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DOCTORAL THESIS

Realized By :

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TO OBTAIN THE DOCTOR'S DEGREE

IN ENERGY ENGINEERING

Smart Cities: The Next Generation of Energy Transition and the Role of Intelligent Transportation Systems for a Sustainable Development

Defended on: 11 / 10 / 2025 in the presence of the examination jury :

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Laboratory of Thermal and Energy Systems LR99ES31

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Dedication

I am dedicating this work.

In the air I breathe, I hope I deserve the unexpected efforts for all the love, sacrifices, and prayers that have brought me here.

To the best parents, my mother and my father.

To the first person who believed in me, In the light of my days, the source of my efforts, the flame of my Heart, my life, and my bliss.

Mom, I love you

For the people I want to impress the most, I hope to be a good example, worth your trust.

Friends and superiors alike.

I dedicate this modest work to you.

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List of abbreviations

Abbreviation	Acronym
ACTSC	Adaptively Coordinated Traffic Signal Control
ADAS	Advanced Driver Assistance System
AI	Artificial Intelligence
API	Application Programming Interface
ATSC	Adaptive traffic signal control
BEBs	Battery Electric Buses
CACC	Cooperative Adaptive Cruise Control
CDBs	Conventional Diesel Buses
CER	Renewable Energy Communities
CVs	Conventional Vehicles
DAS	Driver Advisory System
DRL	Deep Reinforcement Learning
DTSC	Dynamic Traffic Signal Control
DoS	Denial-of-Service
ECO-AnD	Eco Approach and Departure
EDAS	Eco-Driving Assistance System
EDS-CSI	Continuous Speed-limit signalized Intersections
EIDM	Enhanced Intelligent Driver Model
EMC	European Smart City Group
ET	Energy Transition
EVs	Electric Vehicles
FF	Fossil Fuel
FL	Fuzzy Logic
FL-GLOSA	Fuzzy Logic-based Green Light Optimal Speed Advisory
FR	Fuzzy Rules
GHGs	GreenHouse Gas emissions
GIS	Geographic Information System

GLOSA	Green Light Optimal Speed Advisory
GPS	Global Positioning System
GPUs	Graphical Processing Units
HBEFA	Handbook Emission Factors for Road Transport
HUI	Habitat Agenda Urban Indicators
ICEs	Internal Combustion Engine vehicles
ICT	Intelligent Communications Technologies
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
ISAS	Intelligent Speed Advisory Systems
ISAS	Intelligent Speed Advisory Systems
ITS	Intelligent Transport Systems
ITU	International Telecommunication Union
KPIs	Performance Indicators
LADs	Lane Area Detectors
LARBEM	Large Language Model-based Agentic ReAct Bus Eco-Driving Model
LLM	Large Language Model
MF	Membership Functions
MITM	Man-In-The-Middle
ML	Machine Learning
MPC	Model Predictive Control
OSM	OpenStreetMap
PCU	Passenger car units
PFs	petroleum-based fuels
PHEBs	Plug-in Hybrid Electric Buses
PTBs	Public Transport Buses
PTS	Public Transportation Sector
RBT	Rapid Bus Transit
ReAct	Reasoning and Acting
RL	Reinforcement Learning
SCs	Smart Cities
STCS	Static traffic control systems
STLs	Static Traffic Lights
STM	Static Traffic Management

SUMO	Simulation of Urban Mobility
TraCI	Traffic Control Interface
TSCS	Traffic Signal Control Systems
TT	Travel Times
U.N	United Nations
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything

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Abstract

Rising emissions and rapid urbanization, with cities becoming increasingly dense, necessitate the development of greener mobility solutions in urban spaces. The purpose of this thesis is thus to further the aim of smart city transport management by exploring Intelligent Transport Systems (ITS) in optimizing energy efficiency and emission standards in smart cities through the use of innovative approaches. The research work therefore offered an adaptive traffic signal control approach, Fuzzy Logic (FL) GLOSA, and a Large Language Model-based Agentic ReAct Bus Eco-Driving Model (LARBEM) with Reinforcement Learning (RL). These approaches were evaluated in terms of energy utilization and emission reduction using the Simulation of Urban Mobility (SUMO) as a simulation tool. The study is based on actual field data and signalized intersections, specifically Mouhamed V Signalized Intersections and the Sousse–Kalaa Kbira Bus Route in Tunisia. Three types of vehicles were selected: conventional diesel buses (CDBs), battery electric buses (BEBs), and plug-in hybrid electric buses (PHEBs). Several experiments have shown significant improvements: the FL-GLOSA reduced fuel usage by up to 54% in adaptively coordinated traffic situations with the integration of V2X; LARBEM's energy savings ranged from 42% to 54%, and CO_2 emission reductions ranged from 39% to 54%, regardless of the bus type. Thus, it demonstrates how ITS can be used to enhance cities, making them more environmentally friendly and intelligent. Nevertheless, these studies face several challenges, including infrastructure costs, data security, and climatic volatility, as areas for improvement need to be addressed in future projects.

Keywords : Emission, Mobility, Intelligent Transport Systems, Smart City, Energy.

General introduction

The accelerating pace of urbanization has transformed cities into hubs of human activity, with a more densely populated urban area now expected to grow significantly in the coming decades. This shift has heightened the demand for efficient and sustainable transportation systems, which are crucial for economic prosperity and a high quality of life. However, the continued reliance on fossil fuel vehicles for transportation has exposed them as one of the significant causes of greenhouse gas emissions and environmental pollution. In this context, the concept of a "Smart City" has been coined, a futuristic idea that has revolutionized and created a new frontier in the urban world. A Smart City is not just an innovation; it is a system in a world. The promise that a Smart vision presents is a challenging umbrella, which incorporates perfected technology, information technology, and green energy to redesign the city's structure and transportation system.

However, at the center of this change process, it is critical to identify how innovation through an integration of technology fulfills the organization's responsibilities to the environment. Around the world, efforts to fight climate change have led to more electric and hybrid cars replacing gas-powered vehicles, along with better traffic management systems. We remark that some countries are using policies and incentives to encourage this shift, which seems promising for growing cities, incentives haven't been fully studied yet. High-level communication applications and the integration of IT help promote the strategic routing of traffic while consuming less fuel, thereby reducing emissions and laying the foundation for a smart city.

This thesis focuses on the potential of ITS to enhance sustainability levels in urban areas by proposing and evaluating new traffic control and efficient driving strategies. Specifically, while operating in the Tunisian urban environment, the system incorporates the following aspects of ITS: dynamic traffic signal control, a Fuzzy

Logic-based speed advisory system, and a new eco-driving model utilizing a large language model and reinforcement learning.

This research aims to expand knowledge on transition energy, smart cities, and smart transportation, focusing on improving sustainability in the Tunisian urban environment. It is designed to create and assess ITS-based measures, including dynamic traffic signal control, Fuzzy Logic-based advisory speed control, and a new eco-driving framework that combines Large Language Models and reinforcement learning to address the interrelated issues of energy, emissions, and traffic throughput. This thesis is achieved through five chapters dedicated to the research.

Chapter 1: establishes the conceptual framework linking energy transition, smart cities, and intelligent transportation systems to sustainable development. The chapter examines energy transition fundamentals, explores smart city components and applications, investigates smart transportation evolution and systems, and analyzes how ITS enables effective traffic management in smart urban environments.

Chapter 2: summarizes the methodological framework by presenting the research methods, tools, and simulation platforms used in this study. The chapter examines traffic signal control systems along with communication technologies, eco-driving approaches. Additionally, it presents the adopted Artificial Intelligence and Machine Learning tools, while comparing conventional and electric vehicle technologies, and outlining the key performance indicators in the thesis.

Chapter 3: demonstrates the practical application of these concepts through a field study evaluating adaptive traffic signal control at urban intersections. The chapter examines adaptive and coordinated traffic control systems along with Green Light Optimal Speed Advisory (GLOSA) technologies. It presents a case study on the Mouhamed V signalized intersections featuring Fuzzy Logic-based speed advisory algorithms and various signal control strategies integrated with V2X communication. Finally, it analyzes the resulting energy efficiency and emissions reduction achievements while addressing limitations and future research opportunities.

Chapter 4: builds upon the approach introduced in Chapter 3, expanding the focus to public transportation by examining energy consumption patterns and profiles of bus fleets. The chapter reviews the state-of-the-art in bus optimal speed advisory systems and eco-driving models, presents the design and implementation of a Fuzzy Logic-based Green Light Optimal Speed Advisory (FL-GLOSA) algorithm with detailed study zone characteristics and simulation setup. Additionally, it analyzes energy efficiency and emissions reduction achievements while discussing real-world implementation challenges and future research directions.

Chapter 5: describes an advanced eco-driving system suitable for diesel, electric, and hybrid buses while accounting for various factors. The chapter examines the state-of-the-art on ambient temperature's influence on energy efficiency, the role of LLMs in autonomous driving, and Machine Learning-based eco-driving models, and presents the design and implementation of **LARBEM** (**L**arge language model-based **A**gentic **R**eAct **B**us **E**co-driving **M**odel). With detailed study zone characteristics and simulation setup, the chapter analyzes energy consumption and emissions reduction achievements while comparing results with previous studies and discussing real-world implementation challenges and future directions.

Chapter 1 : Smart city and smart transportation for a sustainable development

Introduction

In the ongoing process of evolving in urbanization and increasing demand and need for power and sustainability, the concept of a Smart City (SC) in transition and sustainability reflects humans' innovation and efficiency maximization ability. The idea of smart cities (SCs) is a collaborative process in balancing edge-cutting technology, data-driven, and green power approaches in a city's infrastructure. SCs do their level best to improve the life conditions of humans with operational modes of transport in working conditions for an efficient carrying of both humans and merchandise in a short time, with wastages and pollutants in their least state in judicious conservation of resources. Not only do smart cities tackle contemporary societal issues, but they pave the way to a greener future in a better way in every definition. This chapter discusses the nexus among transition in energy, SCs, smart transport, and their complementary contribution based on Intelligent Transportation Systems (ITS), which define future cities and their potential to develop better cities in prosperity for achieving sustainable development.

1.1 Energy transition

The goal of addressing both climate change and reducing greenhouse gas emissions (GHGs), along with ensuring efficient resource usage, has added pressure on energy transition (ET) as a significant path toward a greener future. ET is a systematic process away from traditional carbonaceous energy resources, such as oil, coal, and natural gas, and towards cleaner and renewable resources, such as wind, bioenergy, hydropower, and solar (S. Chen et al., 2023; Kabeyi & Olanrewaju, 2022). The transition is not a matter of switching resources. Still, it includes fundamental shifts in production, distribution, and usage in the energy system based on technology, policies, and societal pressure on sustainability. In a quest to converge with global models, the transition in the energy system is a basis for attaining a level of sustainability in economic growth, enhanced energy security, and the prevention of environmental destruction.

Energy transition significance extends across four interrelated areas, which include environmental, economic, societal, and technological. It challenges conventional patterns in the energy field in favor of a digitalized, decentralized, and decarbonized system that supports resilience and inclusivity. Limited fossil fuel (FF) reserves have forced society to take necessary actions to manage dangerous environmental issues caused by these elements. Current discussions about the energy sector transition promote crucial steps toward renewable technology integration for power production, improved power utilization methods, and the creation of low-emission urban infrastructure technologies and industrial processes.

1.1.1 Brief overview

The transition in energy is a process known for its complexity, involving the departure from FF, increasing energy efficiency, and utilizing sustainable resources. Policy debates, collaborative efforts, and technological innovation are required to drive investment decisions and achieve sustainability goals by increasing ET efficiency worldwide by 30% by 2035 (Petit, 2017). It involves investment in emerging technologies and driving innovation in the renewable energy sector (Adelekan et al., 2024). The transition in energy is necessary to mitigate GHGs, avert climate change, and offer a future with sustainability. The ET depends on having specific aims in diverse scenarios and overcoming setbacks such as pandemics, supply chain backlogs, and war. "The success in the transition in energy to achieve a lower carbon fossil-free future depends heavily on how efforts are collectively aligned with specified aims in diverse scenarios." (Kaspar & Kunsch, 2022). So, in order to achieve this goal, a cohesive strategy that bridges global challenges with actionable solutions is essential. This requires not only setting clear objectives but also adapting to disruptions while maintaining momentum toward a sustainable, low-carbon future.

Sustainable development policies prioritize transitioning to renewable power and enhancing power efficiency, and models such as Renewable Energy Communities support these policies. “Sustainable development policies highlight the need to transition to renewable energy and improve energy efficiency to achieve economic, social, and environmental sustainability″ (Kaspar & Kunsch, 2022). Countries worldwide have committed to increasing the proportion of renewable energy and reducing emissions by 84% (Song et al., 2024). Meanwhile, there are different challenges and priorities related to the transition in energy which is gradual, but there are also experiences with rapid transition on a different scale “Naturally, such divergent views of energy citizenship can create tensions and incoherence between different scales in terms of what form public engagement should take.” (Wahlund & Palm, 2022).

The process of transition in energy has attracted a great deal of attention in recent years because there is growing concern regarding global warming and the necessity to abandon fossil fuels. This transition represents a fundamental change in how societies produce and consume energy, aiming to overcome environmental issues, enhance security in the field of energy, and promote sustainable development, especially in the transport sector. To better understand the intricacies of this multifaceted transition, it is essential to dissect its components and examine how various elements interconnect to drive this pivotal shift in the global energy landscape.

Figure 1.1 explores the critical components of the energy transition, shedding light on the pivotal role of renewable energy sources, technological innovation, policy frameworks, and societal engagement in shaping the future of energy production and consumption.

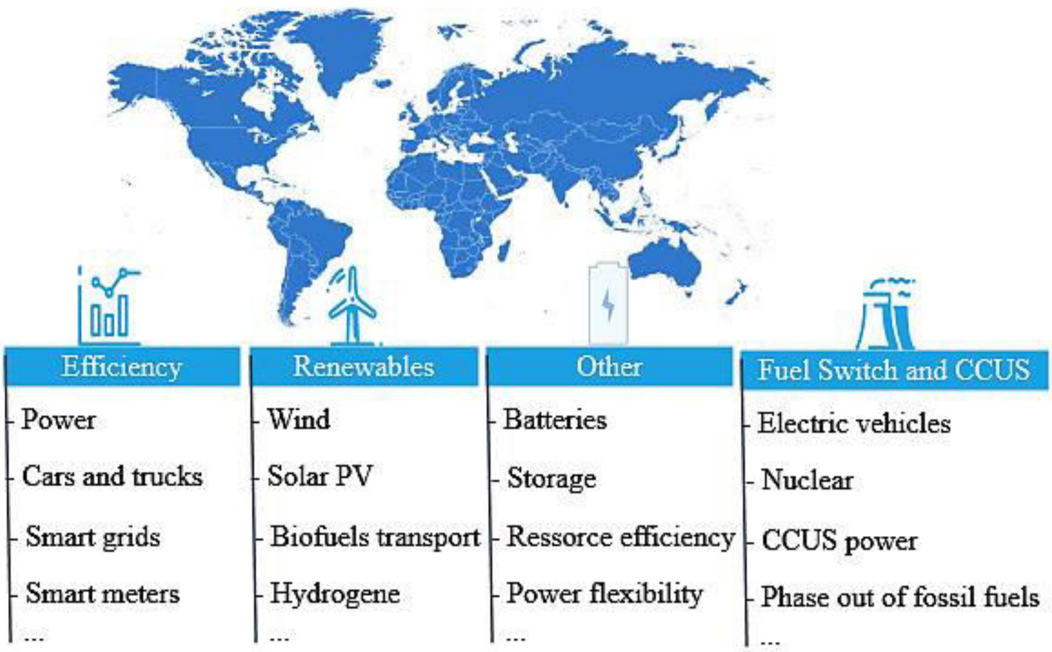

Figure 1.1. Energy transition components (Pastukhova & Westphal, 2020)

The previous figure provides the main components capable of defining the energy transition. We mention the following components: First, energy efficiency is a valuable gauge of the amount of energy gained in proportion to the total energy supplied to avoid wastage of energy and minimize the consumption of energy resources to get better results while decreasing energy consumption and related costs. The second and third elements, switching fuel sources and renewable energy, are in close and intrinsic connection with the greater transition in the energy space. Switching fuel sources supports integrating renewables' role by replacing conventional carbon-emitting fuels with cleaner resources. Solar, wind, and hydropower are also transitioning from coal, oil, and natural gas to lower-emission fuels such as natural or cleaner hydrogen-derived ones. The last component is technological advances, especially in enhancing batteries, developing new energy storage devices, implementing sophisticated power management systems, etc., aiming to tackle essential problems when integrating renewable energy systems. These components are pivotal in mitigating climate change, enhancing energy sustainability, lowering energy production costs, and offering economic and environmental benefits for more sustainable development, particularly in the transport sector.

The energy transition components are essential for GHG reduction and clean energy promotion. The transport sector has a significant role in curbing global warming. It could play an essential role in combating climate change with the introduction of efficient technologies and a move toward electric vehicles. By developing other fossil fuel substitutes or advancing the capacities of batteries or smart power management products, the transport sector could advance even faster in lowering greenhouse gas emissions and fostering a sustainable future. Investing in renewable infrastructure, e.g., solar-powered vehicle charging points, could reduce the dependence on fossil resources in the sector. Moreover, the transport sector can achieve sustainability by creating hydrogen fuel cells and biofuels as clean alternative energy technologies. A sustainable environmental outcome, together with decreased dependence on fossil fuels, enables the reduction of energy production expenses, which creates beneficial circumstances for economic growth while protecting the environment.

In order to move beyond the initial overview, we need to focus on the benefits and specific goals underpinning the energy transition. These benefits and goals comprise a variety of necessary goals and benefits, such as the mitigation of climate change, energy security, and sustainable development. The following section will address these goals and benefits in detail.

1.1.2 Main goals and benefits

The ET marks an essential transformation in energy toward achieving important targets and creating multiple advantages. At its core, the primary goal of the energy transition is to fundamentally transform how societies produce and consume energy, aiming for a sustainable, resilient, and environmentally responsible future. Some key goals of the energy transition include:

The focus is on achieving economic, social, and environmental sustainability by shifting away from fossil resources and towards renewable resources, in order to improve energy efficiency and to increase awareness of energy consumption. We assert that the Renewable Energy Communities (CER) is a viable model to finance redevelopment projects in urban areas and instill responsible actions to protect the environment (Cavallaro et al., 2023). In Nepal, the energy transition involves transitioning from traditional energy resources to cleaner ones like hydropower, biogas technology, and solar home systems, leading to lower the environmental impacts in rural areas (Pokharel & Rijal, 2021).

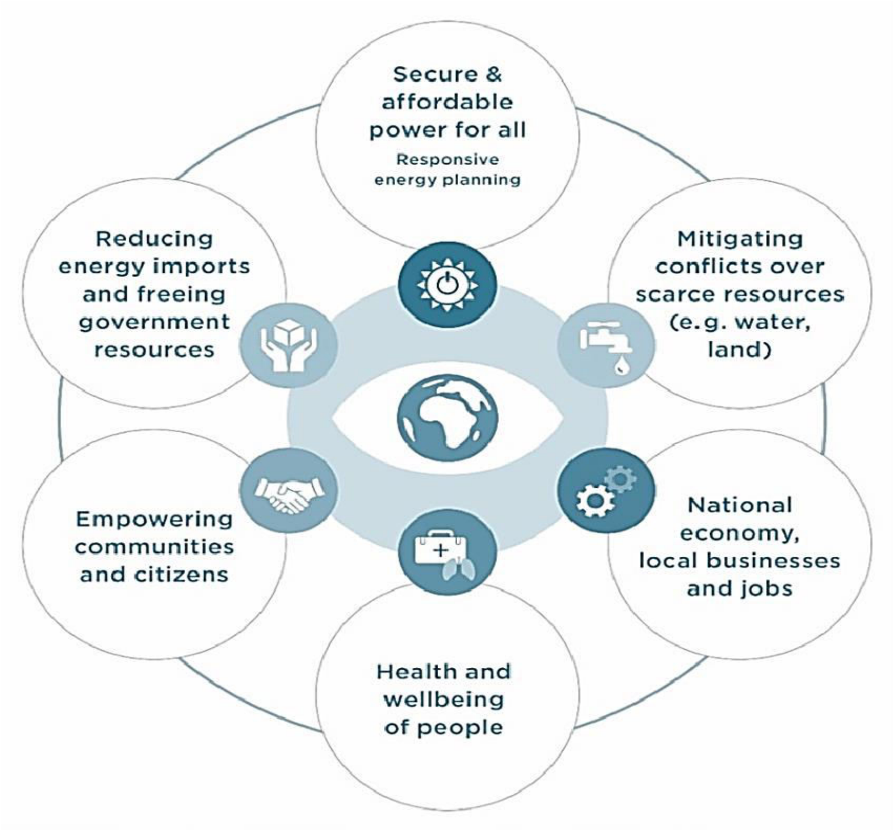

Figure 1.2. Energy transition advantages (Quitzow et al., 2019)

Based on Figure 1.12, the energy transition brings forth a multitude of advantages:

Firstly, the advantage of this strategy is providing a lower-cost entrance to clean energy, which leads to the accomplishment of the Sustainable Development Goal and the promotion of clean, renewable power. The transition is paving the way for the future, where power is not only cheaper but also more sustainable. Secondly, the transition has profound environmental benefits; for example, the transition of sources from coal and oil to wind, solar, and hydropower resources resulted in GHG emissions reduction, which plays a major role in the response to climate change. Thirdly, Energy security has substantially improved thanks to the shift to renewable energy sources that provide diverse, sustainable options for power production, which avoids market instabilities and power disruptions between energy sources, which plays a key role in building and sustaining a better life in the world.

Fourthly, the energy transition process becomes a driving force behind creating new jobs in addition to economic expansion. Fundamentally, renewable energy keeps expanding through extensive investments directed at renewable technologies, infrastructure, and research initiatives. The increased energy transformation creates additional job markets, which contribute to improved economic success. Fifthly, ET in transportation produces three critical benefits: lowered GHG emissions, cleaner air quality, and reduced fossil fuel usage.

The road transportation sector can potentially contribute significantly to mitigating climate change and promoting public health by transitioning to cleaner forms of energy, including renewable fuels and electric vehicles. The ET in this sector can, in addition, drive technological advancement and innovation and lead to the creation of new jobs and economic growth. Besides, the transformation into electric vehicles and renewable fuels can also reduce consumer and business costs by 30-40% in the long run, while reducing costs and releasing financial resources, which allows the resources to be invested in other areas and promotes economic growth and development even further (Al Shurideh et al., 2025; Chatuanramtharnghaka et al., 2024).

Overall, the transition to cleaner forms of energy in the transport sector has environmental and health benefits and also yields economic gains at the societal level. Lastly, the transition to clean energy translates to improved health in the population. By reducing air pollution and the attendant health hazards, cleaner forms of energy translate to healthier societies. During the shift toward clean energy, the population is making health improvements. The switch to cleaner energy results in healthier populations because it decreases air pollution and its associated health dangers. The transition brings both healthcare systems and fosters overall well-being.

In conclusion, the transition process is a complex process that has its own advantages. It deals with the global threat of climate change, secures energy supply, enhances economic prosperity, and is a public health benefit. Embracing this transition is not merely an environmental imperative but a pathway to a more sustainable and prosperous future for all. The transition aims and benefits reflect a future with livable and sustainable cities combating global warming, optimizing energy efficiency, and securing resources in the future. Smart cities are looking to harness the power of wind, sun, and other renewable resources, ensuring diverse energy sources, particularly in the transportation sector, and promoting future sustainability.

As we have explored the ET goals and advantages in this section, the stage is now set to dive a little deeper into the practical applications where these goals are being put into practice. Application domains included those associated with transitioning to cleaner and more sustainable energy sources in various aspects of life. Later, in the subsequent sections, we will go over these applications, renewable energy sources, their efficiency measures, etc.

1.1.3 Energy transition application domains

The application domains for energy transition include optimizing energy production and shifting from fossil fuels to alternative and eco-friendly sources that promote sustainable practices in various sectors, as presented in Figure 1.3.

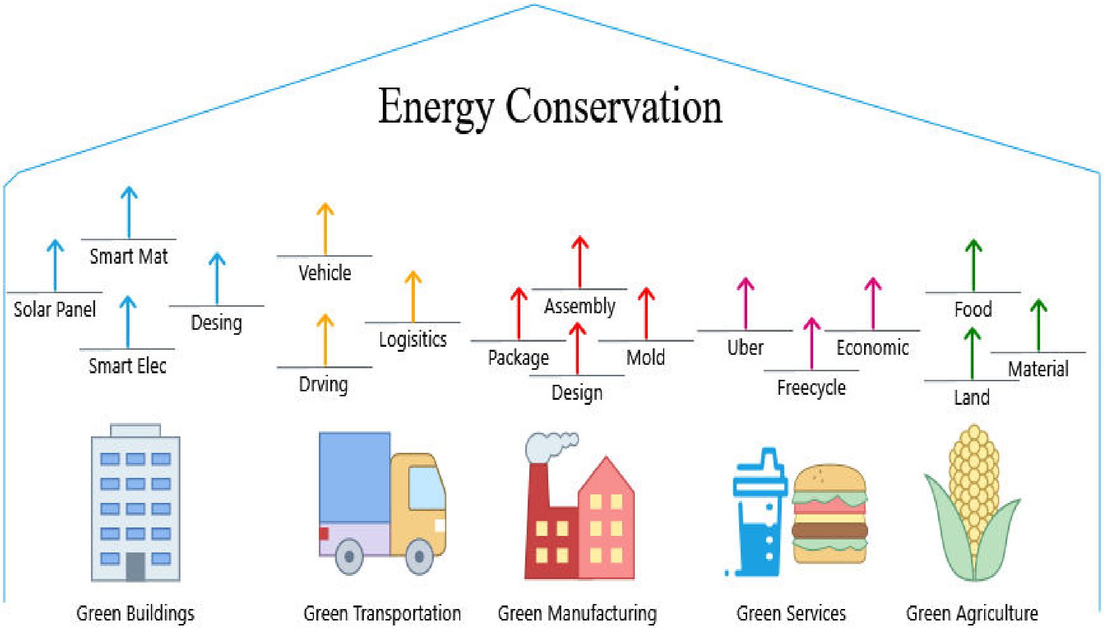

Figure 1.3. Energy transition domain of applications (S. Yi & Zou, 2023)

The concept of transition in energy encompasses an exhaustive list of sectors of application, and all these sectors are important in advancing sustainability and reducing carbon footprints. Most notably, it extends and reaches various sectors such as green buildings, green mobility, green production, green services, and green agriculture. Green buildings encourage environmentally friendly, energy-efficient buildings with renewable energy and sustainable materials. Green transportation encourages sustainable mobility solutions like mass transit and electric vehicles. Green manufacturing involves using processes to minimize the strain put upon the environment. Green services provide professional support as well as capital for sustainability. Still, agriculture is the switch that encourages sustainable agriculture measures as well as renewable energy use in order to promote a greener and more prosperous future by addressing environmental challenges. ET has a major impact on other components of the city, varying from efficient buildings and EV infrastructure to smart grid systems and distributed generation.

These applications synergistically complement SCs' broader aims, paving the way for cleaner and more sustainable urban landscapes, as indicated in Figure 1.4.

