # Initializing list to store number of moving vehicles

all_lanes = lanes_in_G2H1 + lanes_in_D1B2  # Combining all lanes

step = 0  # Initializing simulation step counter
max_steps = 32000  # Setting maximum simulation steps
cycle_length = 7  # Setting traffic light cycle length

# training data
X_train = [[0, 0, 0, 0, 0, 0, 0] for _ in range(1000)]  # Assuming 1000 data points
y_train = [1 for _ in range(1000)]  #witch green light

# Train Random Forest model
model = RandomForestClassifier()
model.fit(X_train, y_train)

while step < 5000:  # Running simulation loop for a certain number of steps
    lanes_currently_moving, lanes_stopped_by_light = get_lane_lists(lanes_in_D1B2,
lanes_in_G2H1, traffic_light_id)

    vehicles_in_red_lanes = get_vehicles_in_lane(lanes_stopped_by_light)
    vehicles_in_green_lanes = get_vehicles_in_lane(lanes_currently_moving)

    no_vehicles_in_red_lanes = len(vehicles_in_red_lanes)
    no_vehicles_in_green_lanes = len(vehicles_in_green_lanes)
    no_moving.append(no_vehicles_in_green_lanes)
    no_stopped.append(no_vehicles_in_red_lanes)
```

```
        # Calculate waiting times for all vehicles
        all_vehicles = traci.vehicle.getIDList()
        waiting_times = [traci.vehicle.getWaitingTime(vehicle) for vehicle in all_vehicles]

        # Calculate feedback for each vehicle based on waiting time
        vehicle_feedback = [calculate_feedback(waiting_time, 0, waiting_time_threshold,
queue_length_threshold) for waiting_time in waiting_times]

        # Accumulate total feedback for the current step
        total_feedback += sum(vehicle_feedback)

        vehicles_waiting_time = vehicle_waiting_time_in_lane(vehicles_in_red_lanes)
        if vehicles_waiting_time:
            max_waiting_time_in_red_lanes = max(vehicles_waiting_time)
            total_vehicle_waiting_time += sum(vehicles_waiting_time)

        emv_waiting_time_red_lane = get_emv_waiting_time(vehicles_in_red_lanes)
        emv_waiting_time_green_lane = get_emv_waiting_time(vehicles_in_green_lanes)

        emv_waiting_time += emv_waiting_time_red_lane
        emv_waiting_time += emv_waiting_time_green_lane

        emv_current_lane = get_emv(vehicles_in_green_lanes)
        emv_other_lane = get_emv(vehicles_in_red_lanes)

        no_emv_current_lane = len(emv_current_lane)
        no_emv_other_lane = len(emv_other_lane)

        # Count emergency vehicles
        for vehicle_id in all_vehicles:
            if traci.vehicle.getTypeID(vehicle_id) == "emergency":
```

```
                total_emergency_vehicles += 1

        if (step > 0) and (step % cycle_length) == 0:
            if no_vehicles_in_green_lanes == 0:
                # Use the trained Random Forest model to predict whether to switch the green light
                features = [no_vehicles_in_red_lanes, no_vehicles_in_green_lanes, max_waiting_time_in_red_lanes, emv_waiting_time_red_lane, emv_waiting_time_green_lane, no_emv_current_lane, no_emv_other_lane]
                prediction = model.predict([features])
                if prediction == 1:
                    current_phase = traci.trafficlight.getPhase(traffic_light_id)
                    traci.trafficlight.setPhase(traffic_light_id, 4 if current_phase < 5 else 9)

        traci.simulationStep()
        step += 1

    traci.close()  # Close the SUMO simulation
    print("Total Vehicle Waiting Time:", total_vehicle_waiting_time)  # Print total vehicle waiting time
    print("Emergency Vehicle Waiting Time:", emv_waiting_time)  # Print emergency vehicle waiting time
    print("Total Feedback:", total_feedback)  # Print total feedback
    print("Total Emergency Vehicles:", total_emergency_vehicles)  # Print total emergency vehicles

    # Save data to files using pickle
    with open("amount_stopped_vehicles.txt", "wb") as fp:
        pickle.dump(no_stopped, fp)

    with open("amount_moving_vehicles.txt", "wb") as fp:
        pickle.dump(no_moving, fp)
```

```
    print('Number of Stopped Vehicles:', len(no_stopped))  # Print number of stopped vehicles
    print('Number of Moving Vehicles:', len(no_moving))  # Print number of moving vehicles
    input('Press any key to exit')  # Wait for user input before exiting

def calculate_feedback(waiting_time, queue_length, waiting_time_threshold, queue_length_threshold):
    # Function to calculate feedback based on waiting time and queue length
    # Example: Penalize vehicles for exceeding waiting time or high queue lengths, reward otherwise
    if waiting_time > waiting_time_threshold or queue_length > queue_length_threshold:
        return -1  # Apply penalty
    else:
        return 1   # Apply reward

def run_simulation_cycle():
    # Function to run the simulation cycle
    setup_sumo()  # Set up SUMO
    traffic_light_id = traci.trafficlight.getIDList()[0]  # Get traffic light ID
    max_steps = 32000  # Set maximum simulation steps
    cycle_length = 7  # Set traffic light cycle length
    waiting_time_threshold = 30  # Set waiting time threshold
    queue_length_threshold = 50  # Set queue length threshold
    simulate_traffic_light(traffic_light_id, max_steps, cycle_length, waiting_time_threshold, queue_length_threshold)  # Simulate traffic light behavior

if __name__ == "__main__":
    run_simulation_cycle()  # Run the simulation cycle
```

APPENDIX C Survey Questioner

1. What is the primary objective of traffic control systems discussed in this study?
2. What is the SUMO Simulation Environment, and how does it contribute to traffic management systems?
3. How does the fuzzy logic system adaptively modify traffic signal durations?
4. What are the potential opportunities for future research and development in traffic management systems?