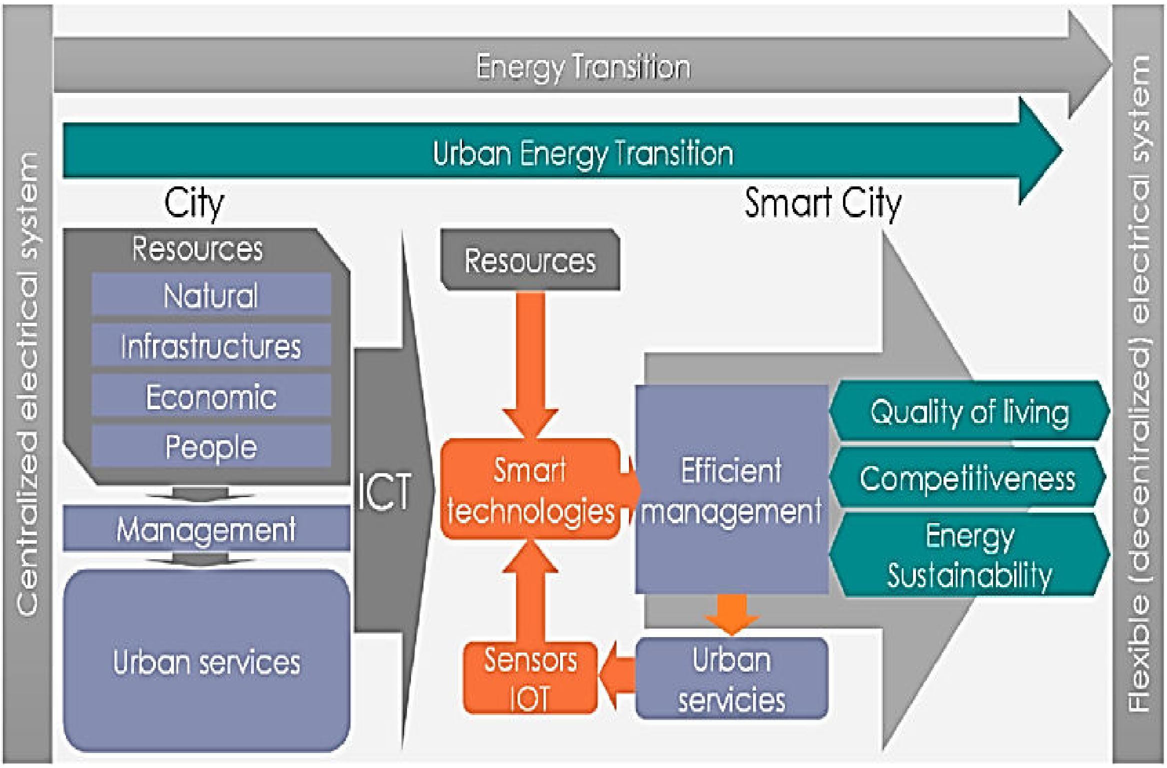

Figure 1.4. Energy transition and Smart cities (Villa-Arrieta & Sumper, 2019)

In response to global calls for environmental responsibility, the energy transition under the Smart City model takes center stage. By adopting renewable and sustainable energy resources, cities embark upon the path of low carbon emissions, energy resilience, and living in harmony with nature for sustainable living, energy efficiency, and environmentally friendly transportation, as seen in the previous figure. Through the diverse applications of ET, we notice one remarkable destination, which is the beacon of innovation and green progression, which is Smart Cities. Within the vibrant tapestry of ET applications, SCs stand out as hubs where clean and efficient energy principles find dynamic expression.

In the following section, the role of Smart Cities as energy transition innovation hubs is explored, with cutting-edge technologies and solutions rooted in data coming together to fuel sustainable and resilient city living.

1.2 Smart cities

The rapid growth of technology happened because of the growing urbanization of the world's population, over 56%, which gave birth to the notion of the smart city as a new paradigm for city growth (Sonet et al., 2025). A smart city combines the use of information and Intelligent Communications Technologies (ICT), data analysis, and green measures in efforts to upgrade the quality of city living, optimize the use of resources, and drive the economy (Al-Mujahed, 2024; Mehmood et al., 2024). As city centers struggle with rising traffic jams, ecological deterioration, and limited resources, the drive for the implementation of the smart city is geared toward the provision of productive, livable, and sustainable places that meet the intricacies of contemporary city living.

The underlying foundation of a smart city is the strategic use of digital technologies in gathering, evaluating, and responding to large flows of city-level data, thereby enabling more responsive and effective governance. By leveraging the use of technologies like the Internet of Things (IoT), artificial intelligence (AI), and big data analysis, smart cities enable the monitoring of city-level systems in real-time, improved decision-making, as well as citizen engagement (W. Shafik, 2024; Wolniak & Stecuła, 2024; Zarrabi & Doost Mohammadian, 2024). These fusion transposes traditional city infrastructure into dynamic networks that can be configured according to the requirements of society. As the world's cities strive with each other to meet the ideals of sustainable growth and resilience, the city is seen as a necessary paradigm for dealing with city problems, enhanced economic competitiveness, and ecological sustainability.

This section covers the conceptual foundation of smart cities, their defining characteristics, objectives, benefits, and probable disadvantages. It also covers the diverse areas where the smart city approach is being applied, with its transformative capabilities across numerous sectors.

1.2.1 Definition, components, and aims

SCs, according to researchers, are urban areas that utilize technology-based solutions. “Smart Cities tend to represent the information, communication, and technological” (Allam & Newman, 2018). They have been founded to improve sustainability, livability, and resilience, where the data-driven fusion insights, technological prowess, and human-centric design converge in order to enhance its inhabitants quality of life, “the technology inherent in Smart Cities promises efficiencies and options that could allow cities to be more “inclusive, safe, resilient, and sustainable” as required by the United Nations (U.N)”(Allam & Newman, 2018).

Shifting from defining the smart city to its constituents, there is a need to break through the intricate layers that characterize these innovative urban environments, where the Smart City has several constituents working in its favor toward its functioning as well as development. These include the policies, strategies, practices, and instances of the utilization of the city, as illustrated in Figure 1.5.

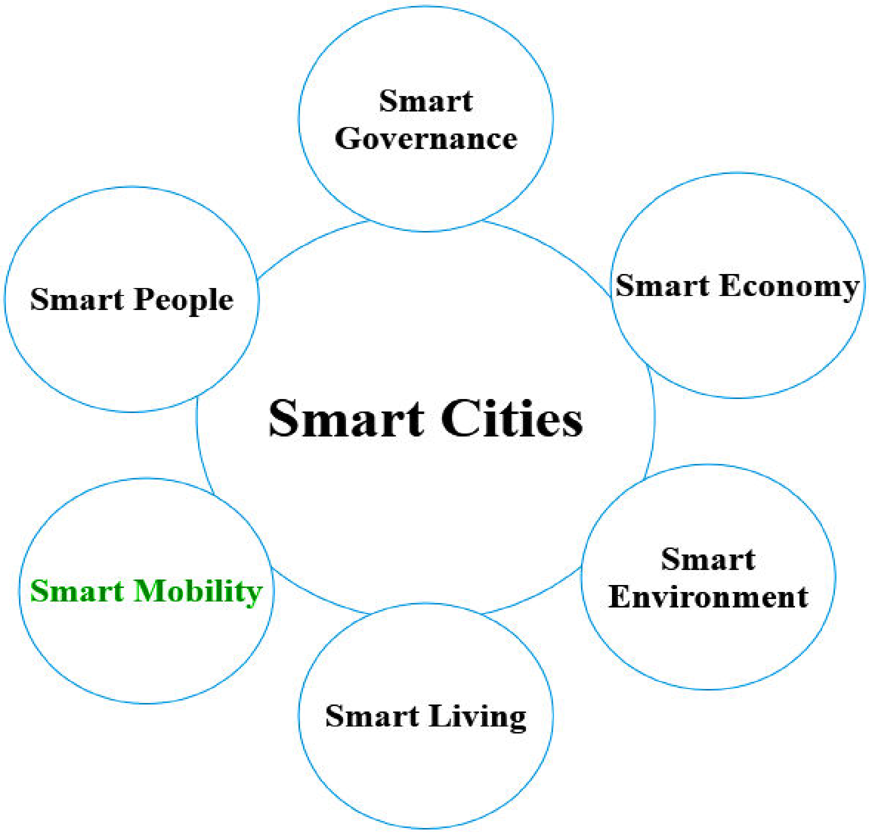

Figure 1.5. Smart cities components (Pop & Proștean, 2019)

As indicated in Figure 1.5, smart cities also involve the incorporation of data-driven technologies and solutions, such as analytics and various kinds of science, such as big data, to enhance their performance. The components also involve sustainable urban development planning, incorporating eco-city and compact urban design strategies, along with technological solutions. The ontological components of a city, such as the changed physical place and knowledge distributed in the system, also help in the understanding and description of smart cities. Smart living is also an essential component of an SC, encompassing such dimensions as a smart economy, smart people, smart government, smart mobility, and smart environment. For example, Smart People is a component concept that gives everyone equal digital access and skills, then keeps them learning and creative so they can fully use and shape the city's tech services. As we examine the components that make up smart cities, it becomes clear that each element serves a specific purpose in achieving the overarching objectives of these technologically advanced urban spaces, where it has different aims that need to be fulfilled in different domains to obtain sustainability and safety, as mentioned by the U.N.

Smart cities are a concept of urban development that aims to improve the quality of life for city residents and create more efficient infrastructure by using new technologies and data management techniques. So, these intelligent cities integrate data-driven technologies, solutions, real-time data utilization, and intelligent resource allocation to render home service and traffic green, reliable, and flexible to reduce energy use and carbon footprint for a sustainable environment, while reducing costs (Gharaibeh et al., 2017). Having elucidated the vision, components, and all-encompassing aims of Smart Cities in the previous section, attention is directed toward a sweeping examination of their virtues and faults. Though Smart Cities have a radiant vision for city expansion, there is a requirement for scrutiny of the tangible virtues they have to offer the populace, as well as the extended social world (Gharaibeh et al., 2017). However, alongside these benefits, there also have to be considered the inherent complexities and limits of implementing and sustaining Smart City schemes. This section is intended to give a balanced view, bringing out the potential returns from Smart Cities as well as the limits at which their transformative power operates.

1.2.2 Benefits and drawbacks

Similar to any other concept, the Smart City also has both advantages and disadvantages. The transformative energy potentials of the Smart City radiate through its numerous benefits: They capture the capital, talents, and users through the provision of a state-of-the-art city environment directed at the present (Marchesani et al., 2023). Developing smart cities based on the big-data approach and the rational planning theory can immensely accelerate local economic growth, optimize the operating efficiency of city businesses, as well as contribute to overall national-level growth (Xiao & Xie, 2021). Integration of technology into various aspects of citizen interaction in smart cities enhances convenience and quality of life (Park et al., 2021). Smart green infrastructure is not only resilient to climate change but also promotes the health and well-being of the people living there (Kaluarachchi, 2021). Smart cities, through the priority they give to ecological mobility as well as the optimization of resources, aim to provide people with a green, safe, as well as serene social environment (Schwarz-Herion, 2020). However, these boundless horizons are accompanied by challenges, such as smart cities, which can lead to a global surveillance society and make city dwellers vulnerable to cyber-attacks and terrorism (Schwarz-Herion, 2020). Moreover, the forceful drive toward smart cities is responsible for the rural exodus, soil sealing, and the shortage of vital resources as a result of heightened energy and material needs (Mansoori, 2021). Intelligent city, smart city, and digital city concepts frequently require distinction from one another, and the lines need to be more clearly drawn (Çinar Umdu & Alakavuk, 2020). The implementation of smart cities also faces challenges like subsystem integration, data storage, and infrastructure concerns, etc (Nikolaeva, 2022). Furthermore, the level of organization and dependence on foreign technologies varies greatly among smart cities in different regions (R. Mohanty & Kumar, 2021). As we turn from understanding the aspirations and possible limits of Smart Cities to viewing the diverse areas wherein these cities have their practical uses, we see that Smart Cities have the same ambitions as the energy transition as a whole: they are laboratories for new solutions that aim to advance sustainability as much as efficiency.

In the upcoming section, we will delve into these application domains, examining how Smart Cities integrate cutting-edge technology, policy frameworks, and community engagement to realize their aims while navigating the challenges and opportunities that lie within.

1.2.3 Smart city main applications

The concept of the Smart City requires coordination and an integral approach to integration beyond traditional city planning. Harmony among technological advancements, citizens, and the government is needed to be co-innovative and co-create new and appropriate models of governing. In the orchestration of these factors, the Smart City emerges as a responsive, adaptive, and anticipatory city. The succeeding figure shows the main area of use of the smart city.

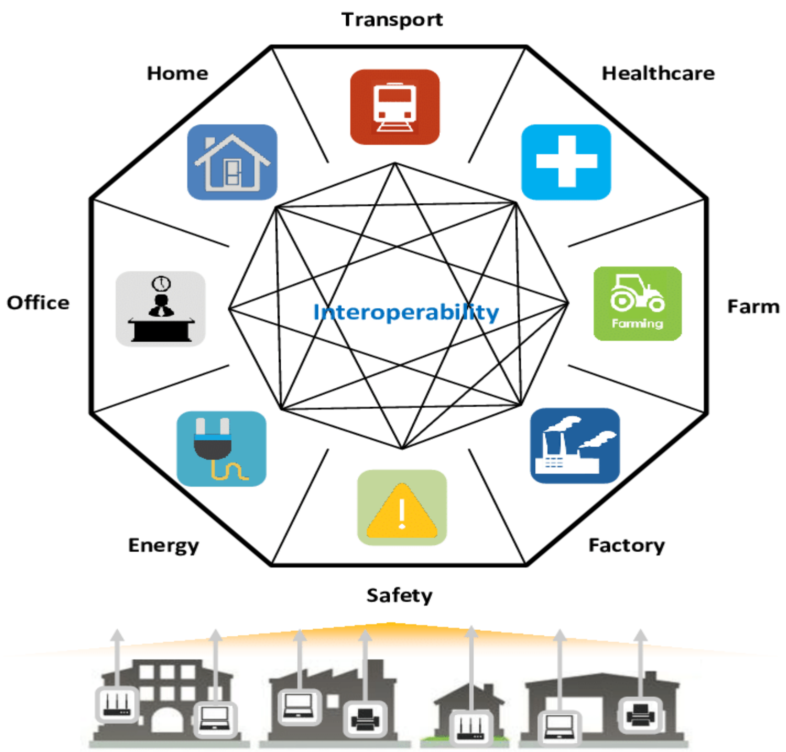

Figure 1.6. Smart city domain of applications (Ryu et al., 2015)

Smart cities have evolved into a concept that is not only concerned with cities but has expanded to different domains related to people's lives. In homes and offices, smart technologies now find their place in the world as cities produce different structures that ensure the automation and control of these structures to give the best options to their citizens. Smart city solutions have also been integrated into healthcare centers, mainly for implementing the technology for monitoring patients, using telemedicine, and managing resources for better healthcare services. Likewise, in agriculture, smart farms use smart technologies such as sensors, the Internet of Things (IoT), and information analysis to enhance crop production and prevent wastage. Underlying smart city technologies are applied in factories and industrial environments in production, safety, efficiency, and timely prevention of breakdowns. Security is an issue of concern in a smart city scenario where surveillance systems, response systems, and Artificial Intelligence (AI) analytical systems come into play. The energy sector is also not left behind; smart grid adoptions and integration of renewable energy sources are key factors in saving the planet from further harm. However, the transport sector is probably one of the most significant transforming domains for the population. Smart city progress is achieved in smart vehicles and connectivity, connected autonomous vehicles, smart traffic management, and smart public transport. These improvements allow for an optimized traffic flow by 20%, reduce emissions by 13%, and enhance the possibility of mobility for individuals within the urban environment (He et al., 2024; Miftah et al., 2025). Therefore, the use of smart city technologies spans many sectors, and the future that is anticipated is one where the lives of individuals in urban facilities are more convenient and interconnected than they are today. In the elaborated claims of Smart Cities, Smart Transportation is a consistent element that develops and transforms urban lifestyles. It is one of the critical components of Smart Cities, as it adjusts transportation and significantly affects the transition to energy balance. Smart transportation, therefore, uses technology, data handling systems, and the use of sustainable practices in order to structure transportation systems that are intelligent and effective in handling traffic-related situations within cities.

As we transition into Smart Transportation, we envision it as a central component of Smart Cities and a primary application of energy transition principles, pointing to the intertwining of these domains.

1.3 Smart transportation

The increasing complexity of urban mobility systems, driven by rapid urbanization, growth in population, and technological advancements, has triggered the transformation of traditional transportation systems into more intelligent, reactive, and sustainable systems. Smart transportation, as one of the subsets of the smart city, constitutes one of the important fields of today's urban planning that deals with problems of traffic congestion, pollution, excessive use of energy resources, which reached 50%, and infrastructural failures or hazards (Aderibigbe & Gumbo, 2024; Tariq, 2024; Yiğit & Karabatak, 2025). Its vision is to develop effective, scalable, and user-centric mobility solutions that improve the performance of urban transportation systems, thereby promoting economic development and environmental protection.

The Application of intelligent technologies in the transport sector ensures an efficient flow of traffic, efficiency in the public transport sector, and an efficient transport experience for the users. Smart transport systems help in real-time data collection and analysis of the condition of traffic, infrastructure, and other related parameters for efficient maintenance and usage of deployed infrastructures. This transformative approach brings important contributions to the development of smart cities as part of worldwide efforts to support sustainable urban mobility, cut emissions, and equalize transportation services that, if not addressed, will increase remarkably by 2030 (Amina Nalongo, 2025; Mystakidis et al., 2025).

The following section will comprehensively review the conceptual framework of smart transportation, along with its evolution, objectives, and structural components. It highlights how smart transportation systems are reshaping urban mobility and fostering sustainable development.

1.3.1 Smart transportation state of the art

The evolution of transportation within the Smart City unfolds as a narrative of disruption and innovation. A departure from traditional modes, smart transportation heralds an era of interconnected mobility, data-driven insights, and transformative urban accessibility. Smart transportation refers to using advanced technologies and systems to improve transportation networks' efficiency, safety, and security. It involves real traffic condition monitoring and management using real-time communication technologies, smart sensors, and data analytics (El Dafrawy, 2015). ST systems can provide transportation and traffic, safety management, and optimal travel services for users (Hatagundi et al., 2017). These systems utilize technologies like geographic information systems (GIS), routing web-based applications, smart cards for fare collection, and Global Positioning System (GPS) modules for tracking distance traveled (Nagappan & Chellapan, 2009; Xu et al., 2017). Smart transportation is directed towards alleviating road congestion, enhancing the use of resources, and improving the transportation experience for citizens. However, security issues like unauthorized access and attacks are obstacles to the implementation of smart transportation systems. Through the utilization of intelligent transportation systems, cities can achieve improved mobility, economic productivity, and reduced pollution. Moving from the brief description of Smart Transportation, it is necessary to focus on its development and general goals. Smart transportation is not a newly woven concept that targets efficiency, environmental impact, and overall makes the cities smarter.

In the next section, we will follow ST's history, observing how it has developed alongside changing urban landscapes and its coordination with the general ET goals. Only through its history and general purpose can we appreciate its part in shaping the future of urban mobility and energy efficiency.

1.3.2 Evolution and aims

The evolution of smart transportation aims to improve global transportation systems. There has been a shift towards electric and self-driving cars and overall innovations regarding traffic flow and sharing economy car services. These goals align, bringing together the goals of managing congestion, increasing public transport effectiveness, promoting intermodal transport, and decreasing sustainability.

The historical evolution of smart transportation is shown below to illustrate this argument.

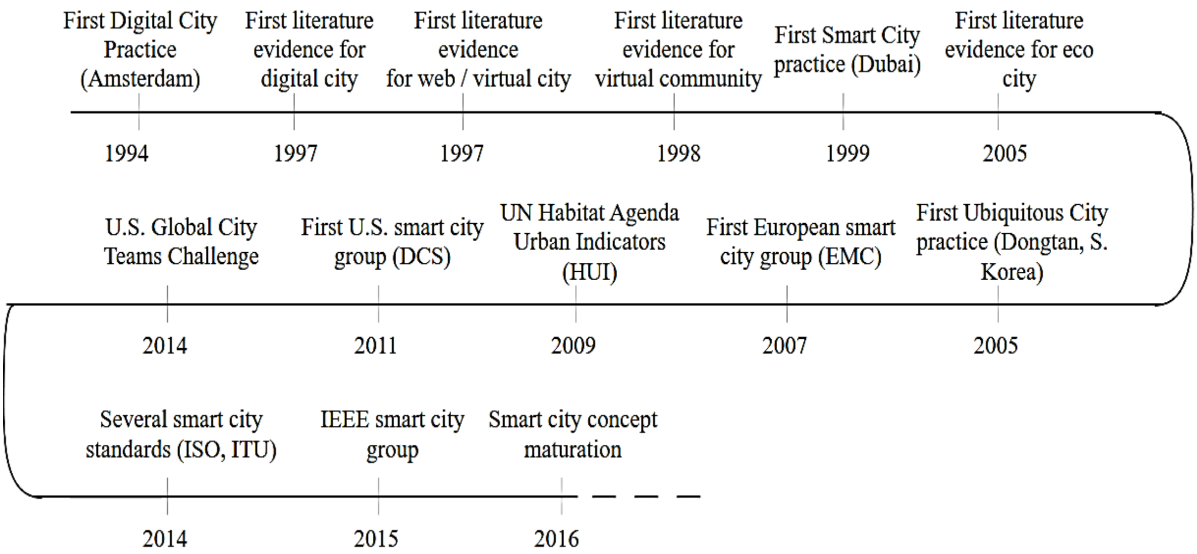

Figure 1.7. Smart transportation evolution (Anthopoulos, 2017)

The timeline illustrates that the smart city concept has undergone a significant evolution over the past few decades, as illustrated in Figure 1.7.

It started in the year 1994 with the Digital City Practice in Amsterdam, signifying the first form of coupled attempt at putting digital networks into a built environment. According to the literature reviewed within the current study, the concept of virtual cities was first introduced in academic discourses in 1997. The very early literature on digital cities encompassed the possibilities of web-based and virtual cities. This was succeeded by virtual community studies in 1998, which sought to understand how people could form new types of associations that stemmed from the trend toward digital networks. The timeline continues to identify another significant event that happened in 1999, which is the physical manifestation of Smart City when Dubai practiced it as an actual concept. Two significant achievements took place in 2005: the first literature on eco-city, which focused on sustainability within cities, where South Korea had implemented the Ubiquitous City practice in Dongtan, calling for integrating technologies into people's daily lives. By the year 2007, the formation of the first European Smart City Group (EMC) presents the emerging institutional focus on SC. This institutionalization was further enhanced at the global level in 2009 by being accorded a place in the United Nations Habitat Agenda Urban Indicators (HUI). The progression was further evident when the first of the U.S smart city groups (DCS) was formed in 2011, signifying that the smart city concept had gone global, starting with the transatlantic. Since 2014, it has involved the U.S. Global City Teams Challenge, and the smart city standards were set by the International Organization for Standardization (ISO) as well as the International Telecommunication Union (ITU). Smart city technology was further endorsed by the Institute of Electrical and Electronics Engineers (IEEE) by establishing a dedicated group in 2015. This timeline up to 2016 clearly illustrates that smart cities are gradually evolving from being experiments to global concepts that combine sustainability, technological development, and policy into the operation of such cities in the contemporary world.

Like any established concept, smart transportation has come to life for many reasons, to be more specific, to fulfill a bunch of objectives, as illustrated in Figure 1.8.

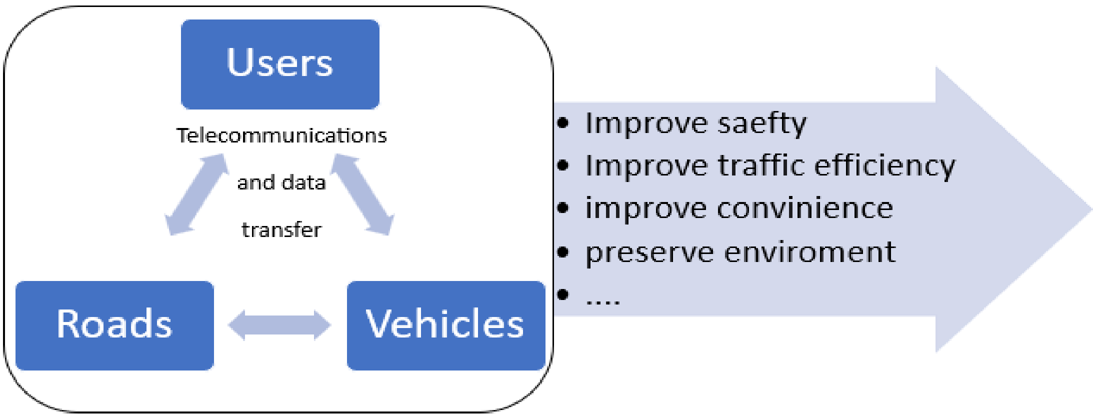

Figure 1.8. Smart transportation aims (Obana et al., 2006)

As inferred in the previous figure, Smart transportation focuses on optimizing the traffic flow, safety, and security through extra technologies such as intelligent communication technologies (ICT), smart sensors, and smart vehicles, which enable the vehicles, infrastructure, as well as users to be able to pass information to each other. The following includes reducing traffic congestion, taking the time, fuel use, and consequently, carbon dioxide emitted into the environment. It aims to cut down traffic congestion and time, fuel usage, and CO_2 emission levels. Smart transportation systems offer services that entail traffic and transportation management, safety management, and carpooling. This type of system applies optimization models and routing algorithms in order to get the best routes depending on the traffic headache and then relieve the headache by providing an uncongested route, especially during rush hours. In the same respect as smart technology applications in operation, a smart transportation system also improves the efficiency of fare collection and congestion management by employing smart cards and GPS devices. However, there is a threat, such as unauthorized access and attacks, that slows down the implementation of smart transportation systems. The general objectives of smart transportation are to increase traffic flow, decrease traffic congestion, optimize the travel delivery process, and experience fewer negative consequences for the environment. Based on the foregoing discussion of the development and redemption purpose of Smart Transportation, this paper will shift its focus toward the intricate parts of this revolutionized domain.

This section allows for identifying the elements and technologies that go underneath the concept of Smart Transportation and how they contribute to fulfilling the goals that are set. In the following section, we will provide insight into the basic constituents of smart transportation that will give an understanding of the various technologies and strategies that help make transportation systems for cities smarter and environmentally friendly.

1.3.3 Smart transportation components

Smart transport systems primarily have sub-systems that enable the achievement of their goals for efficiency and sustainability. These parts incorporate sensors and data analysis to control the flow of traffic and thereby control and minimize energy utilization and pollution, along with enhancing safety. The following figure shows how these components interact with each other to create a seamless and intelligent transportation network.

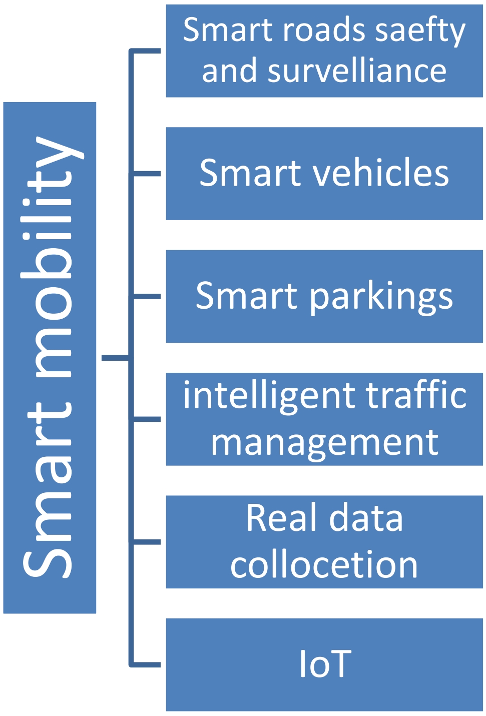

Figure 1.9. Smart transportation components (Paiva et al., 2021)

As illustrated in the previous figure, the smart transportation system consists of several components. These include smart road safety and surveillance, smart vehicles, smart parking systems, the Internet of Things (IoT), smart traffic management, etc (Paiva et al., 2021). These components work together to create a good and effective transport system. Smart road safety and smart surveillance enable the usage of advanced technologies like sensors and cameras to detect traffic conditions and other dangers. The features present in intelligent cars include self-driving and real-time driving directions in order to increase safety and reduce possible congestion. Smart parking systems are technically implemented by sensors and applications downloaded on smartphones to direct drivers so that drivers can park safely. The Internet of Things integrates all these, facilitating the flow of information and data between the components for the improvement of the decision-making process. Efficient traffic flow basically refers to the singling out of traffic lights to perform their job of traffic regulation optimally; this is done by using smart data analysis on traffic flow patterns through the use of efficient algorithms. These are parts of integrated smart transportation systems that should work together towards increasing safety, decongestion of traffic, and generally enhancing the comfort of transport. A whole smart transportation system also includes additional components such as predictive maintenance, a smart ticketing system, and automated toll collection. Predictive maintenance uses data analytics to anticipate and prevent probable vehicle and infrastructure issues or breakdowns. This contributes to a seamless and dependable transportation network by minimizing interruptions. Integrated ticketing is an efficient and contactless payment option that passengers can use to access different modes of transport. The automatic toll system allows for paying tolls and eradicating congestion at toll booths. These components enhance the effectiveness and utility of a smart transportation system. After analyzing the elements of Smart Transportation, it has taken us to present one of its core elements, namely Intelligent Transportation Systems. ITS significantly contributes to improving mobility in terms of capability, safety, and sustainability in the urban environment.

In the next section, we are going to delve into ITS and its relation with Smart Transportation in detail to make necessary positive changes in transport and to build smart networks on a foundation of vehicular information communication technology that holds the potential to make cities intelligent and efficient.

1.4 Intelligent transportation systems

Higher complexity levels of urban mobility observed in the development of urban spaces, coupled with technological advancement and the need for efficient transport systems, make the development of transport networks more intelligent, dynamic, and optimal. ITS has, therefore, been developed as a progressive approach to implementing innovative technologies, the use of data, and communication initiatives aimed at improving overall mobility (Verma et al., 2024). Therefore, ITS uses current information and technology systems to offer effective traffic management, environmental impact minimization, safety, and provision of uninterrupted mobility experiences (Verma et al., 2024).

ITS represents a critical element in the development of modern urban environments and plays a central role in achieving the objectives of smart cities. It contributes to the improvement of the transport systems in terms of sustainability and efficiency because it connects and coordinates different modes, manages the traffic, and informs the users in real-time. They also help minimize traffic problems, including emissions of greenhouse gases and the risk of accidents and injuries by 30%, when modern technologies are employed in their operation (Aditya et al., 2025).

This section aims to explain ITS to begin with by explaining what it entails, what it is composed of, and how it can be of significance in traffic management within the smart cities' domain. The goal is to emphasize the importance of ITS, which would improve the accessibility of automobiles in urban centers, spearhead tactful, environmentally friendly standards, and contribute to economic development.

1.4.1 Definition and functions

Intelligent transportation systems (ITS) can be defined as communication and information technology systems that are designed to offer comfortable, efficient, and secure transport services to users (Tyagi & Sreenath, 2023). These systems involve the integration of vehicles, technologies, sensing devices, and surveillance cameras to achieve intelligent transportation (Jawad & Nitulescu, 2023). It incorporates intensive application of artificial intelligence, neural networks, and necessary techniques for recognizing and categorizing objects as well as behavior. Thus, ITS applications are different from specifications related to some equipment and involve the analysis of transportation problems and their optimization (Ghatee, 2021). Regression, clustering, and classification models, which are categories of optimization models, are employed to acquire insight and solve transport problems (H. Li et al., 2023). The ITS main goal is to enhance the transportation systems through the utilization of sensor networks, electrical appliances, and computerized units. It is evident that ITS is highly relevant within the smart city paradigm and provides mobility services for urban and inter-city networks. It stands a lot for technological innovation for mobility, using computers to monitor and collect real-time information, advanced communication systems, and various algorithms.

After defining the ITS, and as with any other established system, the ITS also has main functions. ITS aims to improve overall mobility and transportation management. Let's delve into some key ITS functions that are pivotal in achieving these objectives, as illustrated in Figure 1.10.

Figure 1.10. ITS functions (Hess et al., 2009)

According to the previous figures (Figure 1.8 and Figure 1.10), Intelligent transportation systems have many tasks and functions, which consist of traffic management, transportation planning, traveler information systems, and vehicle control systems. The traffic management system is used to help manage traffic by using the data concerning the traffic, real-time traffic signal control, and traffic incidents. It is the process of data analysis and modeling to identify the transportation and infrastructure, and to plan for the improvement of the transportation system. Traveler information systems used to provide real-time information to travelers with regard to the traffic conditions, schedule of transit schedule, and the number of available route options. Some examples of vehicle control technologies include adaptive cruise control and collision avoidance systems, among others, that have the goal of improving the safety and efficiency of vehicles on the roads. Altogether, all these functions cooperate in developing an advanced transport system, not forgetting the data transfer in addition to the communication part that it entails between three significant parts, which include the users, infrastructure, and vehicles. Having clarified the ITS definition as well as its core tasks, it is now essential to describe ITS as the set of practical implementations in urban settings. As an innovative technology solution with the vision to enhance mobility through the efficient management of data and its application to transport systems, ITS plays a key role in the development of smart cities and sustainable living in urban environments.

In the subsequent section, we will describe the components of ITS that enable its integration into the urban environment. This transition will clarify that ITS is a versatile approach to solving the challenges that different sectors and elements of urban systems.

1.4.2 ITS components

As we continue with the implementation and use of Intelligent Transportation Systems (ITS) within the urban context, the dynamic, as well as the diversity of ITS, is more apparent as it continues to evolve with the developing needs of the smart city, wherein there is a need to identify its constituent parts. These components are akin to the building blocks in which a multitude of innovative solutions can be erected in order to fulfill the objectives and functions mentioned earlier. Figure 1.11 illustrates the main ITS components.

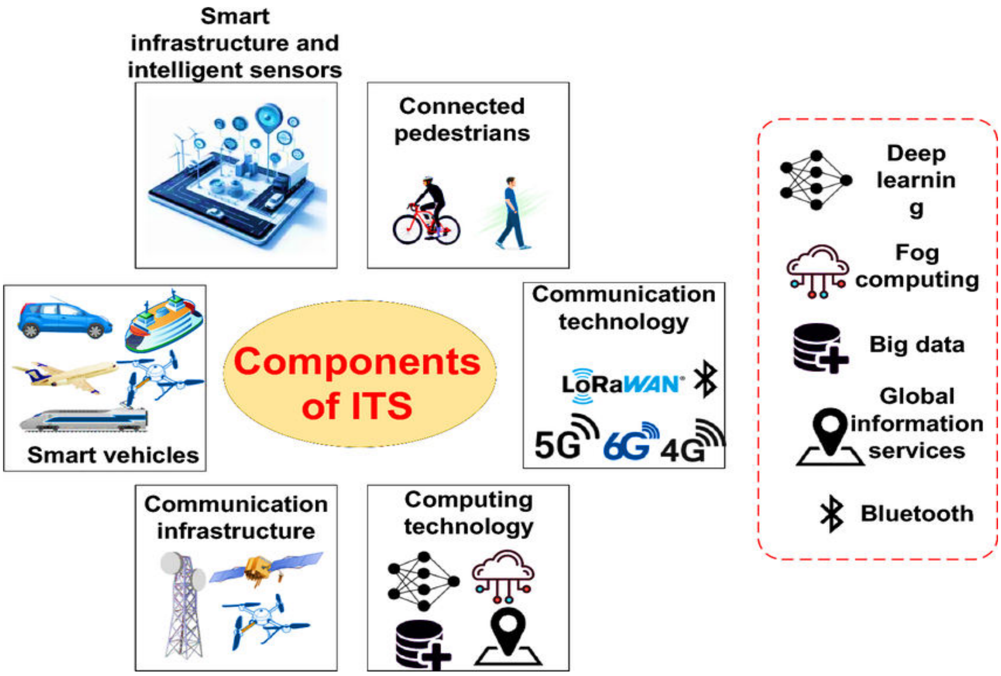

Figure 1.11. ITS components (Vidyakant et al., 2024)

An analysis of the figure reveals that ITS consists of important components, including smart infrastructure combined with intelligent sensors and smart vehicles, as well as connected pedestrians and communication infrastructure and computing technology, followed by advanced communication technologies. Smart infrastructure enables the free exchange of information between different ITS components, while computing technologies enable sophisticated decision-making and data processing. Smart vehicles are self-controlled and interconnected, with various categories that improve traffic safety as well as their effect on the environment. Connected pedestrians contribute to traffic optimization by enabling safe interactions between individuals and transportation systems. Communication means allowing efficient, smooth, and integrated passing of information between the various components of an ITS. On the other hand, computing technologies mean systems that enable the proficient and efficient processing of information in order to reach an informed decision. These components complement one another and work to optimize traffic flow, minimize congestion, and enhance road safety, fostering sustainable, efficient, and livable smart cities.

Cities can solve the intricate challenges of mobility in the urban environment by connecting informatics, transportation, urbanism, and economics. For this reason, Informatics provides policymakers with information on traffic patterns that help them make rational decisions. Transportation planning ensures that the mode of transportation is well equipped to support physical needs, while urbanism ensures that the structures are well prepared to support transportation in their procedure of development in the metropolitan area.

Generally, it is important to understand the components of ITS to appreciate their various aspects in relation to the context of smart cities. They are the basis for various solution requirements to tackle the intricate mobility problems of such cities. Now, we will discuss how these ITS components can be synergistic and sustain many applications in creating smarter and more effective cities.

1.4.3 ITS applications for traffic management in smart city

The realm of Intelligent Transportation Systems (ITS) is vast and consists of networks of sensors fusing data algorithms, communications protocols, and end-user interfaces. ITS applications are so vast that they can be found in intersections, highways, mass transit networks, and more, enabling a cohesive transportation system.

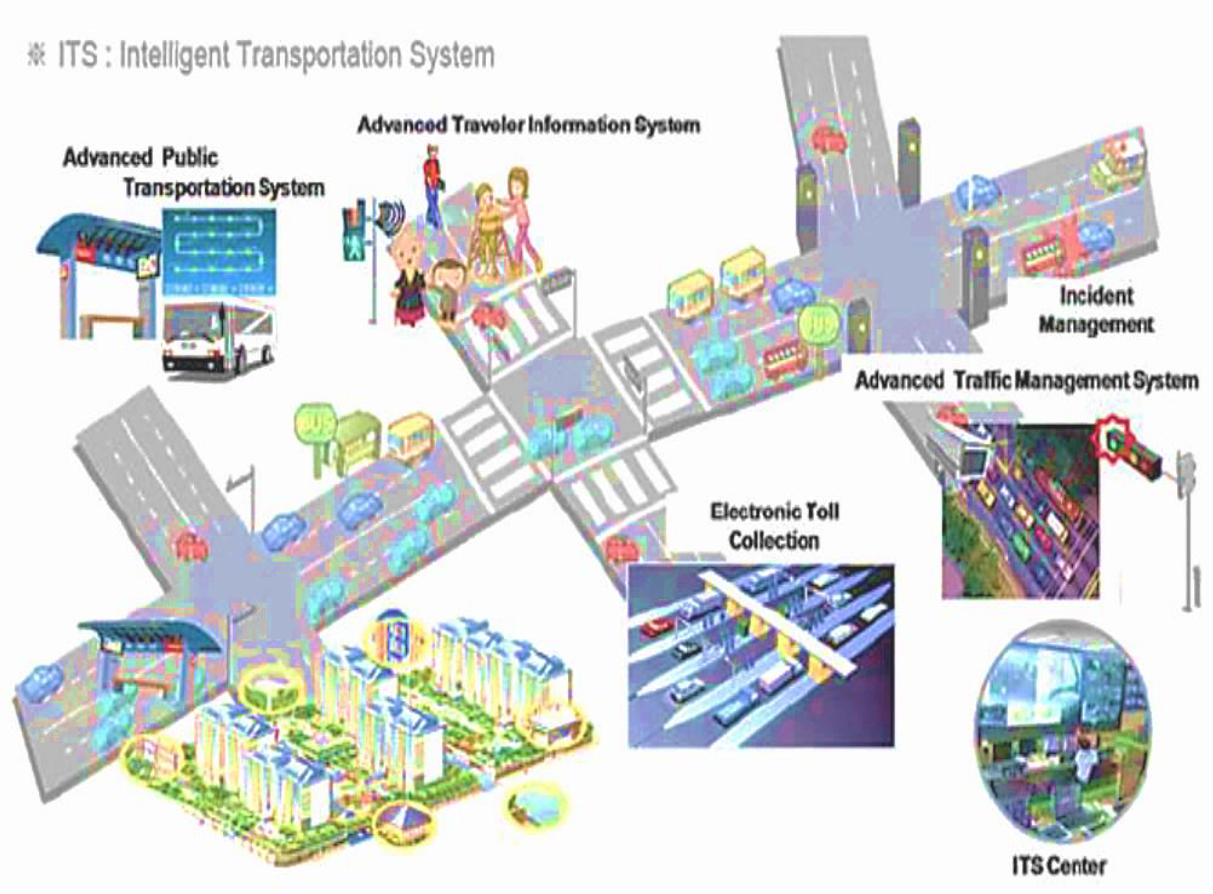

Figure 1.12. ITS application Domains in a Smart city (Sherazi, 2013)

We can see from Figure 1.12 that ITS has many applications in smart cities, such as emergency services, traffic management, parking systems, public transit, and environmental monitoring. These ITS applications contribute to a city's overall efficiency and sustainability by decreasing traffic congestion, improving transit routes, and ensuring citizens' safety and security. In addition, ITS plays a significant role in enhancing the connection and accessibility of many city-level services, such as healthcare, education, and entertainment, from the perspective of livability and ease of the city for the citizens, along with many other applications in building an integrated and connected city landscape. For example, ITS can be applied in smart parking systems, which can guide vehicles through the use of real-time information. It saves the hassle and time of parking as well as avoids energy waste from using the car, emissions, as well as traffic jams. Furthermore, ITS can also be used for the networks of the public transportation system in order to help people access various modes of transportation, as well as promote environmentally friendly modes like buses and trains.

Overall, ITS's numerous uses contribute toward the development of sustainable, eco-friendly cities with a focus on efficiency, security, and comfort. In traversing the intricate landscape of Intelligent Transportation Systems and Smart Transportation, we have uncovered the transformative potential of these innovations in defining the transportation system of the future, as well as energy efficiency. From their past development through their extensive uses, we have seen how these innovations have been the linchpin toward achieving the vision of the smart city and the energy transition objectives with the use of Smart mobility and ITS.

As we draw this chapter to a close, let us now consolidate our insights, recognizing the pivotal role of Smart Transportation and ITS as catalysts for sustainable urban development and the pursuit of a greener, more efficient tomorrow.

Conclusion

In this chapter, we had a basic view of energy transition, smart cities, smart transportation, and ITS, as well as the link between all of them. The symphony of smart transportation and SC harmoniously plays out on the grand stage of sustainable development. As cities become more populated, the concepts described in this chapter act as a light of hope for resilient, energy-efficient, and livable city dwellings. By combining the brilliance of the age of technological advancement, the energy and transportation revolution is needed for an eco-friendly, sustainable future. It also serves as a prelude to the transformative potential that awaits us as we navigate toward a future defined by the equilibrium between urban dynamism and ecological responsibility. In the following chapter, we will see information about the chosen city and the methodology used to model it, which will be turned into a smart city.

Chapter 2 : Methodology and formulations for smart traffic systems: from dynamic signal control to intelligent speed advisory

Introduction

This chapter will thoroughly explore the technology behind intelligent transportation systems in smart cities, along with the different methods and formulas used to optimize traffic flow. Examining how changing traffic lights in response to varying traffic intensities in real-time to minimize congestion is known as Dynamic Traffic Signal Control (DTSC). Meanwhile, Intelligent Speed Advisory Systems (ISAS) refer to using technology to improve the traffic flow and reduce energy consumption in road networks by suggesting speeds for safe and ecological driving. Such advanced solutions as DTSCs and ISASs applied within smart cities may reduce travel time and energy consumption. By the end, commuters would be less exposed to harmful emissions. These applications could result in developing a smart city wherein a solution like DTSC or ISAS will be an imperative aspect of a livable urban environment.

As we delve deeper into the various components of ITS, the following section will explore the specific technologies and methodologies employed in Traffic Signal Control Systems (TSCS). By understanding the foundational principles of these systems, we will build a comprehensive view of how they contribute to optimizing traffic flow and urban mobility within smart cities.

2.1 Traffic signal control systems

Traffic Signal Control Systems (TSCS) are indispensable elements in traffic management for maintaining traffic flow and road safety and minimizing congestion and energy consumption at urban sites. These systems regulate the vehicles and pedestrians through intersections by implementing a signal network with sensors and controllers (Agrahari et al., 2024; Vieira et al., 2024). While traditional traffic lights typically operate on fixed timers or based on pre-determined sequences, their modern versions use cutting-edge technologies of real-time collection and monitoring of traffic data and Intelligent Communication Technologies (ICT) to adjust signal phases against present traffic conditions automatically (Chowdhury & Kapoor, 2024; Elassy et al., 2024a; Shrivastava et al., 2024). The Adaptive Traffic Signal Control (ATSC) system is an intelligent control that monitors traffic saturation data collected from sensors or cameras deployed at the intersection using detectors or cameras at their starting points. That's how the system adjusts its signal lengths for optimized traffic flow, reduced queue time, and minimized emissions from unnecessary idling (LOULHACI & BENSOUNA, 2024a). Besides, this may prioritize some traffic classes, such as emergency vehicles or public transportation, by extending a green light when they approach an intersection. More recently, with connected vehicles, it has included ICT so that transportation means can directly engage with traffic lights, enhancing the ability to make much more precise predictions for arrivals of vehicles and make proactive adjustments to signal timings to optimize overall traffic management (Elassy et al., 2024b; Muzzini & Montangero, 2024).

Examining the foundations of static traffic control is essential to building upon the understanding of traffic signal control systems. The following section will critically review static traffic control systems, exploring their advantages and limitations. This analysis will provide a comprehensive view of how static control systems function within traditional traffic management frameworks and highlight their challenges in optimizing urban mobility.

2.1.1 Static traffic control: a critical review

Static Traffic Management (STM) uses fixed or non-dynamic systems to control traffic flow in the interest of safety at crossroads, highways, and pedestrian crossings presented in the form of traffic lights and road signs, giving coherent guidance to drivers, cyclists, and pedestrians. Traffic lights, speed limits, and stop or yield signs are warning devices that give drivers clear and identical information. Although static traffic control has traditionally constituted the basis of urban and highway traffic management policies, there is great debate regarding its effectiveness and evident limitations. The strengths are that static systems are engineered to ensure reliable operation, and their simplicity reduces technical failures, which can be more prevalent in more complex systems (Firoozi et al., 2024). It is inexpensive in comparison to dynamic or adaptive traffic systems. It does not require sensors or complex software to adjust signal timings, which can reduce both initial costs and long-term operational expenses. Prefixed traffic signals are reasonably easy to install and require relatively simple infrastructure compared to adaptive systems. It also provides a straightforward and relatively uniform approach to handling or controlling traffic, making it easier for drivers to adapt to the signal patterns, irrespective of location (Cai & Wei, 2024; J. Chen et al., 2024; Hosseinian & Mirzahossein, 2024). A set of uniform actions or rules that drivers operating within that environment should observe. For instance, traffic signals automate traffic flow by a fixed timing cycle, allowing implying waiting or stopping traffic flow. When the traffic light signal is adhered to, the driver may avoid accidents to promote orderly traffic flow. The system provides a predictable pattern for road users, helping to regulate traffic flow with set cycles (Franzl et al., 2022). Drivers can anticipate when to stop or proceed, enhancing safety and reducing the chances of confusion or accidents. The traffic signal information prediction was adapted for ecological driving algorithms that aim to reduce the signalized intersection queue lengths and waiting time, enhance traffic flow speed, and even reduce fuel consumption (Joa et al., 2024; Yan et al., 2024).

Despite these advantages, the static nature of such systems presents several limitations, especially under rapid changes in traffic conditions and high variability in traffic volume, speed, and behavior. Among the significant disadvantages of static traffic control systems (STCS) is their inflexibility, which operates on fixed cycles that cannot change in real time depending on fluctuations within the traffic flow (Amarnath et al., 2024). This may lead to inefficiencies, such as waiting at intersections with low traffic volumes or contestation cases, where cars unnecessarily wait for a green light. Moreover, static systems cannot adjust dynamically based on traffic situations, so static control also increases the risk of traffic incidents, congestion, higher fuel use, and emissions due to frequent idling, where vehicles are forced to wait at red lights even when there is little or no cross traffic (PILLAI, 2024). Similarly, it does not consider real-time factors such as weather, road conditions, or even traffic incidents that may require adjustments for optimum safety and flow (LOULHACI & BENSOUNA, 2024b). Also, static signalized intersections tend to be less concerned with the needs of vulnerable road users, such as pedestrians, cyclists, or public transport vehicles, who often suffer from delays or conflicts with motor vehicle traffic. Further limitations of Static signals are that they typically operate independently of other traffic management systems, such as smart city infrastructure or coordinated traffic control networks, which can also dynamically respond to emergency vehicles or accidents (Kamal et al., 2024). This lack of integration can prevent traffic flow optimization across broader areas, leading to inefficiencies. Furthermore, most static traffic control systems cannot usually monitor and use real-time data. Modern ITS integrates sensors, cameras, and vehicle-to-infrastructure communication, enabling a range of valuable insights into traffic behavior, none of which have generally been integrated into traditional static systems (Elassy et al., 2024b). Many opportunities are missed to enhance traffic flow, improve safety, and decrease environmental impacts. While robust Static Traffic Lights (STLs) served for several decades, views that such a system may no longer satisfy the pressures placed upon urban transport in the modern city, which keeps growing, implying increased traffic demand where Static traffic controls cannot effectively manage traffic. This demand has resulted in the increasing impetus toward integrating dynamic and adaptive traffic management systems to adaptively satisfy ever-complex demands on a contemporary traffic system. These systems take advantage of technologies that monitor traffic conditions on a real-time basis with dynamic adjustment of signals and speeds, and routing for the optimization of the traffic stream and the reduction of congestion (Elassy et al., 2024b).

Having critically reviewed static traffic control systems, we now focus on dynamic traffic signal control. The next section will explore the various strategies employed in dynamic systems, including actuated, adaptive, coordinated, and adaptively coordinated approaches. By examining these methods, we will better understand how they offer enhanced flexibility and efficiency in managing traffic flow, addressing congestion, and improving overall traffic management within modern urban environments.

2.1.2 Dynamic traffic signal control: actuated, adaptive, coordinated, and adaptively coordinated strategies

Dynamic Traffic Signal Control (DTSC) is an advanced traffic management strategy that adjusts signal timing in real-time instead of depending on pre-programmed fixed cycles. DTSC's primary objective is to optimize the flow and safety of vehicles across junctions with minimum congestion. Among the major dynamic strategies widely employed, we mention actuated, adaptive, coordinated, and adaptively coordinated traffic lights (Othmani et al., 2023; Othmani, Boubaker, Rehimi, Halawani, et al., 2024).

Actuated traffic signal systems depend on real-time input from embedded roadway sensors that detect a vehicle's presence, as illustrated in yellow in the Figure. 2.1.

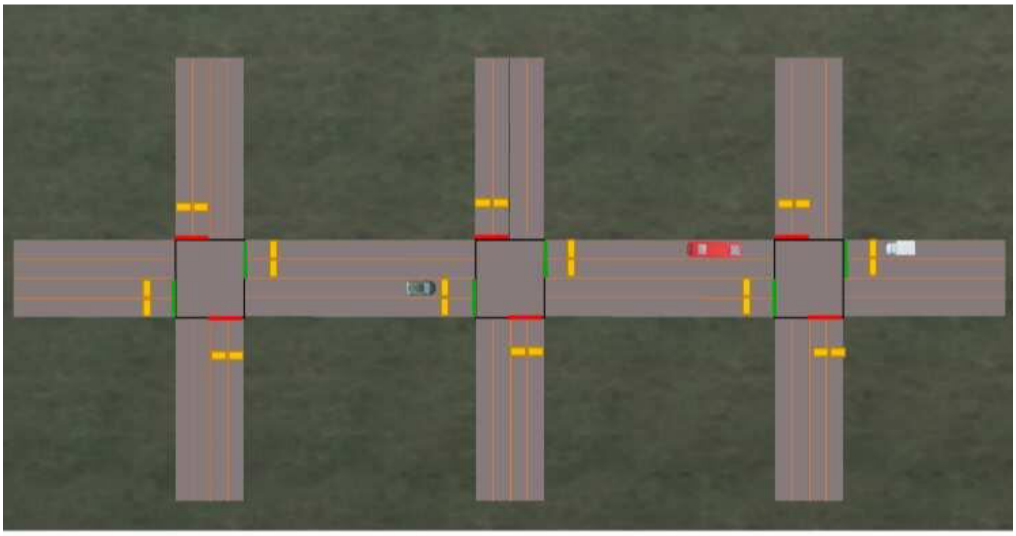

Figure 2.1. Actuated traffic signal systems (Othmani et al., 2023)

These sensors enable the actuated signal system to dynamically extend and adjust signal timings according to traffic volume demand in all lanes, rather than the fixed signal systems. Such control would work effectively in an environment with fluctuating traffic volumes, like peak and off-peak hours, since it reduces unnecessary waiting and optimizes throughput (Saxena, 2024). So, the system modifies the signal timing accordingly using the following equation (Eq. 2.1) (Koonce & Kittelson & Associates, 2008):

$$PT = MAH - \frac{V_l + D_l}{1.47 \times A_v} \tag{2.1}$$

Where PT represents the vehicle passage time in seconds, MAH represents the maximum allowable headway in seconds, V_l is the vehicle length in meters, D_l is the detection zone length in meters, and finally, the A_v is the average vehicle approach speed in km/h.

Meanwhile, adaptive traffic signal control systems represent the next generation of dynamic control, where continuous changes in signal phases occur through real-time traffic flow analysis. In contrast to actuated systems, which respond to vehicle detection, an adaptive system analyzes a broader range of data, such as traffic density, speed, and queue lengths, for better decisions on signal timing using a variety of sensors and means, as illustrated in Figure 2.2.

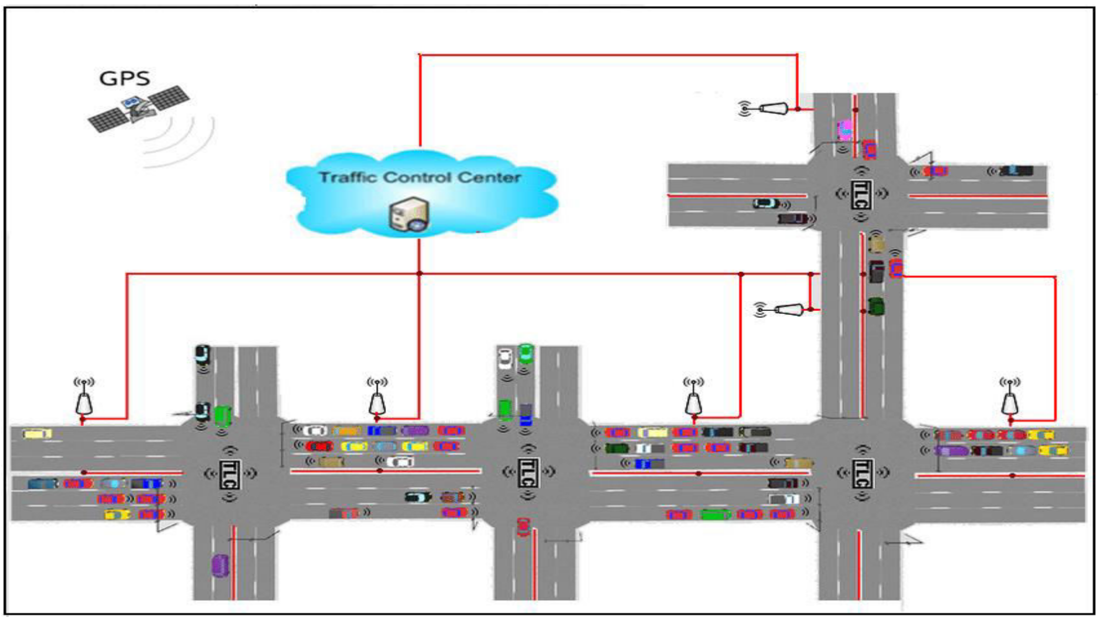

Figure 2.2. Adaptive traffic signal control systems (Tomescu et al., 2012)

Adaptive traffic lights mostly operate based on algorithms, including mathematical equations, Fuzzy Logic, or even optimization techniques. These algorithms vary the green phase length, yellow intervals, and red phases based on traffic demand in real-time.

To estimate the adequate green time based on the traffic demand, first, we need to convert the detected vehicles into Passenger car units using the PCU conversion table (Srisakda et al., 2021), then we apply the illustrated equation (Eq. 2.2) (Othmani, Boubaker, Rehimi, Halawani, et al., 2024):

$$Gt = T_s + N \times T_h \tag{2.2}$$

Where Gt is green light time in seconds, T_s is the start-up delay in seconds, N is the number of waiting vehicles in each direction in PCU, and T_h is the average discharge headway in seconds.

An Adaptive traffic light is effective for areas with variable traffic volume or congestion patterns. It responds to traffic condition changes in real-time with minimal delays and enhances overall network performance (Q. Jin, 2024; Zahwa et al., 2024).

Next, coordinated control traffic signal strategies are employed in areas that need to coordinate several intersections due to a common objective, such as smoother traffic flow along a corridor or significant network. Coordinated TSC aims to reduce stops and delays by ensuring that successive intersection traversability occurs without stops or reduces waits on red light signals, as illustrated in the Figure. 2.3.

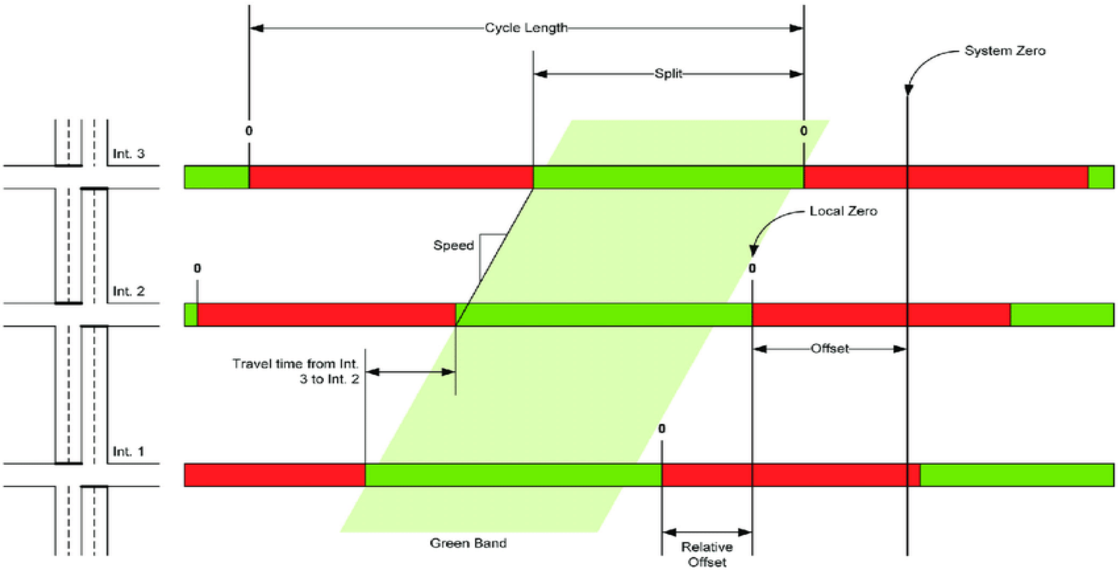

Figure 2.3. Coordinated traffic signal control (Day et al., 2014)

Signal coordination is commonly undertaken by adjusting the signal timings of a series of intersections such that vehicles catch several green lights in their journey, otherwise known as going through the "green wave" (Othmani, Boubaker, Rehimi, Halawani, et al., 2024). The signal timing of coordinated systems can be either fixed or real-time, as may be determined by prefixed timing or traffic data using adjustments by an estimated offset delivered using the following equation (Eq. 2.3) (Othmani, Boubaker, Rehimi, Halawani, et al., 2024):

$$\alpha = D / V \tag{2.3}$$

Where α is the estimated offset in seconds, D is the distance between the intersection and the master intersection in meters and V is the road's maximum speed in meters per second.

Coordinated systems contribute to reducing fuel consumption and decreasing fumes emitted due to the lower number of stops and idling (Romero et al., 2024).

The Adaptively Coordinated Traffic Signal Control (ACTSC) systems bring together the strengths of both adaptive and coordinated strategies. These systems adjust the timing and coordination of signals in real-time at multiple intersections to meet current traffic conditions while maintaining coordination among the signals to optimize the overall traffic flow across the network (Othmani, Boubaker, Rehimi, Halawani, et al., 2024). Unlike fixed coordinated systems, which rely on a predetermined schedule, an adaptively coordinated system responds dynamically to actual traffic data. Therefore, it can be more responsive and flexible to fluctuating conditions. For instance, if congestion builds up on one part of a network, the system can adjust the signal timings to minimize delays at that intersection while maintaining coordination with adjacent signals (Othmani, Boubaker, Rehimi, Halawani, et al., 2024). This is very effective in urban environments where the traffic patterns are complex and constantly changing, and where rigid schedules are less effective. Because an adaptively coordinated system can make dynamic adjustments in coordination among multiple intersections, significant enhancements in network-wide traffic efficiency, delay reductions, and air quality improvement because of reductions in emissions result in a more sustainable transportation network (Othmani, Boubaker, Rehimi, Halawani, et al., 2024).

These dynamic signal control strategies will play a critical role in improving city traffic management. It leverages advanced sensor networks, real-time data processing, and intelligent algorithms to optimize the signal timing and adapt to traffic demand changes for better transportation that is safer, more efficient, and environmentally friendly. With the further development of machine learning and the integration of connected vehicle technologies into transportation systems, dynamic traffic signal control will further increase its capability to enable sophisticated management of urban traffic flow.

Building upon the dynamic traffic signal control strategies in this section, it is essential to explore how advancements in communication technologies in the next one, such as Vehicle-to-Infrastructure (V2I), Vehicle-to-Vehicle (V2V), and Vehicle-to-Everything (V2X), can further enhance the efficiency and adaptability of traffic management systems.

2.1.3 Communication technologies for advanced traffic control: V2I, V2V, and V2X

Dynamic traffic signal control is one of the main methods in state-of-the-art traffic management systems that seek to optimize current traffic flow by real-time adjustments in signal timings. The dynamic nature of such systems can respond flexibly to variations in volume, pedestrians, and environmental factors, unlike traditional fixed-time signal systems (Othmani, Boubaker, Rehimi, Halawani, et al., 2024). Conversely, Intelligent Communication Technologies (ICTs) take it to the next level by incorporating sophisticated techniques that gather and help analyze real-time traffic data at particular intersections and surrounding areas. We can mention various communication technologies, including Vehicle-to-Infrastructure (V2I), Vehicle-to-Vehicle (V2V), and Vehicle-to-Everything (V2X) (Othmani, Boubaker, Rehimi, Halawani, et al., 2024).

V2I communications are among the transformational technologies for traffic management, whereby real-time data exchange between vehicles and road infrastructures includes traffic signals, signs, and sensors. This kind of technology helps improve traffic flow: it enables cars to adapt their speed according to information about what is ahead, including signal status or congestion. It even helps to adjust the adaptive traffic light signals, as illustrated in the Figure. 2.4.

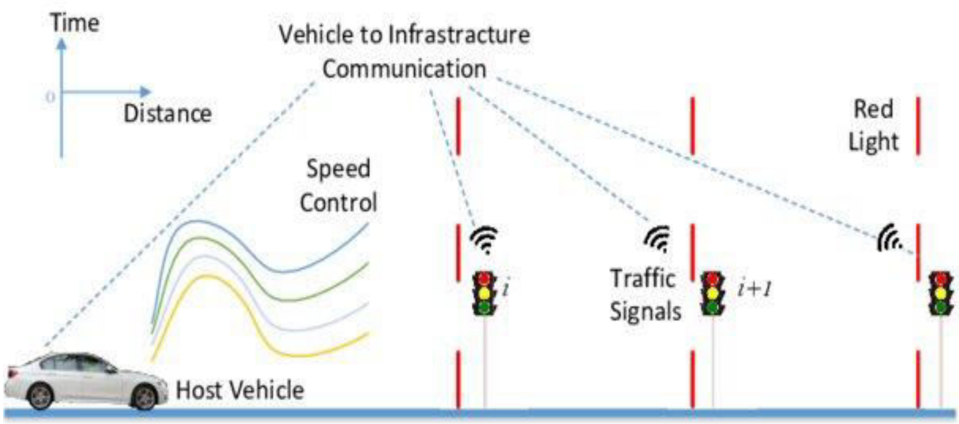

Figure 2.4. V2I communication technology (C. Sun et al., 2018)

The integration of V2I further improves road safety through early warning systems for drivers concerning impending dangers like accidents, construction areas, and malfunctioning signals. Besides, V2I supports the introduction of autonomous cars and Advanced Driver Assistance System (ADAS) due to critical data that assists in the navigation and decision-making processes. With new technologies, V2I shall continue gaining momentum regarding less congestion, less emission, smart, intelligent road administration, and generally smarter transport networks (Elassy et al., 2024b).

Meanwhile, V2V communication technology greatly enhances traffic management while reducing fuel consumption and emissions. The technology allows vehicles to talk to each other about speed, position, and driving intention in real-time, enabling better coordination between vehicles on the road (Othmani, Boubaker, Rehimi, Halawani, et al., 2024). The next figure (Fig. 2.5) presents V2I communication technology.

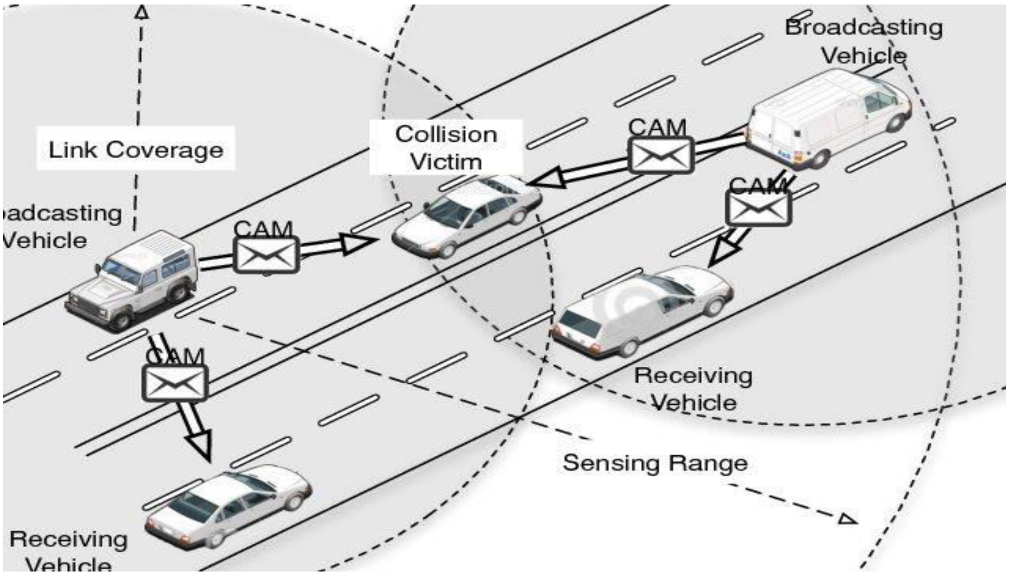

Figure 2.5. V2I communication technology (L. Shi & Sung, 2014)

This increased coordination reduces traffic congestion and sudden braking and acceleration, the biggest causes of fuel wastage and high emission levels. In that case, the vehicle can adjust speed to avoid stop-and-go driving, which translates into smoother traffic and reduced acceleration, directly translating into fuel savings (Hira & Hira, 2024). Besides, V2V can enable more efficient driving strategies, such as cooperative adaptive cruise control, whereby vehicles maintain optimal speeds and safe distances from each other. This coordination further enables platooning, whereby vehicles can travel close to each other, reducing aerodynamic drag and thus improving fuel efficiency (J. Zhou et al., 2024). It also reduces overall time spent idling or stuck in traffic, contributing to lower emissions and reducing transportation's carbon footprint.

Finally, V2X extends V2V and V2I communication to include a vehicle's interaction with other road users, pedestrians, cyclists, and even traffic management systems. The V2X system helps a car share information from many external sources, as illustrated in the Figure. 2.6.

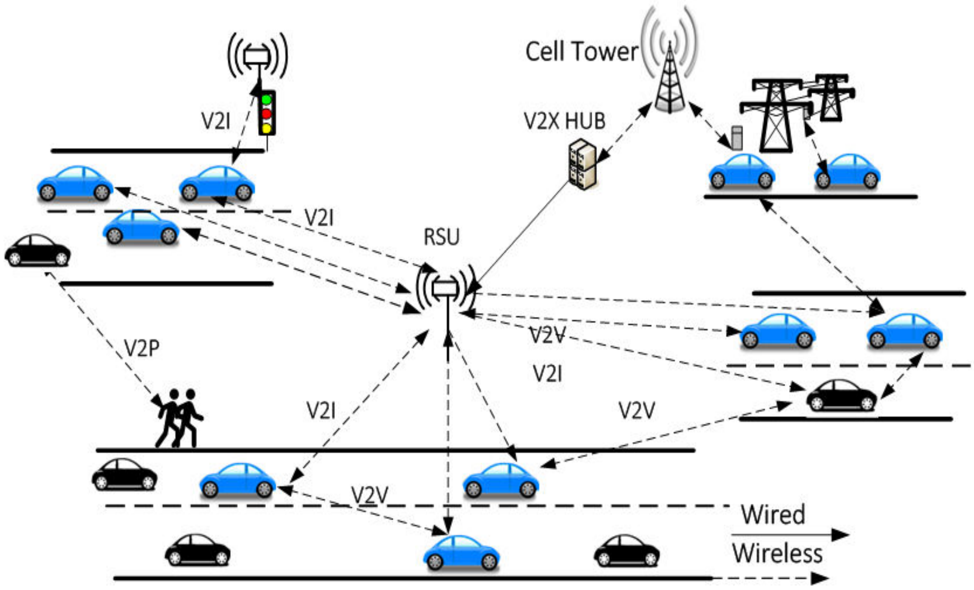

Figure 2.6. V2X communication technology (Okpok & Kihei, 2023)

V2X enhances drivers' situational awareness, enabling better decision-making by a driver or automated system. V2X links the vehicle with information on traffic conditions, roadway detriments, weather updates, pedestrians in proximity, and other information to avoid accidents. Further, with V2X, several activities will go a long way in assuring smooth streamlining of traffic: Optimize signal timing at intersections by providing real-time updates on traffic signals (Othmani, Boubaker, Rehimi, Halawani, et al., 2024). Moreover, the technology has enabled autonomous vehicles to interact with infrastructure and other users in real-time to improve their navigation capabilities. Besides, V2X contributes to environmental sustainability by improving traffic flow efficiency and reducing unnecessary idling time, fuel consumption, and resultant emissions (Othmani, Boubaker, Rehimi, Halawani, et al., 2024). Eventually, V2X will form the important pillars for designing smart cities and intelligent transport systems, as it becomes the momentum required to move closer to a connected, safer, and sustainable transport ecosystem.

Having explored the role of communication technologies in advancing traffic control systems, we now turn our attention to intelligent speed management. The following section will delve into Intelligent Speed Advisory systems and vehicular technologies, examining how they improve traffic flow, energy consumption, and emissions in real-time.

2.2 Intelligent speed advisory systems and vehicular technologies

Intelligent Speed Advisory Systems (ISAS) are critical to the evolution of road safety, traffic management, and energy use efficiency, particularly in an era. Integrating vehicular speed control technologies plays a transformative role in ensuring safer and more efficient transportation with lower energy use (M. N. Khan & Das, 2024). These systems utilize real-time data, satellite navigation, and advanced sensors to provide drivers with timely information regarding the appropriate speed for the road conditions they are navigating (Newsome & WSP, 2024). Therefore, ISAS will depend on inputs from traffic signs and lights and real-time flow to inform drivers about speed limits, reducing speeding cases, and enhancing road safety and energy use efficiency.

Moving to vehicular technologies, the transformation from Conventional Internal Combustion Engine vehicles (ICEs) running on diesel and gasoline to Electric Vehicles (EVs) has entered a whole new dimension for the transport sector. While conventional vehicles (CVs) are still operational and very much in use, the arrival of EVs has introduced an attractive option, particularly in terms of environmental viability due to their zero-emission nature (De et al., 2024). EVs ensure a reduction in both harmful pollutants and greenhouse gas emissions (GHGs), tackling some of the most important environmental concerns resulting from ICEs. Besides, the integration of intelligent systems like ISAS with these heterogeneous vehicular technologies holds great promise for the overall efficiency and sustainability of transportation. There is huge potential in this synergy between advanced technologies and both ICEs and EVs systems that will shape the future with less environmental impact, better energy efficiency, and a more streamlined and safer approach to transportation.

This section provided a general introduction to ISAS and vehicular technologies. The next section will provide more information about the systems' concepts, constituent elements, operation mechanisms, and how they will revolutionize modern transportation.

2.2.1 The concept of Intelligent Speed Advisory Systems

ISAS helps drivers or autonomous vehicles comply with speed limits by recommending the proper speed in real-time and based on various parameters such as traffic conditions and traffic lights. In fact, it also forms part of a whole range of systems that will contribute to enhancing road safety, reducing accidents, and improving fuel efficiency by ensuring drivers can keep appropriate speeds according to different conditions of the road and its conditions, traffic rules, and environmental conditions (Chaudhry et al., 2024). ISAS relies on multiple parallel inputs, including GPS systems, road maps, speed sign recognition, and other systems, such as vehicle-to-roadside communication systems. ISAS can prevent drivers from unknowingly exceeding the speed limit, especially at places where the speed limits change frequently or with which drivers are unfamiliar, by providing drivers in real-time with advanced information on upcoming speed limits and road conditions. Further, the system can favor energy-efficient driving since the consistency of speed and its appropriateness reduce fuel consumption and lower emissions (Chaudhry et al., 2024). This is especially important for congested urban environments with mostly stop-and-go traffic when speed frequently changes, significantly raising fuel consumption and output of harmful emissions. Multiple Intelligent Speed Advisory Systems exist to assist autonomous drivers alike, including the Green Light Optimal Speed Advisory systems (GLOSA), presented in the Figure. 2.7 (Seredynski et al., 2013).

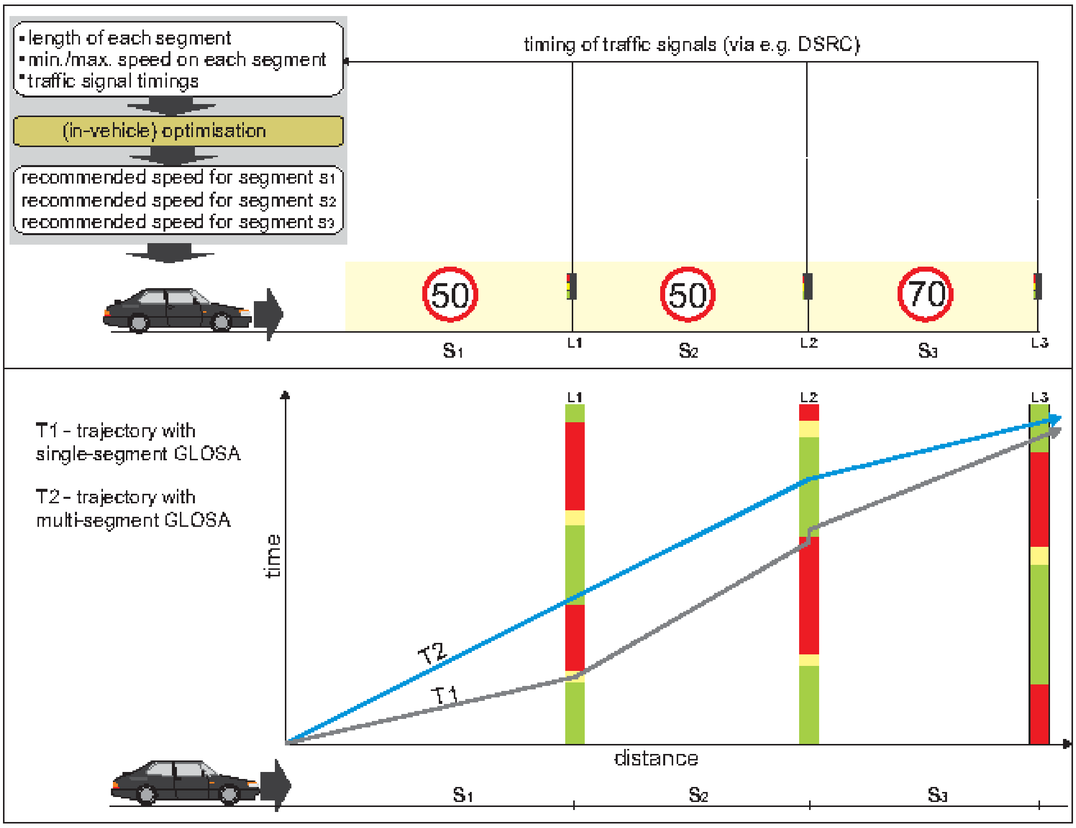

Figure 2.7. Green Light Optimal Speed Advisory System (Seredynski et al., 2013)

GLOSA is a higher-order traffic management technology designed to optimize the flow of vehicular traffic by providing real-time speed advisories (Chaudhry et al., 2024). The system uses data from traffic signals, sensors, and V2I communications to calculate the optimum speed that a vehicle should reach to be able to pass up to a series of connected traffic lights without stopping. GLOSA systems will reduce fuel consumption, lower emissions, and optimize the efficiency of traffic flow by informing drivers of where to maintain the optimal speed. Improved safety, reduced congestion, and travel time are what GLOSA offers in store as a solution for urban transportation networks. Moreover, GLOSA, as part of ITS, works in conjunction with other technologies to further the goals of sustainable and smart city infrastructure (Kovačević, 2023).

The application of GLOSA requires simple steps, and the methodology must be followed so that the approach can be used in real-time traffic conditions. First, the vehicle should gather the remaining distance to reach the signalized intersection ahead, along with the signal phase (Red or Green lights) and remaining phase time. Then, the total time to spend before crossing the intersection when the traffic signal turns green is estimated based on the signal remaining, the timing of the signal, and the remaining distance to reach the traffic lights. Finally, the adequate speed is calculated using the following equations (Wágner et al., 2023a):

$$Dist_{TL} = v \times t + \frac{1}{2} \mathrm{a} \times t^2 \tag{2.4}$$

$$A_S = \begin{cases} \begin{cases} V_{max} & ; \quad If\ Phase\ =\ green \\ \frac{2 \times Dist_{TL}}{T} - v; & If\ Phase\ \neq green \end{cases} \\ A_S < V_{max} \\ A_S > V_{min} \end{cases} \tag{2.5}$$

$$T = \begin{cases} TTL + T_{red} & ; \ If\ Phase\ is\ red \\ TTL + T_{yellow} + T_{red} & ; \ If\ Phase\ is\ yellow \end{cases} \tag{2.6}$$

$$T_{TL} = \begin{cases} \frac{Dist_{TL}}{v} & ; \ If\ a = 0 \\ -\frac{v}{a} + \sqrt{\frac{v^2}{a} + 2 \times \frac{Dist_{TL}}{a}} & ; \ If\ a \neq 0 \end{cases} \tag{2.7}$$

Where the estimated adequate speed in m/s is presented by A_S, T_{red} and T_{yellow} are is the remaining time, so the signal turns green in seconds, $Dist_{TL}$ and T_{TL} are the remaining distance and time for the vehicle to reach the relevant traffic light in meters and seconds, respectively. T is the total time to be spent in the intersection in seconds. v and a are the vehicle velocity and acceleration, respectively, in m/s and m/s². and finally, V_{max} and V_{min} are the maximum and the minimum allowed road speed limits in m/s.

The following table (Table 2.1) summarizes the GLOSA algorithm function:

Table 2.1. Green Light Optimal Speed Advisory algorithm (Wágner et al., 2023a)

Green Light Optimal Speed Advisory algorithm
Consider the traffic light (TL)ahead.
Calculate the remaining distance to the traffic light ahead ($Dist_{TL}$)
Calculate their Time to Traffic Light (T_{TL}).
Check the phase (Ph) of the TL.
If *Ph is Green,* ***then:***
Continue trip
Advisory speed $A_S = V_{max}$.
End if
Else If *Ph is Red,* ***then:***
Calculates remaining red time (T_{red}).
Calculate the signal time $T_s += T_{red}$.
Calculates the advisory speed A_S for $T_s + T_{TL}$.
End if
Else If *Ph is Yellow,* ***then:***
Calculates remaining Yellow time (T_{yellow}).
Calculate the signal time $T_s = T_{yellow} + T_{red}$.
Calculates the advisory speed A_S for $T_s + T_{TL}$.
End if
Advisory speed $A_S = Max(A_S, V_{min})$ && $A_S = Min(A_S, V_{max})$.

The coordination of the GLOSA system would contribute significantly to traffic flow optimization, with congestion minimized. The system will talk to infrastructure like traffic lights, roadside sensors, and sensors on the road to predict traffic patterns in real-time and update its recommendations for a tailored driving experience (Kovačević, 2023).

Furthermore, widespread ISAS adoption supports related transportation priorities: reducing traffic emissions while developing sustainable urban mobility systems. As governments and municipalities continue to address road safety and environmental challenges, the role of Intelligent Speed Advisory Systems will undoubtedly extend to creating safer, more efficient, and environmentally friendly roads. In this context, Fuzzy Logic emerges as a powerful tool for enhancing the adaptability and accuracy of ISAS systems. By utilizing Fuzzy Logic principles, these systems can better handle uncertain, imprecise, or incomplete information, facilitating a more flexible and intelligent speed adaptation mechanism. The next section explores how Fuzzy Logic contributes to the development of advanced ISAS systems.

2.2.2 Fuzzy Logic, Large Language Models, and Deep Reinforcement Learning: powerful tools for intelligent speed advisory

Fuzzy Logic, Large Language Models, and Deep Reinforcement Learning represent pivotal advancements in intelligent systems, particularly in the context of Intelligent Speed Advisory systems. A fuzzy logic control system is selected when there is a lot of imprecision involved, and the system acts according to the fuzzy set theory and fuzzy rule base. Large Language Models (LLMs) are exemplified by architectures such as GPT, Deepseek, Claude, etc. It incorporates a large dataset of examples to determine contextually relevant responses and assist in and aid natural language understanding. Deep Reinforcement Learning (DRL), on the other hand, is an ideal system for coping with dynamic and uncertain environments like traffic management and learning optimal behaviors.

Starting with Fuzzy Logic (FL), it is a robust implementation method for intelligent speed adaptation. It treats complex, uncertain, and imprecise systems with general features in real-life applications, especially transportation and traffic management (A. Mohanty et al., 2025). Most conventional control systems are based on binary decisions about the inputs that can be true or false, yielding rigid and inefficient decision-making. Fuzzy Logic, in contrast, can imitate human reasoning and decision-making processes where either a complete yes or a full no is not needed, giving the ability to handle partial truths (Satam, 2022). The difference between binary and Fuzzy logic is illustrated in the Figure. 2.8.

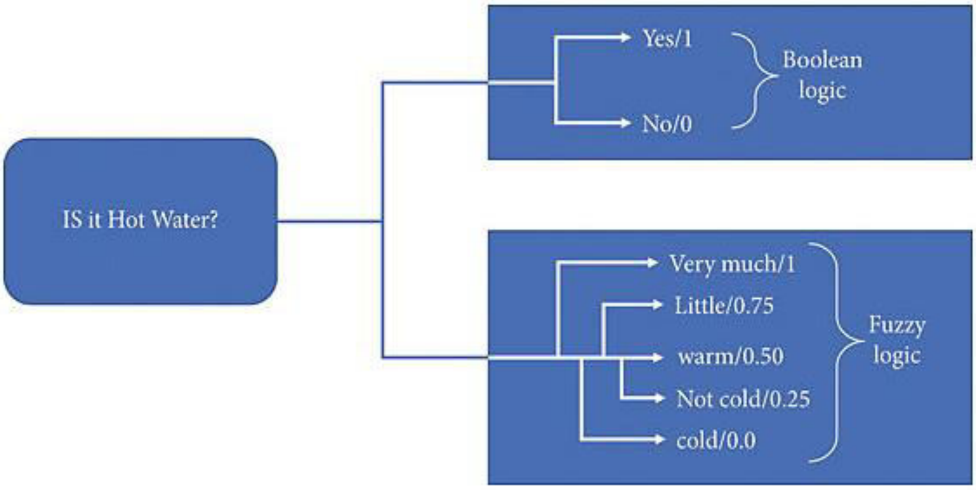

Figure 2.8. Difference between Fuzzy Logic and Binary Logic (Satam, 2022)

This flexibility is quite important when the variables, like weather conditions, road conditions, the stream of traffic, the vehicle's performance, and other factors, are vague and difficult to represent with precise values. In this respect, the role of Fuzzy Logic in ISA functions is to dynamically adjust the vehicle's speed based on various environmental factors in real-time. Two types of FLs are mainly adopted, the Mamdani and Sugeno types, as illustrated in the Figure. 2.9 (Datta & Banerjee, 2005).

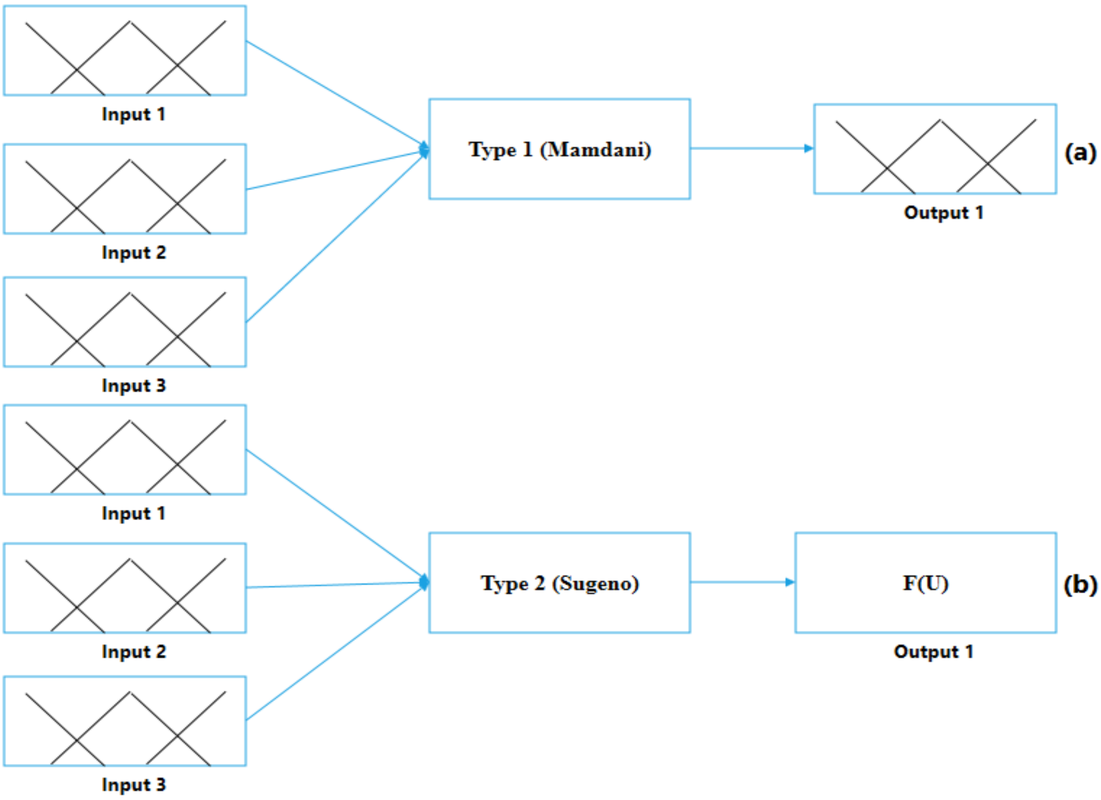

Figure 2.9. Fuzzy Logic types: a) Mamdani, b) Sugeno (Datta & Banerjee, 2005)

Each type is applied based on the complexity of the estimated output, where FCs allow the establishment of a set of membership functions that represent linguistic variables, such as "high traffic," "positive road slope," or "fast vehicle." Each variable will have a degree of membership according to real-time data. These inputs are consequently fed into a rule-based system, where the adequate output will be selected based on the system's Fuzzy Rules (FR) (Satam, 2022). Additionally, FL can be integrated with other Technologies to enhance its efficacy, like ICT, through which constant information concerning traffic signals and other aspects will inform adequate speed changes for responsive and eco-driving performance. Thus, Fuzzy Logic enhances the performance of single vehicles well and thereby enhances traffic conditions to enable smooth and safe travel. Many studies have proven its efficiency as a powerful tool in ISAS, showing its capability to reduce energy consumption and emissions, along with extending electric vehicle ranges (Beşkardeş et al., 2024; Maghfiroh et al., 2024; Rostami & Al-Shibaany, 2024; Siddula, 2024).

Shifting to LLMs is a significant improvement in the advancement of artificial intelligence. It was built and modeled to be capable of writing human-like text and making recommendations based on the vast training data, as shown in Figure 2.10.

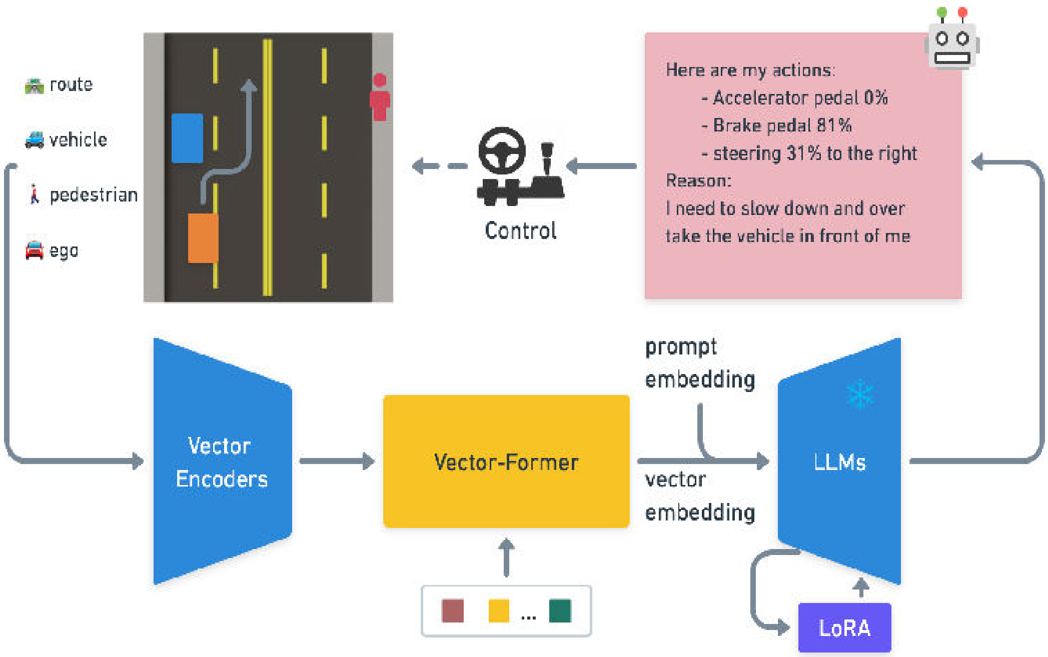

Figure 2.10. LLMs for Eco-Driving (L. Chen et al., 2024)

The LLMs have the crucial responsibility of intermediation in terms of eco-driving when applied within smart cities (Pimenow et al., 2024). These models are effective in the analysis of environmental and traffic situations so as to enhance the performance of vehicles in terms of energy consumption and emissions reduction. Thus, they can process immediate traffic information, weather data, and road conditions effectively and advise on recommended car speeds, paths, and acceleration that can be used to conserve fuel and the environment (Gan et al., 2024a; Prabhod, 2023). Moreover, their adaptability to diverse datasets and rapid decision-making capabilities make LLMs invaluable for integrating with smart city infrastructures, where they contribute to enhancing traffic flow efficiency, reducing congestion, and promoting sustainable transportation practices (Gan et al., 2024a; Prabhod, 2023).). This synergy emphasizes the great benefits of LLMs in the enhancement of eco-driving within urban areas, thus being a major step towards attaining efficient transport systems globally.

Concluding with DRL models is a highly advanced process under artificial intelligence in which an algorithm exists and learns an optimal policy for executing an action, mainly to maximize the total reward over time, as shown in Figure 2.11 .

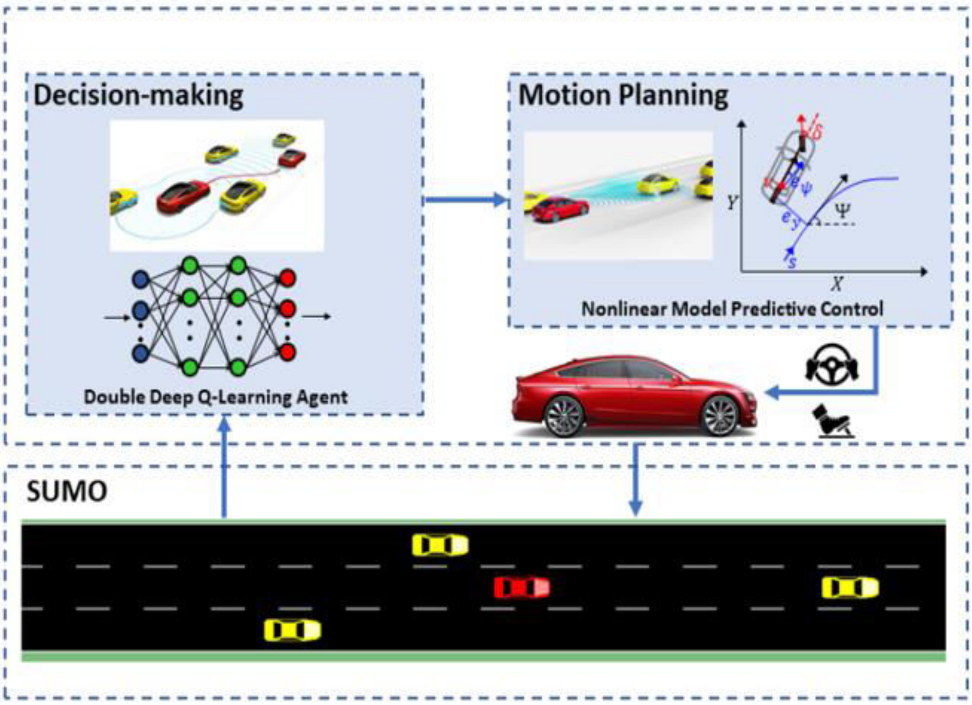

Figure 2.11. Deep Reinforcement Learning for Eco-Driving (Albarella et al., 2023)

DRL models reveal deep capability when applied to eco-driving since it involve such factors as decision trees to enhance the efficiency of operations in a vehicle. These models are usable in developing expertise on large-scale datasets relative to traffic flow, road infrastructure, and driver behaviors, which aim at developing and implementing driving strategies that are energy efficient and environmentally conscious (J. Wu et al., 2024). The DRL-based eco-driving systems can autonomously drive through congested urban spaces and vary vehicle speed, navigation, and acceleration patterns with respect to real-time traffic conditions and environmental factors within smart cities. This capability can improve traffic flow efficiency and reduce fuel usage while reducing air pollution levels, which correspond to sustainable urban development targets (A. F. Khan & Ivan, 2023). Moreover, DRL models can also adjust to the various and changing urban environments over time and improve driving strategies adaptively to achieve maximum energy efficiency while maintaining safe and reliable transportation. Integrating DRL in smart city infrastructures, therefore, has an important role in providing greener and more sustainable transportation ecosystems across the globe.

FL, LLMs, and DRLs are still the cornerstone in continuous development regarding autonomous driving in the area of speed adaptation, which entails smooth, contextual, dynamic decision-making. It can integrate human reasoning with the progress of computational techniques to lead to an effective and sustainable environment in modern traffic conditions. The following section will provide a comparative analysis of conventional and electric vehicles and the mathematical energy consumption models.

2.2.3 Vehicular technologies: a comparative analysis of conventional and electric vehicles

In recent decades, in-vehicle technologies have undergone radical changes, and one of the most profound changes in motor cars has been the switch from conventional ICE vehicles to EVs. Traditional transportation uses either gasoline or diesel as a source of power, which is one of the major causes of environmental pollution, especially in urban areas, as vehicles are rated as one of the major sources of air pollutants. Electric vehicles rely instead on electric motors powered only by rechargeable batteries that use any source of electrical energy, even renewable sources such as solar or wind. This transition to electric vehicles has been considered the most crucial step towards reducing the carbon footprint for transport and mitigating climate change (Güler et al., 2021). The next figure (Fig. 2.12) illustrates the ICEs and the EVs' powertrain structures.

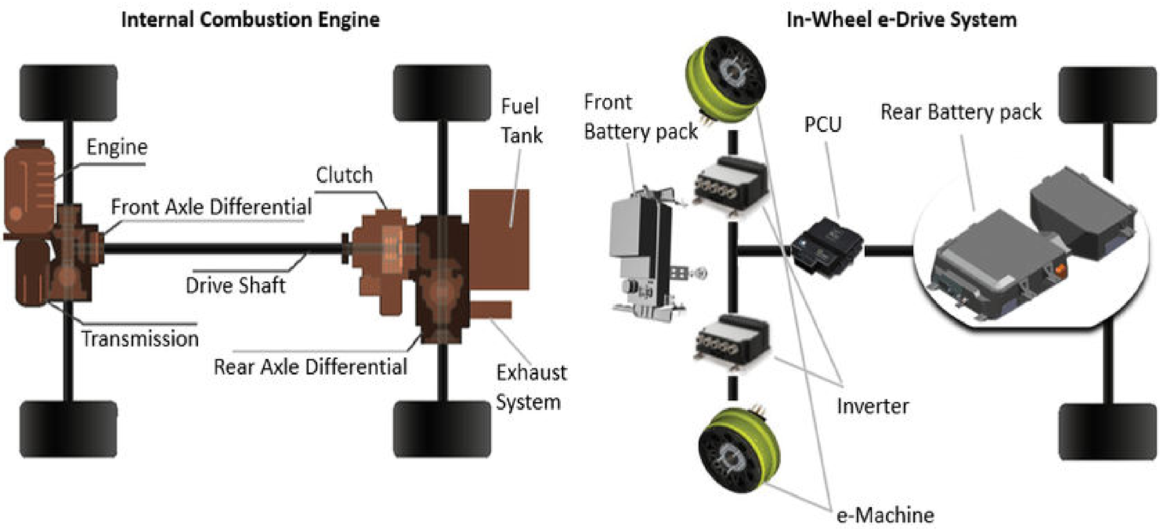

Figure 2.12. ICE VS EV power train structure (Güler et al., 2021)

The EVs emit no direct emissions, reducing the quantity of harmful pollutants common in urban environments (Güler et al., 2021). On the other hand, despite their greatly improved fuel efficiency and emission standards over these years, conventional vehicles continue to contribute significantly to air pollution and GHGs in highly populated areas (Azhar et al., 2024). Another major difference between conventional and electric vehicles is energy efficiency. Electric vehicles are intrinsically more energy-efficient than their conventional counterparts, with the electric motors converting a far larger percentage of electrical energy to mechanical power compared with internal combustion engines, in which a large part of the energy is lost as heat (Güler et al., 2021). Besides, the recuperative braking system widely applied in EVs enables them to recover and store some energy that would otherwise dissipate during braking, further raising their efficiency (Güler et al., 2021). Speaking of energy consumption, the following equations represent the required power of internal combustion and electric vehicles to overcome the resistive forces (J. Ma et al., 2019a; Miri et al., 2021):

$$P_{required}(t) = \underbrace{(Acc_{res} + Grad_{res} + Rolling_{res} + Drag_{res} + Tr_{res})}_{Forces\ (R)} \times v(t) \quad (2.8)$$

$$Forces = \sum \begin{cases} Acc_{res} = \delta \times (M_{Vehicle} + P_{Load}(\mathrm{t})) \times \mathrm{a(t)} \\ Grad_{res} = (M_{Vehicle} + P_{Load}(\mathrm{t})) \times \mathrm{g} \times \mathrm{Sin}\big(\emptyset(\mathrm{t})\big) \\ Rolling_{res} = C_{rr} \times (M_{Vehicle} + P_{Load}(\mathrm{t})) \times \mathrm{g} \times \mathrm{Cos}\big(\emptyset(\mathrm{t})\big) \\ Drag_{res} = \frac{1}{2} \times \rho \times C_d \times A_x \times \big(v(t) - v_{Wind}(t)\big)^2 \\ Tr_{res} = (Acc_{res} + Grad_{res} + Rolling_{res} + Drag_{res}) \times \frac{(1-\eta_T)}{\eta_T} \end{cases} \quad (2.9)$$

$$C_{rr} = 0.01 \times (1 + \frac{v(t)}{100}) \quad (2.10)$$

Where $P_{required}(t)$ is the instantaneous vehicle's required power in kW, Acc_{res} represents the acceleration force, $Grad_{res}$ is the road gradient resistance, $Rolling_{res}$ is the rolling resistance, the aerodynamic resistance presented using $Drag_{res}$, Tr_{res} is the transmission resistance, all the mentioned forces are in Newton (N) δ is the coefficient of rotary inertia, $M_{Vehicle}$ is the vehicle weight in kg, P_{Load} is the passenger load in kg, g is the gravity acceleration in m/s², $\emptyset(\mathrm{t})$ represents the instantaneous road slope in gradient, C_{rr} is the rolling resistance coefficient, ρ represents the air density in kg/m³, C_d is the aerodynamic drag coefficient, A_x represent the vehicle frontal surface in m², and $v_{Wind}(t)$ is the instantaneous wind speed in m/s, and η_T is the transmission efficiency in percentage.

For the ICE, the fuel consumption equation is illustrated in the following equation (Eq. 2.11) (Bisong et al., 2020):

$$Fc(t) = P_{required}(t) \times ge \quad (2.11)$$

Where the instantaneous fuel consumption in g/h is represented by *Fc(t)*, and *ge* is the brake-specific fuel consumption in g/kWh. Moving to EVs, the battery consumed and regenerated energy are presented in the following equations (Miri et al., 2021):

$$E_{bat} = \sum \begin{cases} \int P_{bat\_out} = \int_{traction} (\frac{P_{required}(t)}{\eta_C \times \eta_m}) \times dt; & If \text{ a} \geq 0 \\ -\int P_{bat\_out} = -\int_{braking} \big(K_r \times P_{required}(t) \times \eta_C \times \eta_m\big) \times dt; & If \text{ a} < 0 \end{cases} \quad (2.12)$$

$$K_r = \begin{cases} 0.5 \times \frac{v(t)}{5}; & If\ v(t) < 5m/s \\ 0.5 + 0.3 \times \frac{v(t)-5}{20}; & If\ v(t) \geq 5m/s \end{cases} \quad (2.13)$$

E_{bat} is the amount of output energy from the battery in kWh, P_{bat_out} and P_{bat_in} are the utilized traction energy and regenerated braking energy, respectively, in kWh, K_r represents the regenerative braking factor, η_C is the controller efficiency, and η_m represents the motor efficiency.

We have conducted a sensitivity analysis as illustrated in Figure 2.13, which shows how each input parameter affects bus energy consumption. The analysis reveals that temperature, speed, and road slope are the most influential factors on energy consumption, whereas passenger load has a relatively minor impact.

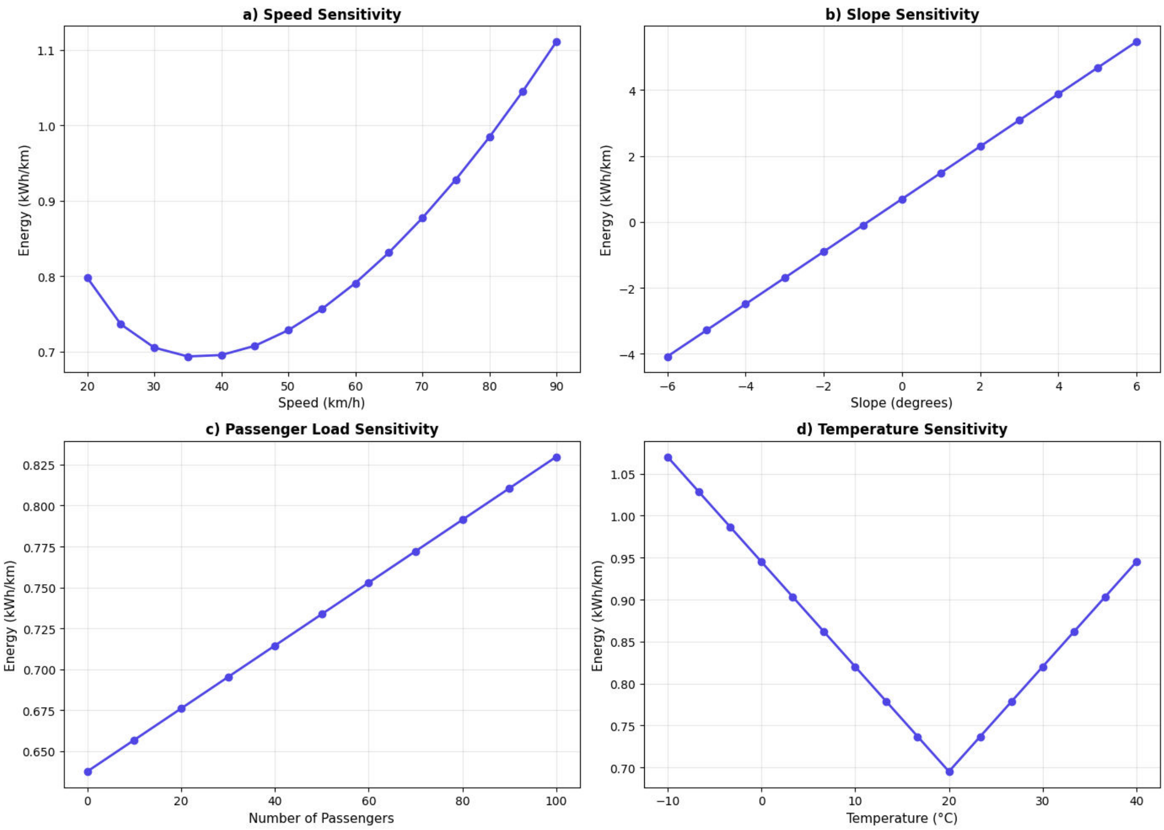

Figure 2.13. Sensitivity analysis of bus energy consumption model variables; a) speed, b) slope, c) number of passengers, d) temperature

The above figure displays the sensitivity analysis of energy consumption per kilometer to individual input parameters, , with all other variables maintained at their dataset mean values. First figure (a) reveals that speed exhibits a non-linear relationship with energy consumption, showing optimal efficiency at approximately 35-40 km/h, with consumption increasing at both lower and higher speeds due to increased motor inefficiency at low speeds and aerodynamic drag at high speeds. Secondly, figure (b) demonstrates that road gradient has a strong linear impact on energy consumption, with uphill slopes (positive gradients) significantly increasing energy demand while downhill slopes enable energy recovery through regenerative braking, resulting in negative consumption values especially for electric vehicles. Additionally, figure (c) shows that passenger load has a moderate but consistent linear effect, with energy consumption increasing proportionally as more passengers are carried due to the added vehicle mass. Last but not least figure (d) indicates that temperature has a U-shaped relationship with energy consumption, with minimum consumption occurring near 20°C; deviations from this optimal temperature in either direction increase energy use due to heightened Heating Ventilation Air Conditioning (HVAC) system demand for heating or cooling. Among all parameters examined, slope and speed demonstrate the most substantial influence on energy consumption, while passenger load shows the least impact within the tested range.

Meanwhile, many research topics confirm that there is a challenge in adopting electric vehicle technologies compared to ICEs, which remains a barrier to EV adoption. Starting with EV prices, which are high compared to ICEs (Gnanavendan et al., 2024). Secondly, the driving range and the number of charging infrastructures remain critical concerns for potential buyers (Gnanavendan et al., 2024). However, all these concerns are expected to gradually disappear with continuous improvement in battery technology, solid-state batteries, and fast-charging solutions (Gnanavendan et al., 2024). In contrast, conventional vehicles enjoy the advantage of a general refueling infrastructure; at the same time, refueling a conventional vehicle takes just a few minutes, while recharging an EV may take 30 minutes to several hours, depending on the method of charging applied (Gnanavendan et al., 2024). Despite such challenges, a combination of environmental concerns, government incentives, and technology drives the shift globally toward electric vehicles. Different countries have implemented several policies to promote the use of EVs, including tax credits, rebates, and even regulations that impose stricter emissions standards on new vehicles (Gnanavendan et al., 2024). Besides, a growing concern with fossil fuel dependency and prices has accelerated the move toward electric mobility. However, the durability and costs of EV batteries remain a concern (Gnanavendan et al., 2024).

With all the ongoing debate about the relative advantages and disadvantages of conventional versus electric vehicles, one thing is for sure: the future of transportation is increasingly leaning toward electrification. With the continuous development of battery technology, expansion of charging infrastructure, and price reduction, electric vehicles will likely dominate the automobile market for the next few decades. This section provides a comparative study of conventional and electric vehicles and underlines each technology's advantages and challenges, along with the energy consumption models. The next section provides an introduction to the simulation tools used to model and simulate the thesis proposed DTSC and ISAS, along with the evaluation metrics to assess the efficiency of the proposed approaches.

2.3 Simulation tools and evaluation metrics

Simulation tools are critical in analyzing and optimizing traffic systems, as they offer valuable insights into the dynamics of transportation networks (Ulvi et al., 2024). By simulating various traffic scenarios, these tools enable the evaluation of different strategies and technologies, allowing for the examination of system performance under diverse conditions. For the evaluation, we need Key Performance Indicators (KPIs), which play a pivotal role in measuring the effectiveness and efficiency of these systems. Additionally, traffic flow optimization, fuel consumption reduction, and environmental impact are critical KPIs that provide quantifiable metrics to assess system performance (S. A. Mohamed, 2024). The use of KPIs ensures a comprehensive understanding of how well the system meets its objectives and guides further development and refinement. The following section provides a basic introduction to one of the simulation tools.

2.3.1 Simulation environment: Simulation of Urban MObility (SUMO)

For the simulation environment, the choice is based on the Simulation of Urban Mobility (SUMO) software (Alvarez Lopez et al., 2024). SUMO is an open-source, microscopic traffic flow simulation tool used for modeling complex urban transportation systems, from the movement of individual vehicles to entire traffic networks (Yavuz & Özen, 2024). It enables detailed simulation of the traffic flow, the behavior of road users, public transport systems, pedestrian movements, and interactions with infrastructure elements such as traffic lights, road signs, and signals. SUMO has been applied in academia and industry for strategy evaluation in transportation, infrastructure designs, and policies toward urban mobility and environmental sustainability. One of the reasons for using SUMO is that the system is simple to use, and the ease of interfacing with external programming languages, such as Python, using the Traffic Control Interface (TraCI) (Yavuz & Özen, 2024), as illustrated in Figure 2.13.

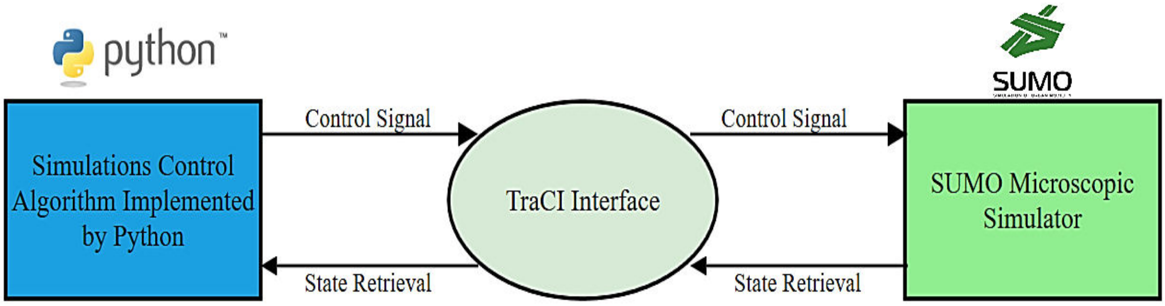

Figure 2.14. SUMO interfacility with Python through TraCI

Mainly, SUMO offers the capability to simulate large networks in great detail, making it a handy tool by offering an extremely customizable environment where we can define many aspects of the simulations, such as the vehicle types, road network, strategies of traffic light control, and even environmental factors regarding road conditions, and so on. This extends the capabilities of SUMO by allowing the incorporation of other tools like Python, data sources, and hourly traffic flow, enabling the modeling of realistic traffic conditions based on real-world data. For instance, traffic flow data, road geometry, and signal timings can be imported from real-life traffic management systems. For vehicles, SUMO can model various vehicle dynamics, such as acceleration, deceleration, lane-changing, and interaction with other road users, along with different vehicles' powertrains, from passenger cars to trucks and buses, providing a full view of the transportation ecosystem (Yavuz & Özen, 2024). It further enables the simulation of various traffic management strategies, such as prefixed and actuated, while allowing the integration of adaptive, coordinated, and adaptively coordinated signalized intersection algorithms, as well as the integration of Intelligent Speed Advisory and the application of Intelligent Communication Technologies.

SUMO has become an indispensable tool for research and the development of urban mobility. It assists cities in developing more intelligent, more sustainable transportation systems that help reduce congestion, improve air quality, and enhance city dwellers' overall quality of life. This section provides details on SUMO as a simulator tool in this thesis, along with its features. The next one will provide detailed information on the thesis's Key Performance Indicators (KPIs) for assessing the designed and applied approach for an eco-friendly and sustainable smart city.

2.3.2 Key Performance Indicators (KPIs): energy consumption and emissions metrics

KPIs are very important measures that enable the evaluation of the efficiency and effectiveness of various transportation systems and or the applied approach for smart and sustainable cities. This thesis is primarily directed at energy consumption and emissions, which are basic KPIs indicating how well a transport system functions on both environmental and operational counts. It reflects the total energy consumed by vehicles across a network, whether fuel for conventional vehicles or electricity for electric vehicles, along with the measurement of a variety of pollutants such as carbon dioxide CO_2, nitrogen oxides (NOx), carbon monoxide (CO), particulate matter (PM), and the nonmethane volatile organic compounds NMVOCs that get emitted while vehicles are being run. By monitoring energy consumption and emissions closely, a city or transport authority may evaluate the effectiveness of energy-saving and environmental impact reduction initiatives: Eco-driving algorithms and intelligent traffic control systems. For the fuel consumption models along with equations 2.8 to 2.13, which are used for a more detailed impact of factors such as road slope, wind speed, and so on, for simple acceleration and deceleration and speed case scenarios, we can use the SUMO implemented Handbook Emission Factors for Road Transport (HBEFA) model version 3.1 presented in the next equation (Eq. 2.14) (Othmani, Boubaker, Rehimi, Halawani, et al., 2024):

$$Fc(t) = \begin{cases} C_0 + v(t) \times a(t) \times \left[(C_0 \times C_1) + \left(C_2 \times a(t) + \frac{(C_3 + C_4 \times v(t) + C_5 \times v(t)^3)}{a(t)} \right) \right] & if\ v(t) > 0 \\ \Delta \times T_{idle}\ ; \qquad if\ v(t) = 0 \end{cases} \tag{2.14}$$

The C_i coefficients are used to estimate the energy consumption provided by the HBEFA emission factor handbook (Notter et al., 2019), T_{idle} is idling time in seconds, and Δ represents the idling fuel consumption rate in grams per second. As for the various emissions estimation $E_i(t)$ in grams per second based on the emissions factor β provided by the air pollutant emissions guidebook for different vehicle and fuel types (Ntziachristos & Samaras, 2021), we use the next equation (Eq. 2.15) (Othmani, Boubaker, Rehimi, Halawani, et al., 2024):

$$E_i(t) = Fc(t)\ x\ \beta \tag{2.15}$$

These KPIs provide a complete view of transportation systems' performance, enabling us to assess the applied approaches and techniques in this thesis and inform us how well these approaches contribute to making urban environments more sustainable and livable. The next section provides a closure conclusion of the chapter, setting the stage for the upcoming chapter.

Conclusion

This chapter provides an overview of traffic signal control systems, both traditional and emerging technologies that aim to improve traffic flow and energy use efficiency. We looked at the evolution from static to dynamic and adaptive traffic signal control, emphasizing actuated, coordinated, and adaptively coordinated strategies. It finds further reinforcement in applying communication technologies such as V2I, V2V, and V2X that enable more responsive and efficient traffic management. Further, the chapter elaborated on ISAS with an explanation of how Fuzzy Logic could be implemented to vary the speed of a vehicle in real-time for efficient and less polluting traffic. The impact of various vehicular technologies, such as conventional vehicles versus electric ones, and their impact on energy consumption and emissions was analyzed. Lastly, SUMO was introduced as a simulation tool along with energy use and emissions KPIs.

The following chapter delves more deeply into DTSC applications combined with ITCs for the sustainable development of urban mobility systems and their role in enhancing traffic while exploring how such technologies can achieve brighter, greener, and more efficient cities.

Chapter 3 : Adaptively coordinated traffic control systems and fuzzy logic green light optimal speed advisory for sustainable transportation

Introduction

This chapter examines two key technologies, ACTSC and GLOSA systems, by reviewing how they improve traffic flow by adjusting traffic signals in real-time to current traffic conditions. Additionally, this chapter explores existing speed advisory systems that use technology to recommend optimal speeds for drivers, helping them pass through green lights safely and efficiently, while also identifying the challenges and limitations of current approaches. It then presents a practical case study on the Mouhamed V signalized intersections, analyzing the area's traffic patterns and developing a Fuzzy Logic-based speed advisory algorithm. Different traffic signal control strategies are tested through simulations, including static, adaptive, coordinated, and adaptively coordinated signals. The integration of Vehicle-to-Everything (V2X) communication technology is also explored to enable real-time signal adjustments. The results section evaluates how effectively these systems reduce energy consumption and lower emissions based on the simulation findings. Finally, the chapter discusses the practical limitations encountered during implementation and outlines future research directions for developing more environmentally sustainable transportation solutions.

The following section presents a comprehensive review of current advancements in these traffic signal control strategies and GLOSA technologies.

3.1 Insights into adaptive, coordinated traffic signal control, and Green Light Optimal Speed Advisory Systems (GLOSA)

Transportation is one major energy consumer sector, involving 25% of all energy demand and is in charge of 23% of the entire emitted carbon pollutants in the atmosphere (Gunko, 2021). Because of the sector's high reliance on petroleum-based fuels (PFs), GHGs and CO2 levels are high (Mohsin et al., 2019). So, regarding the mentioned concerns, it has become increasingly important to embrace effective techniques that would ensure lower use of PFs in transportation, given the increase in environmental degradation and the increasing measures to enhance ecological development. In this matter, academics and policymakers have shown more interest in the techniques that restrict energy demand alongside their impacts on the environment. In an attempt to reduce carbon footprint and energy use along with several other problems relating to both the environment and human health, it is plausible to pin down the necessity for changing climate and preserving natural resources necessary for further transport (Gunko, 2021; X. Li et al., 2022; Lin & Bai, 2024; Mohsin et al., 2019; Shah et al., 2024). These are important endeavors as transportation becomes one of the major emitter sectors of energy consumers and emissions, such as GHG (Kazancoglu et al., 2021). Policies promoting eco-friendly mobility and energy-efficient transportation systems stand out among the numerous strategies being implemented. These policies are established to minimize fuel consumption and decrease emissions, eventually contributing to broader environmental aims such as tackling climate change and improving air quality for environmental sustainability (Ogunkunle & Ahmed, 2021).

From these technologies and strategies that have emerged to mitigate these issues and promote an eco-friendly transportation sector, we can mention GLOSA along with signalized junctions, which we will focus on in the two following subsections.

3.1.1 State-of-the-art in adaptive, coordinated traffic signal control

Previous studies related to the topic of green transportation discussed how to ameliorate traffic situations and lower congestion by applying more intelligent traffic control measures and innovative IT technologies. It investigated the outcomes of coordinated and adaptive crossings on environmental, energy, and traffic aspects (J. Han et al., 2023; Tajalli et al., 2020; T. Wang et al., 2021). Some have attempted to study the works that could be carried out to effectively address challenges with the ICT implementation concerning traffic light management and its effects on the environment (Alsudani, 2023; Devika et al., 2023; Tahir et al., 2022).

From the carried studies, we mention that Kart et al. (2021) have coordinated multiple intersections so they can generate green waves. Because of this, it was possible to attain a 20% reduction in emitted CO_2. However, the authors neglected V2V use in their study. Devika et al. (2023) and Yun et al. (2018) conducted two studies, both of which concentrated on V2V to adequately manage traffic and lower its impacts. The studies' findings illustrate a remarkable drop in fuel use and related air pollution by 10% and 17.83%, respectively. Nonetheless, in both studies, the components of traffic were not investigated, and the utilization of ACTSC was also not integrated. As for

Gankov et al. (2023) and Zhou et al. (2022), they adopted V2X in their study and were capable of lowering fuel intakes and CO_2 levels by roughly 7% and 8.4%, respectively, for the first study and 17.56% for the second. Unluckily, the mentioned studies didn't couple ATSCs with ICTs. Similarly, Liu et al. (2024), adopted an Eco-Driving Strategy for autonomous electric vehicles crossing Continuous Speed-limit signalized Intersections (EDS-CSI) method coupled with V2X. The amount of saved energy was approximately 39.1%, while the Eco Approach and Departure (ECO-AnD) approach resulted in a decrease of 12.1% in fuel intakes compared with the reference scenario. In their study, the two parameters, vehicle speed and queue length, are synchronous. Unfortunately, their involvement has been restricted to electric vehicles.

Consequently, through the evaluation of the study's outcomes and limitations, this chapter categorically analyzes the presented approaches, which can be classified under two domains depending on their research topic, namely Signalized Intersection Control Strategies and ICTs. Commencing with a signalized crossroads Deshpande & Hsieh (2023) defined and assessed signalized intersections by using SUMO and their study algorithms for dynamic and semi-dynamic signalized intersections, which reduced travel time by 12% to 17%. Additionally, in an experimental investigation by Gaddam et al. (2023), where the existing signalized crossroads are transformed into adaptive ones employing self-adapting algorithms, we remark 44% and 39% drop in congestion, flow, and queue length. Similarly, real-world simulations also revealed the efficiency of adaptive junctions in which a noteworthy reduction in average total time was achieved, 59.9%, total stops 17.55% and considerable improvement in the vehicle's speed of 3.4% (Reza et al., 2023).

Moreover, Kart et al. (2021) research dealt with coordinated junctions, with the help of green wave strategies and the SUMO tool, which resulted in a 20 % overall decrease in waiting time and CO_2 emissions, along with a 20 % increase in average speed. Further to this, H. Wang & Peng (2022) developed a two-way coordinated signal control to manage crowded lanes, reducing the average waiting time by 23.6%. Research has also been conducted on the optimization models aimed at improving the coordination of traffic lights. Lu et al. (2023) developed an optimization framework for local green wave synchronization control, where the adopted approach dropped the average delay by 30%, along with a 40% drop in the total number of stops.

Meanwhile, Aleko & Djahel (2020) assessed the impact of coordinated crossroads with dynamic offset based on jam levels, resulting in a 39% drop in average travel time and a 17% drop in both waiting time and queue length. Supplementary research concentrated on ATSCs depending on real-time data on traffic density. Starting with Dampage et al. (2020) have developed a system to promote both traffic coordination and optimal signalized junction control, which resulted in an 18% rise in average speed in several crossroads cases. Next, Ma et al. (2021) put forward an ACTSC method, which dropped the related vehicle average delay at the intersection's entrances by roughly 4%. Collectively, all of these mentioned studies demonstrate the efficiency of coordinated and adaptive traffic signal strategies in lowering congestion, minimizing delays, and enhancing overall traffic effectiveness.

Proceeding with ICTs, and the V2X to be precise, Ko et al. (2023) examined the effect of driving actions on traffic efficiency, paired and unpaired with V2V communication, reporting an average speed increase of 23.18%. Yun et al. (2018) proposed a V2V-based acceleration advisory model for vehicles in congested traffic, leading to a 17.38% drop in fuel intakes and CO_2 emissions. Similarly, Devika et al. (2023) examined the implications of V2V and 5G technologies on energy utilization, showing a 10% drop in both emissions and energy use.

In addition to V2V communication, V2I-based eco-driving control has been explored to optimize traffic sustainability and efficiency. Han et al. (2023) conducted a larger-scale simulation study on the energy impact of V2I-based eco-driving control, demonstrating up to a 40% reduction in energy utilization. D. Wang et al. (2023) combined traffic signal control with connected unmanned vehicles using V2I at isolated intersections, resulting in a 47% decrease in the average total number of stops and a 41% reduction in queuing time. Furthermore, Özdemir & Koç (2023) focused on lowering both energy and emission levels through various strategies using V2I, achieving a 19.8% reduction in total vehicle emissions.

Studies have also assessed the overall impact of V2X-based eco-driving on exhaust air pollution and fuel use. Gankov et al. (2023) evaluated the effectiveness of V2X in eco-driving strategies, reporting a 7% drop in energy utilization and an 8.4% decrease in CO_2 emissions level. Zou et al. (2023) investigated V2X communication technology's influence on vehicle performance, revealing reductions in both average waiting time and energy utilization by 25% and 17.56%, respectively. In addition, Liu et al. (2024) introduced an eco-driving method for unmanned electric vehicles navigating signalized intersections. Their EDS-CSI algorithm achieved a 39.1% energy consumption reduction compared to the reference method and a 12.1% improvement over the ECO-AnD method. They also proposed a co-optimization approach that considers both speed limit and queue release to enhance vehicle energy savings.

Collectively, this subsection focused on these studies, highlighting the substantial benefits of V2X in enhancing traffic efficiency, lowering congestion, and lowering emissions through advanced eco-driving strategies. The next subsection will focus on the existing GLOSA applications.

3.1.2 Existing Green Light Speed Advisory Systems

Various assessment tests have been carried out with a view to determining the ability of the GLOSA-based approach in enhancing the mobility of traffic flow, in addition to the choices made regarding energy and traffic congestion reduction as part of the environmental mitigation measures. Ding et al. (2024) examined GLOSA capabilities on multiple traffic lights, lowering the utilized energy and total travel time. The research's results demonstrated a performance rating of 24.1% reduction in travel time and consumed energy. The research also mentions a few limitations, which include challenges in modeling the traffic signals and vehicles' communication, and the slow growth of the GLOSA-based method. By using a traffic simulator, Zhang et al. (2023) introduced a vehicle speed optimization approach aimed at minimizing delays and queue lengths. Their findings indicate notable improvements in traffic flow, with travel time lowered by 18.4%, queue length shortened by 41.5%, and delays reduced by 24.1%, leading to overall efficiency gains in transportation. However, the study acknowledges certain limitations, including the simplified experimental conditions that overlook external environmental factors like road gradients and related coefficients. Additionally, it does not provide in-depth enhancements regarding the GLOSA system's impact on fuel intakes and emissions. Meanwhile, a study conducted by Shafik and Rakha (2024) explores the application and assessment of the GLOSA-based system integrated with actuated signals, analyzing its interaction with surrounding traffic. Their findings reveal substantial benefits, showing a 35.4% drop in fuel intake and a 31.4% reduction in emissions when accounting for or disregarding the queuing vehicle's standpoint. Furthermore, in a larger network, the adoption of GLOSA can lower both air pollution and energy utilization by 19.7% across different conditions. Also, X. Zhang et al. (2024), propose a new solution-based model to optimize velocity that employs a predictive model-based control approach that would allow dropping both environmental footprint and energy utilization when selecting the driving speed. Thus, their results of fuel saving are 27.21% and 25.89% in addition to emission reductions of 25.30% and 25.97% at speeds of 40 km/h and 20 km/h, respectively. However, the work does not focus on the best approach for attaining the highest speed along with the lowest power consumption. Chen et al. (2024) considered a novel strategy to control traffic signal control and to consider the ineffective energy and lower the travel time using unmanned connected vehicles. The evaluation of the adopted approach proved that traffic congestion was eliminated and overall energy requirement was reduced to a considerable extent; specifically, energy use was reduced to 14%, and traveling time was lowered to reach 38%. Yet, it has been evaluated that there are some shortcomings involved in the research. Firstly, there is no existing accurate speed estimation model that considers forecasts depending on deceleration and acceleration conditions of actual vehicular movement. In another study, Z. Zhang et al. (2024) investigated the applicability of the GLOSA approach simulation to enhance mobility in cities while reducing fuel intakes and emissions. They also provided detailed theoretical calculations proving that GLOSA has a positive impact on efficiency, energy savings, and reduction of environmental effects by 20 percent and 18 percent, respectively. Arnau et al. (2023) proposed a series of tests of GLOSA that involved comparing the algorithms' results in dropping emissions and fuel intakes while maintaining travel time or following a specific schedule. As stated by Mullaney et al., the utility of GLOSA is marked by discovering that it can drop energy use and exhaust by 20%. Also, Gutesa et al. (2021) proposed an unmanned and connected vehicles approach with an aim of improving the management of intersections and vehicle control in an attempt to drop the levels of CO_2 emission and fuel intake. They got the goal, which was a 44% drop in fuel utilization and emissions. However, it must be pointed out that the system was only tested under relatively no congestion, and thus raises questions about its suitability under more complicated traffic situations.

This subsection introduced several studies that have adopted GLOSA as a solution for their studies, mentioning their advantages and limitations. The following subsection will focus on the existing limitations in the adaptive, coordinated ICTs and GLOSA approaches.

3.1.3 Challenges and limitations of existing approaches

Researchers have mainly concentrated on assessing signalized crossroads and ICTs through simulation studies in the prior explained subsections, commencing with coordinated and adaptive approaches. These studies provided significant details about the potential improvement in traffic performance and energy and air pollution levels. Overall, the mentioned studies suffered from limitations, as follows:

- The lack of a common study: refers to the absence of detailed studies that combine ATSCs, coordination approaches, and ICTs simultaneously. An embedded methodology is needed to assess the cumulative effects of the mentioned components on traffic and fuel utilization, along with environmental outcomes, to offer a thorough comprehension of their effectiveness.

- Insufficient Assessment of Unmanned Vehicles: Numerous research studies failed to thoroughly investigate the benefits and possible downsides of autonomous in comparison to human-driven vehicles in both coordinated and adaptive crossroads. This negligence involves inaccurate estimation of fluctuations in energy intakes and emissions levels. These assessments are needed to fully comprehend the rewards of combining unmanned technology with coordinated and adaptive traffic control systems.

In reference to the GLOSA subsection, the indicated studies concentrated on assessing the V2I paired with the GLOSA approach and offered insights into the possible enhancement in traffic and energy, and pollution reductions. In the previous studies, some drawbacks were observed, and they are highlighted below:

- Lack of research on ATSCs: The research has been carried out mostly on the STLs. However, very limited research has been conducted on the performance of GLOSA systems within environments where the traffic signals adjust their phases based on real conditions. It is very important to understand how the GLOSA approach works in the context of ATSC intersections in order to evaluate their broader utilization and effectiveness.

- Lack of adequate realization of conditions and scalability studies: Over and above, most of the proposed works were conducted and tested under certain controlled conditions of environment and very limited vehicle types and network sizes that hardly represent real-world scenarios. Such oversights would yield lesser accurate outcomes when predicting the efficiency of GLOSA, especially during dynamic and complex traffic environments.

- Failure to implement Fuzzy Logic in GLOSA: multiple factors, such as distance to the intersection, traffic light phase, and remaining duration, to calculate the appropriate speed indicate the need to apply FL to enhance traffic, along with energy intakes and environmental consequences.

After discussing each subsection's challenges and limitations, the next section will provide the adopted approaches to resolve these limitations.

3.2 Case study framework : Mouhamed V signalized intersections

The following subsection clarifies the proposed methodology, which includes the data collection approaches, development, and assessment. It presents essential information on the selected zone and gathered data to carry out the study alongside Fuzzy Logic-based GLOSA, dynamic traffic control adoption, and the acquired findings.

3.2.1 Study area and traffic characteristics

The Selected study area is “Mohamed V Boulevard,” a main road that intersects with other roads at various intersections in a densely populated region in Tunisia, North Africa (at 36.8115° N,10.1846° E). Some of these signals include intersections, which are significant links between different transport networks for automobiles and pedestrians. Figure 3.1 depicts the study-selected intersections in the Satellite Map.

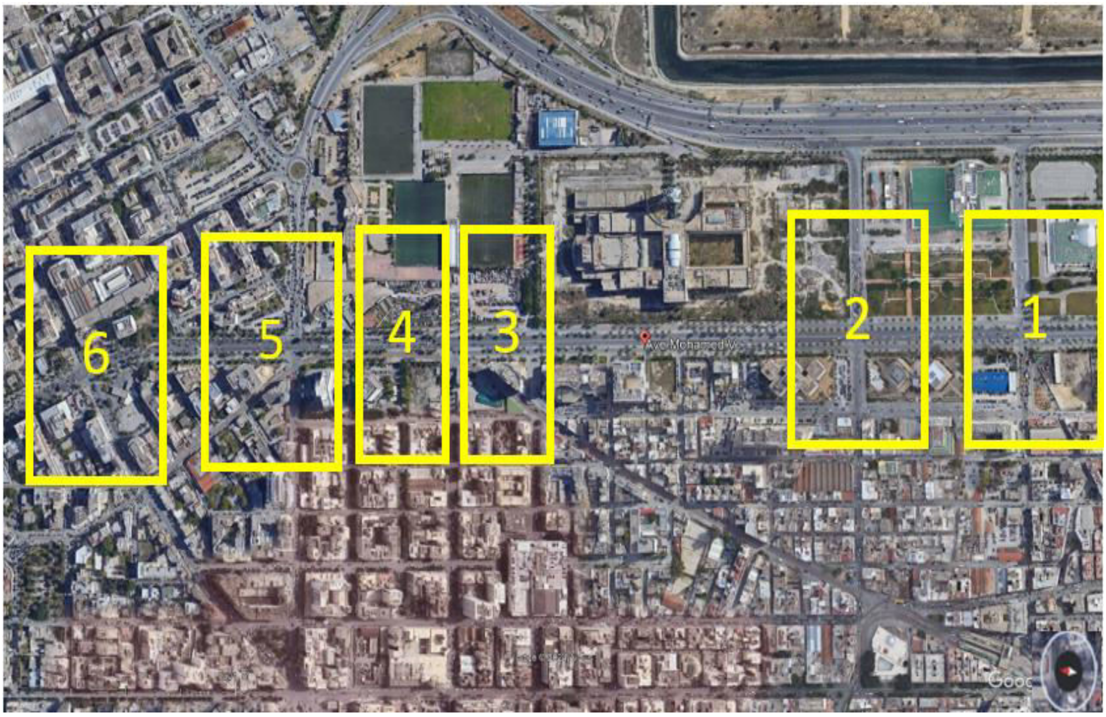

Figure 3.1. Google Earth image of Signalized junctions of Mohamed V

Study Avenue is actually among the famous streets in Tunis, which has many places of interest around a central area. It communicates with the Medina, a quaint neighborhood with narrow alleys, mud buildings, and shops. The avenue extends parallel to Habib Bourguiba Avenue, which is famous for its youth entertainment and various events. Additionally, it leads to Bardo, which is a historical city that has a route to the western suburbs. The Avenue, in other words, has the duty of a strategic communication channel with a proper network of roads that can handle large traffic flows. The avenue comprises several lanes and a sidewalk area that can only be accessed on foot, while the bike lanes are designed to accommodate bicycle riders only. However, due to strong traffic conditions, which persist in this region most of the time, the otherwise operational static traffic signals slow down traffic.

In this project, data that was utilized was gathered manually at each fifteen-minute one-hour interval for each directional flow using a crew of 12 people during peak hours on Mondays (11:30 p.m. - 12:30 p.m.). An example of traffic characteristics includes such elements as directional traffic flows and the relative utilization of directional traffic flows by heavy vehicles. Further, the intersections' traffic light duration, along with cycles, was measured and set separately from the signal delay. Then, the highest recorded 15-minute demand during rush hour was selected to perform the study simulations. Each of the simulations is performed within one hour. Figure 3.2 shows each junction phase, cycle length (CL), and directional flow.

Junction N°	Number of legs	Phase 1	Duration (s)	Phase 2	Duration (s)	Phase 3	Duration (s)	Cycle length (s)
1	4	⇆	24		16		20	60
2	4	⇆	34		11		35	80
3	3	⇆	50		16	x	x	66
4	3	⇆	50		16	x	x	66
5	4	⇆	30		26		24	80
6	4	⇆	34		22		32	88

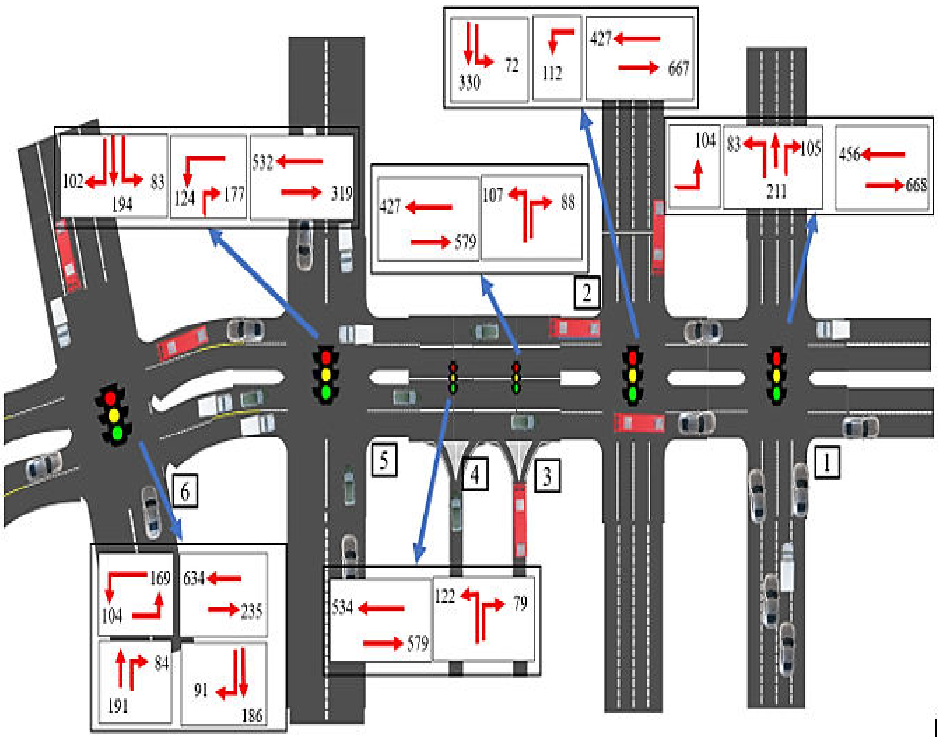

Figure 3.2. Data collection on each junction's directional flow, phases, and cycle length spans one hour, measured in PCU/15 minutes

Thus, after finalizing the selected study zone introduction and the obtained data within this section, next, we have to proceed to the following one that addresses the development of a Fuzzy Logic-based GLOSA approach.

3.2.2 Fuzzy Logic Speed Advisory algorithm development

To develop an FL Sugeno model type 1 that estimates the appropriate speed, we utilized Python 3.10 and its associated library Simpful 2.12 (Spolaor et al., 2020). The outlined system above uses four inputs, whereby the input variables include: The remaining distance (D) in m, the phase type (green or red), the remaining phase time

(St) in s, and the road speed limit (RSL) in m/s; to give out the calculated new speed ($Speed$) of the vehicle in m/s as achieved with the formula shown below in Eq 3.1:

$$Speed = f(Ph,\ D,\ St,\ RSL) \tag{3.1}$$

These are the parameters selected to define this system that is used for estimating the vehicles' speed, which will be integrated within the SUMO simulator using the Python interpreter to make certain changes to inputs to different simulations, as follows, to determine the impact of those changes on the selection of speed by vehicles. The phase type is the foremost phase to have in mind because it defines whether or not the vehicle is facing a red or a green signal. When it is a green light, this means that the vehicle has the right of way and can, thus, move and even travel at a faster rate than other vehicles. In contrast, when it is a red light, it means that the vehicle must either slow down or come to a complete halt (M. Liu et al., 2022). Next, distance is determined depending on the car's actual speed. This info alerts the advisory system to the need to decelerate or speed up, allowing the model to make decisions corresponding to the car's speed requirement on the road (Suzuki et al., 2020). It also enables vehicles to stop smoothly or coast if the speed suits it, and if not, it comes up with the right speed depending on the presence of a green light. For the rest of the period, the FL needs this information to enable it to make advanced speed changes. This makes the road safe by avoiding a driver's entrance to the crossroad at high speed when the light is about to turn red. It also regulates the utilization of green signals by helping vehicles enter the intersection when the light is green, reducing instances where a vehicle has to halt and wait for the signal to turn green (Eom & Kim, 2020). Lastly, the RSU parameter defines features of the legal vehicle's top speed to satisfy both the safety of the passengers and adherence to road laws (Gressai et al., 2021). Considering factors such as: road geometry, visibility, and any likely hazards on the road, making it safer to drive. This parameter enhances safety and efficiency since it incorporates aspects such as speed limits, which enable drivers to gain maximum road flow while observing the maximum safe speed prudent to be maintained.

Using these parameters, the FL-based GLOSA system understands a vehicle's driving context and traffic situation and makes recommendations for the optimal speed that would help lower fuel consumption, promote orderly traffic flow with fewer emissions, offer safer roads, and make driving more comfortable. The upcoming Figure 3.3 shows the input and output of the flow diagram of FL-based GLOSA.

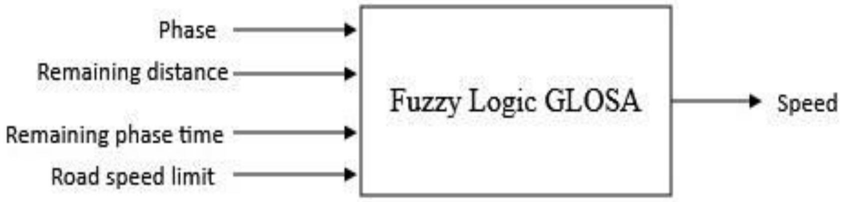

Figure 3.3. Diagram of the FL-based GLOSA

The FL system is designed utilizing Python, and the next figures demonstrate its Membership Functions (MF), which are derived from a snippet of the FL-GLOSA code and used dataset types present in Annex A and B.

The Ph MF is split into two classes: Red and Green lights, also according to Wágner et al. (2023), Yellow light is regarded as red light. Meanwhile, the MF of St is also categorized into three: The low MF ranges from 0s to 20s, while the medium MF starts from 0s, reaching 60s, and finally, the high MF begins from 60s. Figure 3.4 illustrates both the Phase and St membership functions.

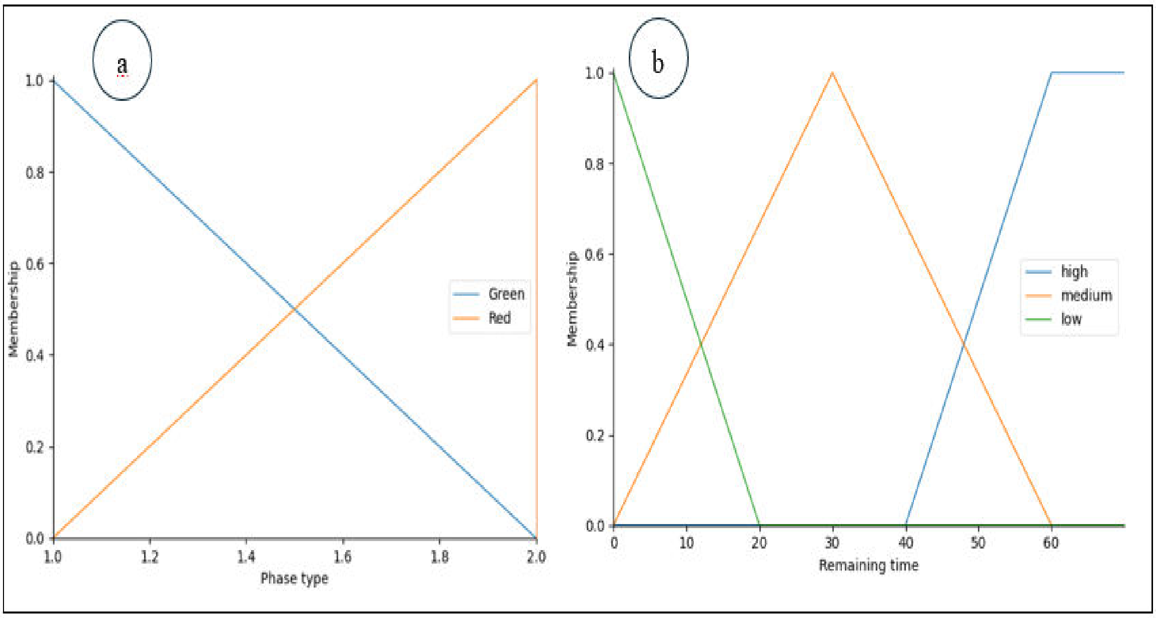

Figure 3.4. Phase type and remaining phase time membership functions; a) Phase type MF; b) remaining phase time MF

As displayed in Figure 3.5, **D** and **RSL** are split into three distinct ranges, starting with **D**: low remaining distance, which covers the range from 0 meters to 50 meters. A medium distance extends between 0 meters and 100 meters. Finally, a high remaining distance refers to any value over 100 meters. Moving to **RSL**, he low-speed limit ranges from 0 m/s to 15 m/s, the medium-speed limit extends between 0 m/s and 30 m/s, and the high-speed limit refers to any value over 30 m/s.

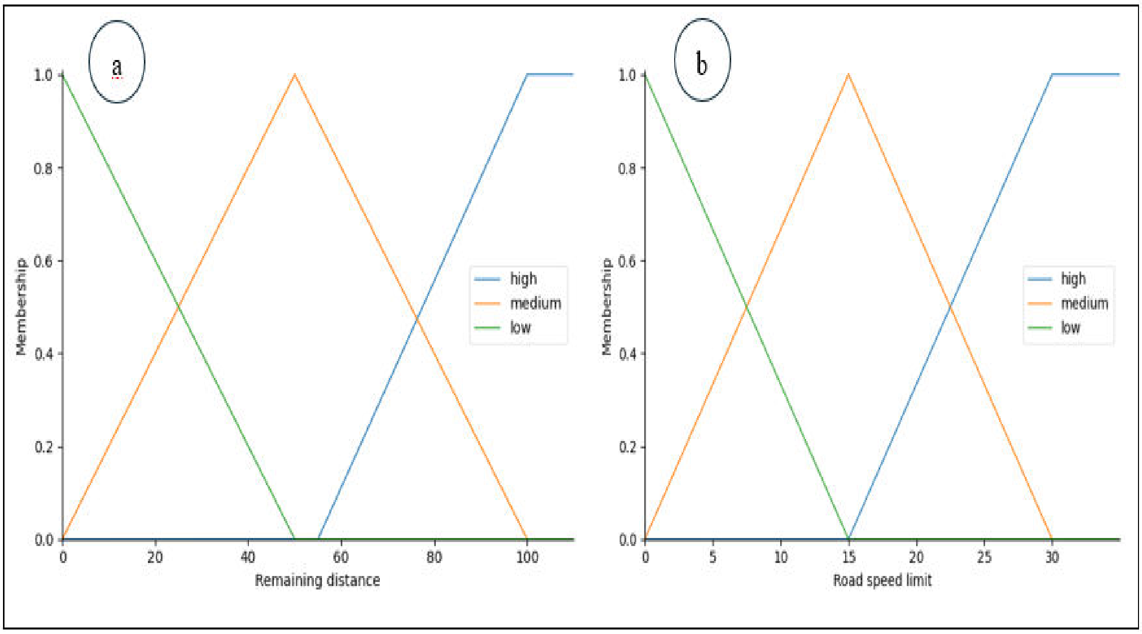

Figure 3.5. Remaining distance and road speed limit membership functions; a) Remaining distance MF; b) road speed limit MF

corresponding to the FL inputs, the *Speed* MF groups the speed outputs to 54-speed ranges starting from the first speed to the seventy-fourth speed before applying to the recalculation of the fuzzification step that was outlined in the rules shown in Figure 3.6.

Linguistic Rules

Rule N°	If Phase is		If D is		If St is		If RSL is	Then speed is
1	Green		Low		Low		Low	Speed 1
2	Green		Low		Low		Medium	Speed 2
13	Green		Medium		Medium		Low	Speed 13
⋮	⋮	And	⋮	And	⋮	And	⋮	⋮
15	Green		Medium		Medium		High	Speed 15
⋮	⋮		⋮		⋮		⋮	⋮
24	Green		High		Medium		High	Speed 24
⋮	⋮		⋮		⋮		⋮	⋮
54	Red		High		High		High	Speed 54

Figure 3.6. Linguistic Rules

This section provided detailed information on the FL-GLOSA development. The upcoming section will focus on intersection modeling and provide details on the adopted approaches.

3.2.3 Simulation scenarios: design and setup

To simulate multiple signalized crossroads, the maximum recorded 15-minute traffic flow has been inserted into full one-hour simulations, and the vehicles were auto-injected randomly in various scenario cases, as shown in Figure 3.7.

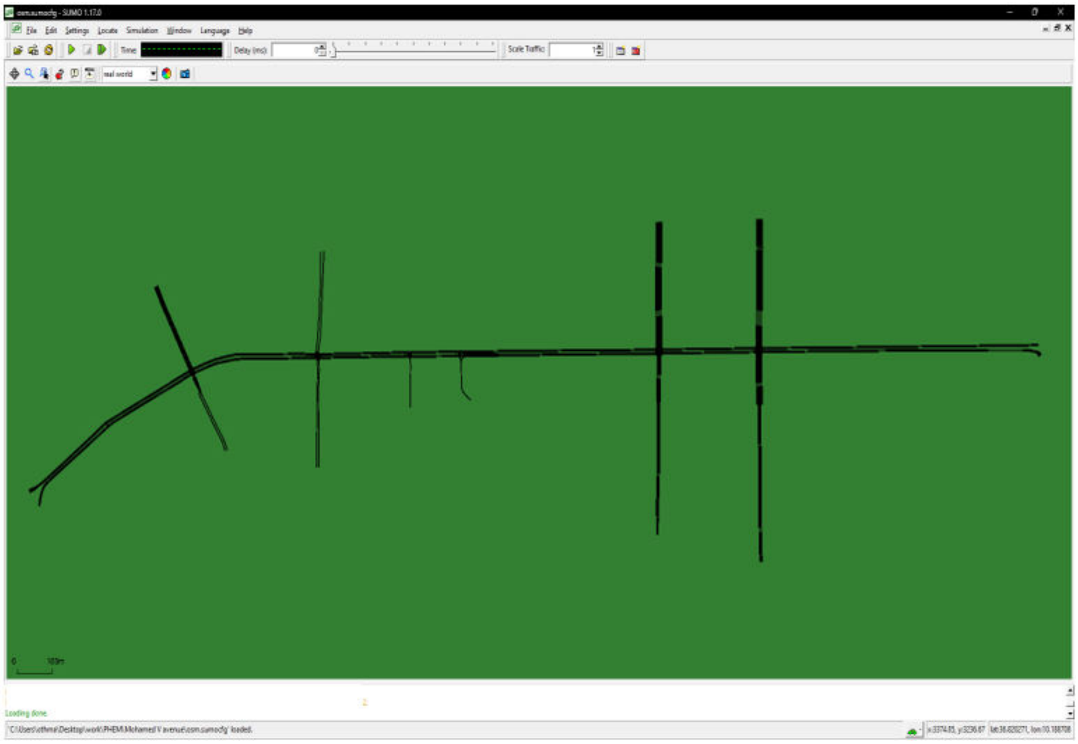

Figure 3.7. SUMO multiple signalized intersection modeling

For this chapter, we utilized the SUMO software, version 1.18, controlled with the Traffic Control Interface (TraCI) and operated by the Python programming language. The car-following behavior of the simulation models was based on the Enhanced Intelligent Driver Model (EIDM), while the Change-Lane model used was the Krauss model. Figure 3.8 depicts the method adopted in this study.

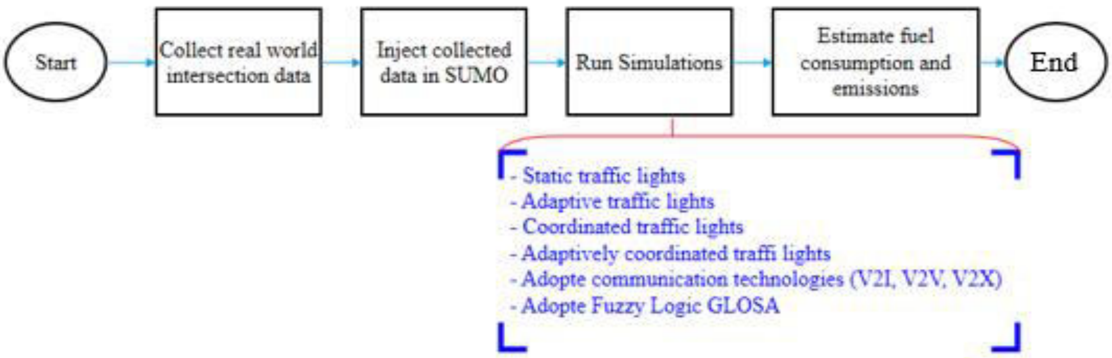

Figure 3.8. The study adopted methodology

This section discusses intersection modeling along the vehicular flow injection. The following will provide detailed information on static, adaptive, coordinated, and ACTSC modeling.

3.2.4 Implantation of static, adaptive, coordinated and adaptively coordinated signals

For the STLs, we do inject the collected data on traffic flows along with each intersection Ph and CL represented in Figure 3.2 into the study zone illustrated in Figure 3.7.

For the ATC scenarios, we will first have to identify SUMO's each intersection entrance existing vehicles. We will then use Lane Area Detectors (LADs), and depending on the documentation about the SUMO traffic simulation, those detectors serve as camera detectors on the intersection entrances (Hossain et al., 2021). Specifically, the used study LADs are located at every entrance of the intersections.

Figure 3.9 illustrates the sensor implantation in the simulations, indicating how to implement cameras to detect vehicles.

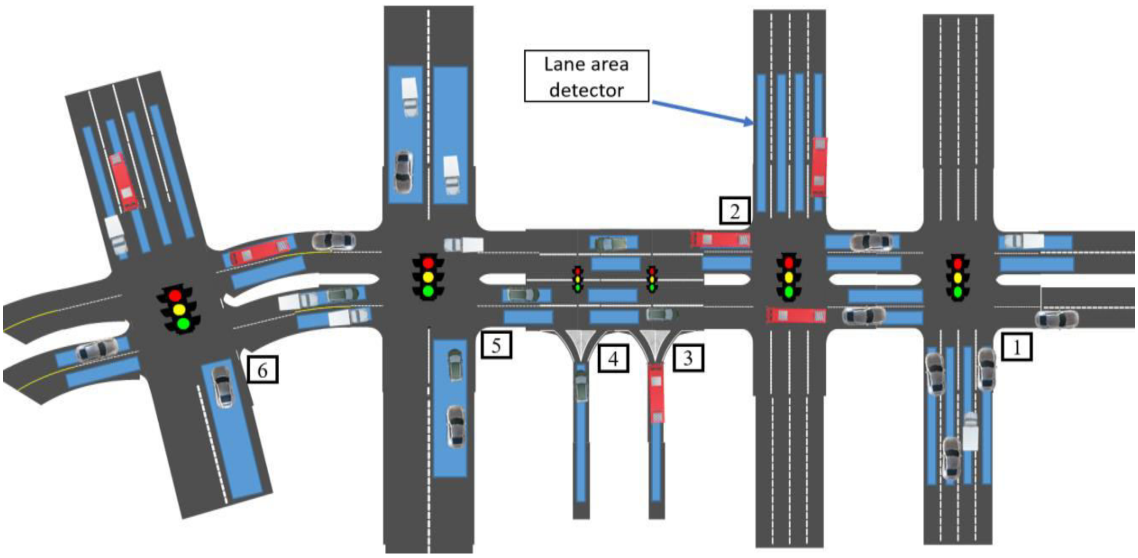

Figure 3.9. LADs' implantation

When the LADs are installed, each sensor produces each lane of the number of detected vehicles and enables estimation of the adequate green light time by converting the vehicle into PCU and using equation 2.2, as indicated in Chapter 2, section 2.1.2.

Figure 3.10 illustrates the adopted methodology to calculate the adequate green light duration of each intersection entrance.

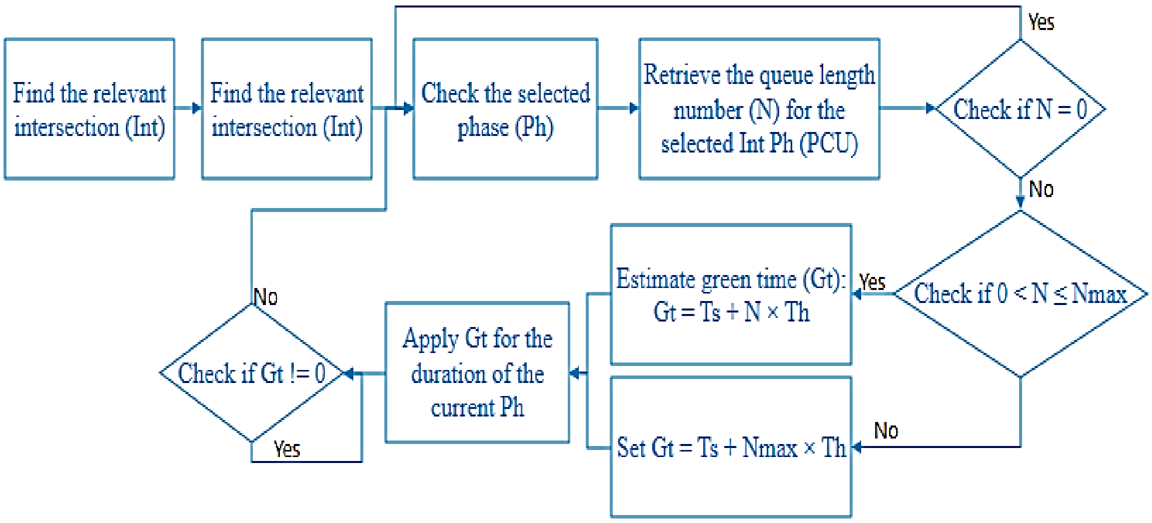

Figure 3.10. The proposed adaptive green light Flowchart

The following are the steps utilized in this chapter's simulation of an ATSC. The upcoming steps will provide a method for developing synchronized traffic signals at both adaptive and static signalized junctions.

Moving to coordinated lights and ACTSC, the disclosed technique of traffic crossroads coordination remains the same for both adaptive and static traffic signals, which helps to enhance the traffic flow and avoid congestion. While the static signals involved the specific signal timings, the ATSC acts appropriately based on the traffic and amends the phase and cycle accordingly. However, the main idea of traffic lights, which is organizing the traffic, that is, the movements of the cars, does not change for either system.

The technique of traffic light coordination involves the linking of signals across a certain route or a few junctions to improve traffic movement, thereby reducing the number of halts and congestion. To achieve this, the green waves for several signalized intersections have to be synchronized, as depicted in Figure 3.11.

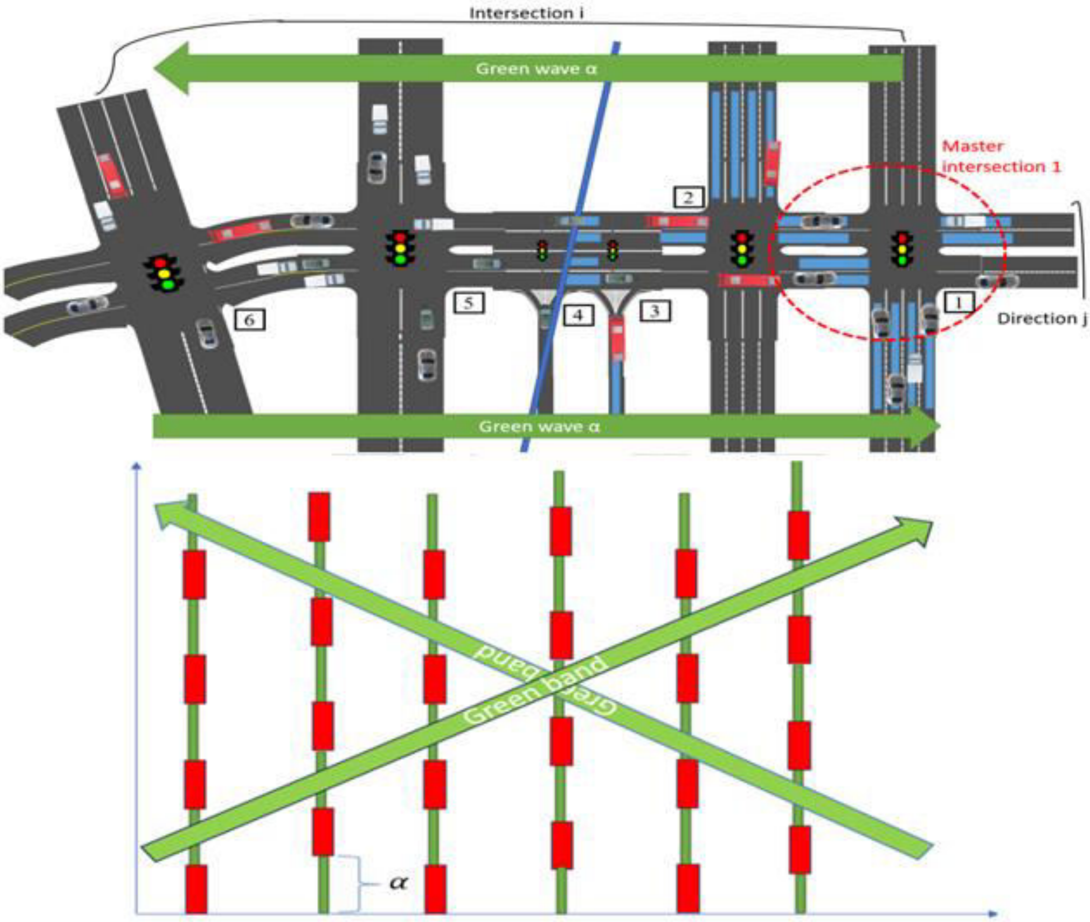

Figure 3.11. Adopted green waves for coordinated traffic lights

As displayed in the preceding figure, to generate green waves for different crossroads for both adaptive and static traffic control approaches for coordination using the described approaches and Equation 2.3 explained in Chapter 2, Section 2.1.2, there is a need to calculate an offset for each direction.

After finishing up with the adopted TSCS in this subsection, the next one will concentrate on the adopted ICT in detail.

3.2.5 Integration of V2X for real-time adaptation

Thus, this chapter has simulated the static, coordinated, adaptive, and adaptively coordinated signalized crossroads in which various ICTs have been integrated.

If the simulation involves V2V, then the adopted library is SIMPLA within the SUMO framework for managing Vehicle-to-Vehicle (V2V) communication and platooning (Krupitzer et al., 2019). As illustrated in Figure 3.12, SIMPLA handles the formation of vehicle platoons on its own and permits the process of defining particular behavior for vehicles that drive inside those platoons (Schweizer et al., 2022).

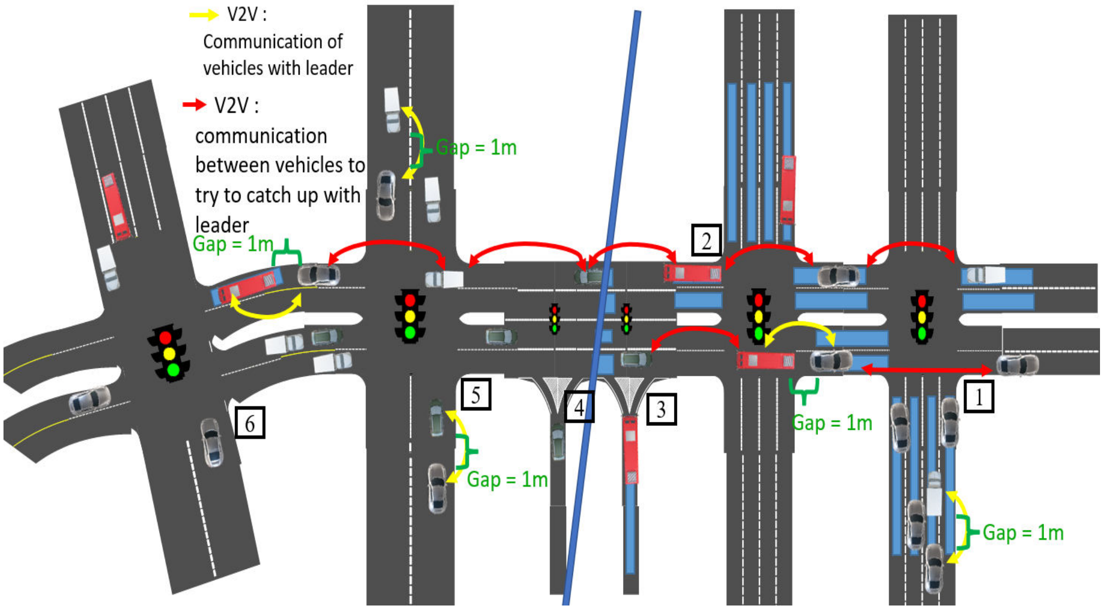

Figure 3.12. V2V application

The SIMPLA library in SUMO allows the vehicles to exchange information with each other, so the vehicles interact with the leader, attempting to minimize the gap between them while leaving a security distance. The leader vehicle can be chosen according to the nearest car to the entrance to the intersection or the farthest car on the exit from it. The gap in this study was set at 1 m, and depending on the vehicle distance based on the leader, the vehicle can be classified into two categories, which are a follower when the gap is less than or equal to 20 m, while higher than 20 m and less than or equal to 100 m, the vehicle is considered a catch-up one (K.-Y. Liang, 2014; Won, 2022; X. Yang et al., 2022). In the prior figure, red arrows represent catch-up vehicles attempting to catch the leader vehicles by increasing their velocity rate upon interacting with each other and gaining their position and speed. Moving to the yellow arrows, they represent the follower range and their attempt to reach their leader vehicle. Lastly, the associated gaps are represented using green brackets.

When the operating scenario includes V2V, both FL-based GLOSA and GLOSA gather the signalized crossroad ahead's D, Ph, and St and estimate $Speed$ for lesser energy usage, as shown in Figure 3.13.

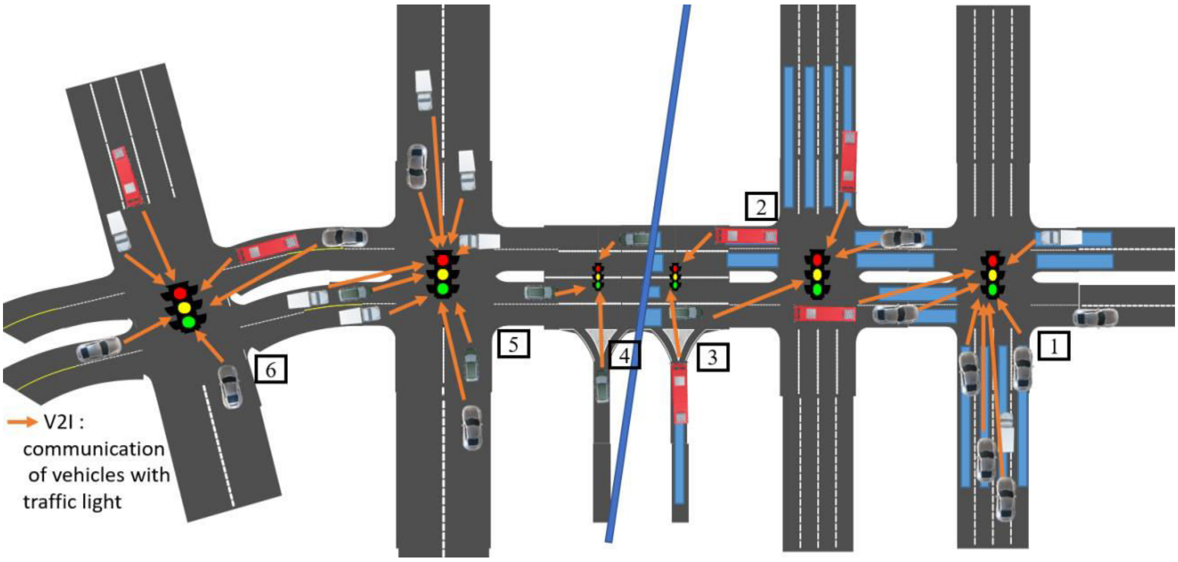

Figure 3.13. V2I and FL-based GLOSA application

To identify the running vehicle advisory speed to be acquired, we utilize this study, FL-GLOSA, in section 3.2.2, or the GLOSA method presented in Chapter 2, section 2.2.1.

It is noteworthy that when applying the V2X, SIMPLA, and GLOSA can receive data from the surroundings, merging V2V and V2I technologies. These values aid in reducing or estimating an appropriate speed that depends on other vehicles and the traffic light in front, as discussed in detail in Figure 3.14.

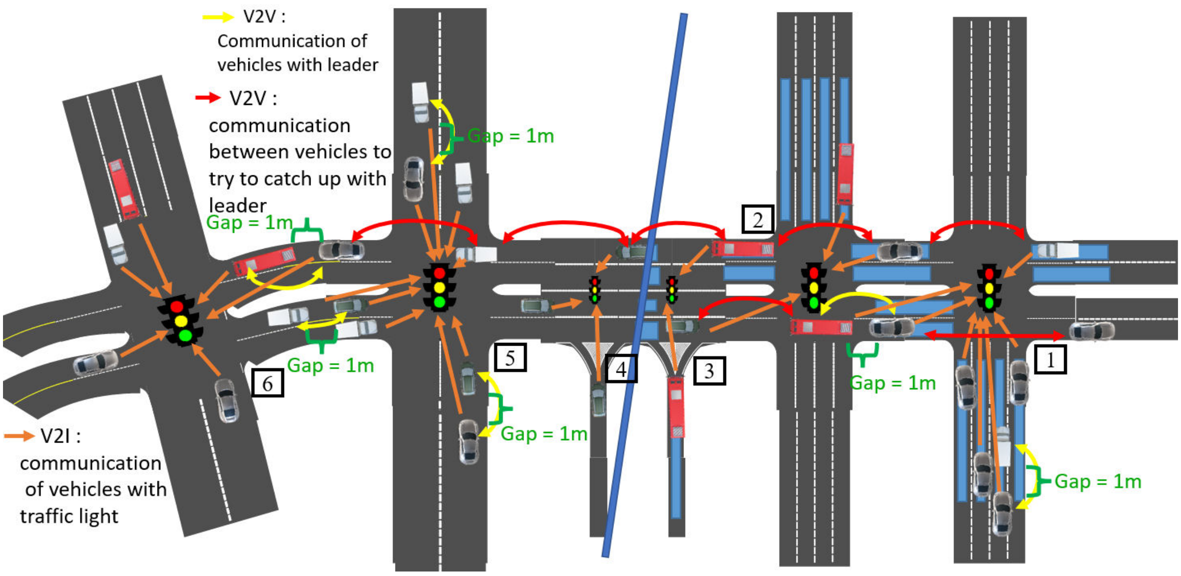

Figure 3.14. V2X implantation

As it was described in the prior figures, V2X is a combination of two powerful technologies. The change of the various colors of the arrows explains the various information that would be exchanged, including the real-time traffic information, any probable road danger, or any important update.

To assess our adopted approaches, we have to calculate the total amounts of burned fuel and emitted emissions into the air. We use both Equation 2.14 and Equation 2.15, illustrated in Chapter 2, section 2.3.2.

This section provided the needed information to enable the V2X, V2I, and V2V technologies alongside the FL-based GLOSA application in the V2X setting. The upcoming section fully assesses the adopted approach regarding emissions and energy use.

3.3 Results and discussion

Each simulation was conducted five times, with the vehicular flow injection varied to assess the proposed approaches under various traffic conditions. Fuel usage and related emissions were collected for the evaluations. The following subductions will present a detailed evaluation of the developed approaches compared with previous studies, alongside each approach with its limitations.

3.3.1 Energy efficiency and emissions reduction achievements

Multiple simulations were performed to compare various traffic systems, and details about the amounts of energy consumed and the impact on the environment were also given. Figure 3.15 provides a bar chart depicting the relative fuel consumption trend in various cases. The trial variability for the proposed dynamic traffic control strategies integrated with communication technology is 3.9% - 8.3%.

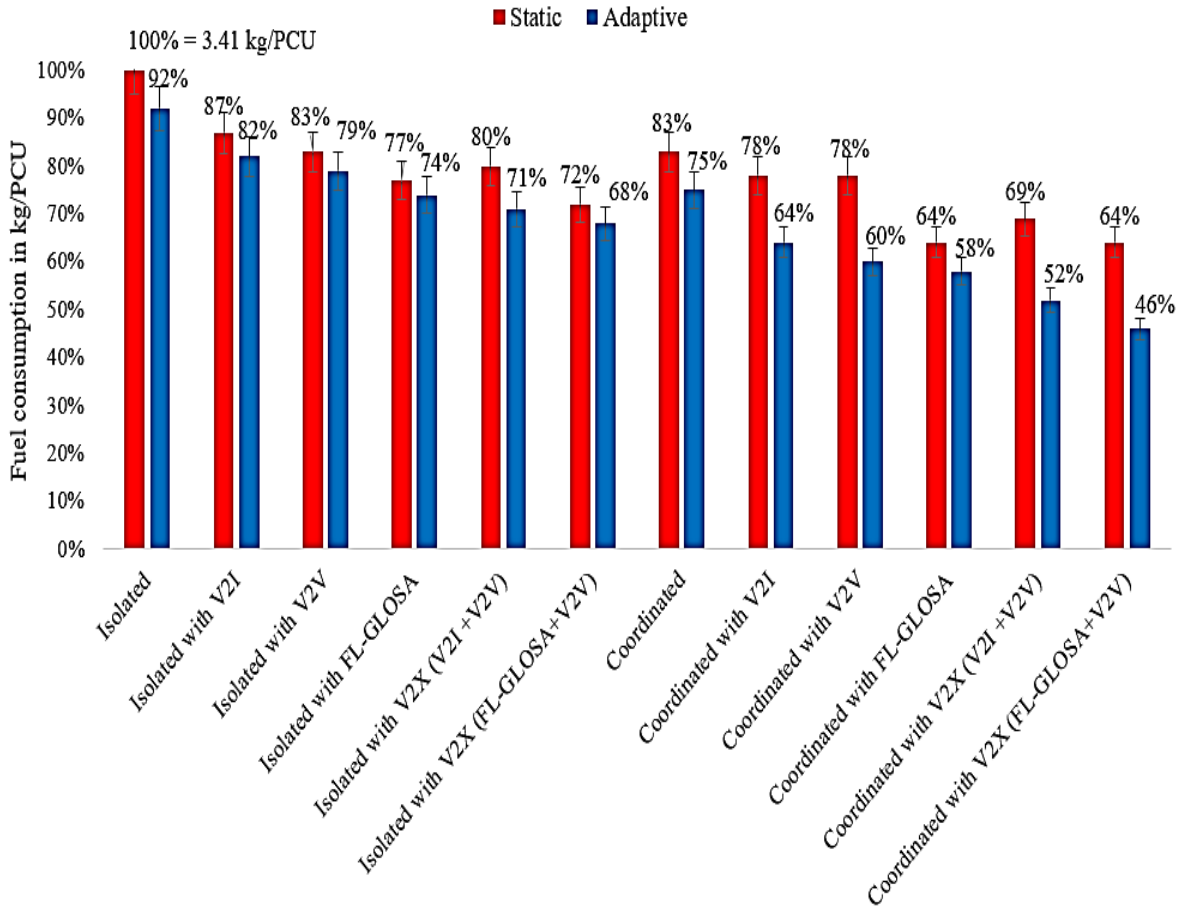

Figure 3.15. DTCSs combined with ICTs fuel consumption

From the figure above, showing the comparison between isolated and coordinated plans, it is clear that the results achieved through the coordination strategies indicate that less fuel is needed. As observed, compared to coordinated cases, both adaptive and STL fuel usage in isolated cases tends to be higher. For instance, the STLs used in the isolated case burn 3.4 kg/PCU, while the corresponding value in the coordinated case is 2.8 kg/PCU, which is a saving of about 17%. As with ATSCs, the amount of used fuel is also lowered by approximately 18% to reach 2.6 kg/PCU, dropping from 3.0 kg/PCU.

Additionally, comparing the adaptive and predetermined time traffic signals in isolation and coordination conditions also explains ATSC's benefits. In both cases, including the coordinated crossroads, the values of fuel usage of ATSC are shown to be less than STL. Compared with isolated prefixed-timing traffic signals, the ACTSC had a difference of 25% in fuel utilization. In the research, a traffic light type comparison was also drawn, where ACTSC noted 2.6 kg/PCU compared to the 3.4 kg/PCU obtained by isolated traffic lights.

In general, for the V2I, the fuel usage was lowered by about 13% for STLs and 11% for ATSC. Similarly, in the vehicle-to-vehicle (V2V) case, CO_2 emissions decreased to about 17% regarding STLs and 14% concerning ATSC. Moreover, under the V2X condition, fuel usage reductions of about 20% for pre-timed and 23% for self-adaptive signals were observed.

Regarding the fuel reduction with the coordination technique, using ICTs for the STLs reduced fuel usage by approximately 22 percent. The latter is also the case for ACTSCs; together with ICTs, we remark a drop of roughly 30% for v2I, 34% for V2V, and 44% for V2X compared to the Unequipped ACTSCs without ICTs.

Consequently, it can be stated that the efficiency of the scenarios with coordinated crossroads considerably improves traffic flow, and the necessary fuel usage is dropped compared with the efficiency of the isolated cases. The comparison shows a remarkable drop of about 25% regarding ACTSCs and pre-timed coordinated traffic lights coupled with V2X. Further, the reduction of fuel usage reaches 48% while using the ACTSCs with V2X compared to the STLs.

Additionally, introducing FL-GLOSA systems further emphasizes fuel consumption reductions, particularly under adaptive and static strategies to compare coordinated and isolated traffic scenarios. In isolated case scenarios, FL-GLOSA systems contribute to lowering fuel utilization compared to traditional methods. For instance, in isolated settings, FL-GLOSA reduces approximately 23% for STLs and 26% for adaptive ones compared to unequipped isolated pre-timed signalized junctions. While in a coordinated setting, we observe that the drop in fuel utilization is even higher, reaching approximately 36% for STLs and 42% for adaptive ones compared to unequipped coordinated pre-timed signalized junctions.

When integrated into V2X technologies, FL-GLOSA's benefits become more pronounced. In coordinated scenarios, FL-GLOSA coupled with V2X technologies results in a remarkable drop in fuel utilization of 54% and 36% in both adaptive and static signalized crossroads, respectively, compared with isolated traffic lights. In addition, it outperforms the isolated settings of coupled FL-GLOSA with V2X for both adaptive and prefixed time junctions by 18% and 4%, respectively.

The table below also shows a stochastic variability of 3.9%–8.3% for all pollutant emissions, mainly due to lower fuel usage. Table 3.1 shows the changes in various emitted pollutants obtained from each case scenario.

Table 3.1. DTCSs combined with ICTs emissions evolution

Traffic light strategy	Emissions type in g/PCU / Intersection type	CO	CO_2 x 10^3	NMVOC	NOx	stochastic variability
Static	Isolated	11	11	3	44	±4%
	Isolated with V2I	-13%	-13%	-13%	-13%	±6%
	Isolated with V2V	-17%	-17%	-17%	-17%	±6%
	Isolated with FL-GLOSA	-23%	-23%	-23%	-23%	±5%
	Isolated with V2X (V2I +V2V)	-20%	-20%	-20%	-20%	±5%
	Isolated with V2X (FL-GLOSA+V2V)	-28%	-28%	-28%	-28%	±6%
	Coordinated	-17%	-17%	-17%	-17%	±4%
	Coordinated with V2I	-22%	-22%	-22%	-22%	±6%
	Coordinated with V2V	-22%	-22%	-22%	-22%	±8%
	Coordinated with FL-GLOSA	-36%	-36%	-36%	-36%	±8%
	Coordinated with V2X (V2I +V2V)	-31%	-31%	-31%	-31%	±5%
	Coordinated with V2X (FL-GLOSA+V2V)	-36%	-36%	-36%	-36%	±6%
Adaptive	Isolated	-8%	-8%	-8%	-8%	±5%
	Isolated with V2I	-18%	-18%	-18%	-18%	±5%
	Isolated with V2V	-21%	-21%	-21%	-21%	±6%
	Isolated with FL-GLOSA	-26%	-26%	-26%	-26%	±6%
	Isolated with V2X (V2I +V2V)	-29%	-29%	-29%	-29%	±5%
	Isolated with V2X (FL-GLOSA+V2V)	-32%	-32%	-32%	-32%	±5%
	Coordinated	-25%	-25%	-25%	-25%	±7%
	Coordinated with V2I	-36%	-36%	-36%	-36%	±6%
	Coordinated with V2V	-40%	-40%	-40%	-40%	±8%
	Coordinated with FL-GLOSA	-42%	-42%	-42%	-42%	±8%
	Coordinated with V2X (V2I +V2V)	-48%	-48%	-48%	-48%	±7%
	Coordinated with V2X (FL-GLOSA+V2V)	-54%	-54%	-54%	-54%	±6%

The numbers seen in the table above prove a significant drop in numerous pollutants such as CO (carbon monoxide), CO_2 (carbon dioxide), NMVOC (non-methane volatile organic compounds), and PM (particulate matter) under different simulated conditions. Coordinated versus Isolated: Adopting coordination techniques results in a considerable drop in emissions. Regarding the coordinated cases, adaptive and pre-timed traffic lights demonstrate lower emissions related to the isolated cases. For instance, concerning the distinct emissions, STLs in the coordinated cases release nearly 17% lower emissions than the isolated cases. Similarly, ATSCs minimize emission levels by 18% compared to the isolated cases. These outcomes emphasize the advantageous effects of coordination approaches on decreasing emissions.

ATSCs versus STLs: ATSCs constantly exceed STLs in terms of reduced exhaust emissions levels in each of the coordinated and isolated cases. For example, in isolated cases, ATSCs emit roughly 8% lower emission levels than STLs. Additionally, in the coordinated cases, the air pollution drops for ATSCs compared to STLs is around 9%. Furthermore, these findings demonstrate that the ATSC assists in a more sustainable approach to controlling transportation emissions.

Integrating various ICTs in coordinated and isolated cases lowers emission levels. Within each technology application, both ATSCs and STLs highlight lower air pollution. For instance, both adaptive and prefixed time traffic lights coupled with V2I exhibit drops in emission levels varying roughly 13%-31% for the STLs and around 10%-44% for the ATSCs. Similar behaviors can be noted for VX2 and V2V cases. These findings emphasize the advantages of ITCs in increasing emission level reduction for a sustainable transportation sector.

FL-based GLOSA lowered emission levels by roughly 23%-26% in isolated cases for both adaptive and static signals juxtaposed to isolated pre-fixed time signalized crossroads not coupled with ICTs. We even notice higher drop rates in coordinated cases, achieving around 36% for STLs and 42% for ATSCs, juxtaposed to unequipped coordinated STL junctions. Additionally, V2X, coupled with FL-based GLOSA, may minimize the environmental consequences of the traffic flow. Moving to the coordinated approaches, we notice that the drop achieves 54% and 36% in both adaptive and static signalized crossings, respectively. Dealing with isolated cases, both adaptive and static approaches coupled with both FL-GLOSA and V2X outperform the isolated cases by 18% and 4%, respectively.

Ultimately, we must also point out that adaptive and coordination strategies, along with ICTs, are essential in dropping emission levels in traffic control systems. Adopting coordinated strategies paired with ICTs has considerably minimized air pollution compared to isolated cases. ACTSCs with V2X exceed STLs in air pollution levels, with a remarkable drop of approximately 48% in isolated cases. In comparison, it reaches a 54% reduction when V2X is combined with FL-GLOSA in coordinated cases.

When comparing this chapter's findings to prior studies, the advantages of the incorporated methods can be noted in terms of decreasing the values of emissions and fuel used. For example, Kart et al. (2021) analyzed synchronized crossroads using the green wave approach and SUMO. They established a 20% drop in fuel and CO_2 pollutants as evidence of the approach's success. However, these enhancements were only slightly below 28% less, juxtaposed to the result found in this chapter. Also, the research done by Yun et al. (2018) regarding a V2V-based acceleration advising model demonstrated a 17.38% drop in fuel utilization and CO_2 pollutants on average. We notice that the author's enhancement is inferior to this study's results, with a difference of 30.62% in emissions and fuel utilization. In isolated cases, the study's FL-based GLOSA demonstrated superior capability in lowering energy utilization for both adaptive and static traffic lights, exceeding. Chen et al. (2024) by 22% - 40%, Zhang et al. (2023) by 17% - 26%, Ding et al. (2024) by 12% - 30%, and Shafik and Rakha (2024) by 4% - 20%, indicating the superior efficiency of the study incorporated V2X paired with FL-based GLOSA in both coordinated and isolated approaches in ATSC in increasing transportation effectiveness and viability.

This section thoroughly assessed the adopted dynamic traffic control signals combined with ICTs and evaluated the proposed FL-based GLOSA. The results were also compared to the prior studies' results to identify the approaches' contributions. The subsequent section will address this study's weaknesses and prospects.

3.3.2 Limitations and future prospects

All these enhanced solutions contribute to a better and eco-friendly future related to the enhancements in the transportation sector, thanks to the DTSCs and ICT solutions. These enhancements will reduce emissions and fuel, which will improve air quality as well as other wider environmental goals. Further, there will be a reduced level of fuel utilization and an increase in the reduction of infrastructural expenditure, which will act as a positive economic impact, while improved traffic will create the required environmentally friendly transport system. It is clear there are still other limitations that have to be further discussed regarding any modern technological applications identified as follows:

- The present chapter concerns a conventional vehicular fleet and excludes other vehicles like hybrids or battery-electric vehicles that possess different operating characteristics that can influence the total system's functionality, along with energy utilization.

- V2X implementation along with ATSC requires important investments in infrastructure adjustments, which might not be practical for all urban areas, especially those with low budgets.

- This chapter study neglects to consider data confidentiality and safety issues that might occur from ICTs. Guaranteeing private and safe data transfer is essential for achieving public consent.

- The proposed system's capability to efficiently operate in wider, more complex metropolitan settings has not yet been assessed. Because of their level of complexity and significant dimensions, issues may happen when handling larger-scale networks.

- Frequent maintenance of DTSCs and ICTs requires considerable funds. The study fails to explore the procedures and costs related to maintenance.

- The shortage of integrating queue length information hinders the FL-based GLOSA system's capability to anticipate and adapt to traffic jams efficiently.

- The study doesn't tackle the tangible issues of launching the FL-based GLOSA model, including the financial fees associated with deployment and repair services, along with the mentioned communication technology worries.

This section discusses the limitations of the adopted approaches and their prospects. The next one will conclude this chapter.

Conclusion

In this chapter, we developed and modeled ACTSC with ICTs as well. We also implemented a system known as the Fuzzy Logic-based GLOSA system. To evaluate the combined effectiveness of the DTSC with ICTs and the Fuzzy Logic-based GLOSA, several simulations were run through both environments, and energy metrics were compared with other simulations to analyze how those models and their interactions are representative of the gathered real-life data through both Python as a programming language and SUMO as a simulator tool. From the outcomes achieved, it is possible to assess the pairing of V2X with the ACS and ACTSC systems, which leads to enhanced fuel efficiency and reduces emissions, along with potential costs, and shows a noticeable improvement in FL-GLOSA's potential as a system for traffic management in contrast to the GLOSA. All are leading to the green and sustainable transport sector in SCs.

In the subsequent chapter, an effective Fuzzy Logic Eco-Driving model for both conventional and battery electric bus emissions and energy usage based on the above-discussed factors will be established and assessed.

Chapter 4 : Public transportation green light optimal speed advisory systems using Fuzzy logic (FL-GLOSA) for energy efficiency

Introduction

This chapter explores developing, implementing, and evaluating the Fuzzy Logic Ecological Driving model to enhance public transport efficiency and reduce energy use. It reviews existing GLOSA technologies, highlighting key methodologies, challenges, and opportunities. A FL speed advisory algorithm is then introduced, designed to calculate bus speed recommendations based on real-time traffic conditions along with other factors. The chapter includes data acquisition, simulation setup, and system performance evaluation regarding dropping both energy savings and emissions. Finally, the chapter discusses implementation challenges and future advancements, emphasizing the FL-Eco-Driving role in sustainable mobility.

The following section will provide a comprehensive review of the eco-driving approach for the public transportation sector (PTS).

4.1 Comprehensive state of the art on buses optimal speed advisory systems

Present-day city infrastructure faces substantial challenges in energy utilization and pollution production throughout its transportation infrastructure. Air pollution within transportation sectors remains high because fossil fuel-powered operations constantly discharge dangerous pollutants into the atmosphere. The energy sector consumes energy at the second-highest rate worldwide and uses 60% of all the crude oil, along with creating 24% of CO_2 emissions from fuel-based activities (S. Li & Yue, 2024). This underlines the critical need to reduce transport emissions, particularly those in cities. With the human population and economic development around the world, the demand for energy and emission levels from transportation are also expected to increase further in the future, especially in 2030 (S. Li & Yue, 2024; Ntuli et al., 2024). Consequently, it is necessary to find transportation solutions to help contain emissions levels and energy utilization. Such efforts should focus on actions that increase awareness of electric vehicles, and improve PTS and its facilities, together with supporting BEBs as a greener method (Borbujo et al., 2020).

While BEBs are environmentally friendly by reducing on-road air pollution and enhancing urban air quality, issues about energy demand for their propulsion constrain the effective range and trip distance of such buses. Others include traffic bottlenecks that arise from Junctions, signals, passenger load factors, and road gradients, along with additional factors that furthermore influence regular buses' energy requirements and emission rates (El-Taweel et al., 2021; Sebastiani et al., 2016). The next subsections will provide a literature review on the GLOSA-based approach to public transport, along with its limitations and the chapter's contribution.

4.1.1 Literature review on buses eco-driving models

The earlier studies on speed profile optimization are concentrated mainly on EVs and light-duty plug-in hybrid vehicles (Y. Hu et al., 2023; Z. Yi & Bauer, 2018). However, while BEBs and CDBs need to follow specific routes and frequently stop for passengers' boarding and alighting with strictly scheduled operations, they also deal with geometries of roads, traffic signalized intersections, etc. Therefore, the optimization approaches commonly tailored for light-duty EVs cannot be implemented in BEBs (Berzi et al., 2016; Gao et al., 2019; Y. Liang et al., 2024). To cater to these challenges, scientists have conducted various studies to determine the effects of the constraints on the routes, traffic, and operation on the buses' energy demand, exhaust, and range. Different measures and approaches have been used and suggested that can be grouped into three categories depending on the specific study area.

(i) Passenger load Impacts on buses

The passenger load greatly influenced both regular and BEBs in terms of total performance. A high passenger load also results in higher energy demand and increased emissions, possibly due to a decrease in the driving range of the bus with specific reference to BEBs. In a recent research conducted by Liu et al. (2019), the impact of a time-varying number of passengers on BEBs and CDBs' energy utilization was examined with the help of recorded data for 65 days. The findings of this study show that, as the vehicle's weight increases, both types of buses consumed more energy due to the power utilized in rolling and acceleration. Nevertheless, BEBs were considerably less sensitive to mass fluctuations since they could somewhat compensate for the increased energy requirement by using regenerative braking. In a research conducted by Shi et al. (2023), they predicted the load of the passengers in the electrified city buses, including weather conditions, wind speed, date, time, temperature, and holiday factors as explanatory variables. The overall proposed approach succeeded in cutting down bus operating expenses by 4% during off-peak periods and by 11% during peak periods. it also promotes better energy utilization and guarantees the right battery charge upon take-off by giving an accurate estimation of the number of passengers that may be carried. Also, Szilassy & Földes (2024) analyzed the energy absorption of BEBs and power consumption by extracting the passenger load with other operational characteristics. The authors' results can benefit transit operators by improving their organizational management by helping to schedule daily operations and predict the energy that will be consumed by the systems. In a study carried out by Zacharof et al. (2023), environmental conditions and passenger number were analyzed as factors affecting auxiliary energy consumption and CO_2 emissions of a bus. This study provides a very important start for developing methodologies to assess vehicle-specific emitted CO_2 depending on various operating conditions. Moreover, Rosero et al. (2021) studied the effect of passengers' loading along with other factors on fuel intakes and exhaust of diesel buses intended for urban business. This is based on the fact that they determined that when passenger load increases, so does fuel intake by 25 percent and, thus, the amount of CO_2 emissions. As such, the authors were able to establish the correlation between passenger weight, efficiency, diesel bus, and CO_2 emissions conclusively.

(ii) The influence of road slope on bus behavior

requirements since roads at higher elevations entail steeper gradients, which taxis find difficult, especially when fully laden. Techniques for both CDBs and BEB have a very large potential to drop energy demand and exhausts; the efficiency varies depending on the traffic conditions and technology. This can be explained by the fact that managing the operating speed of the BEBs has proven to yield significant improvements. For example, the Eco-Driving Assistance System (EDAS) developed on a BEB has resulted in a drop in energy utilization by 7% to 12% (Heuts et al., 2024). Another application of speed change pattern optimization for BEBs provided by Fang et al. (2024) has successfully saved not less than 10% to 20%, which is an indication of the efficiency of the developed approach in the real operation of transit buses. Similarly, by enhancing the driving style based on road slope by using a genetic algorithm, Xue et al. (2024) described how energy can be saved through efficient usage by the electric buses working on certain slopes, up to 5%. The same for CDBs, a Model Predictive Control (MPC) approach was created to optimize travel by expressing hilly roads with the aim of minimizing fuel intake and air pollution levels (Bakibillah et al., 2018). Capacity usage was also improved, leading to its fuel economy being increased by up to 8.24% while having a positive impact on CO_2 levels by the same percentage. As for another attempt, the report of Bakibillah et al. (2024) revealed that the adoption of FL to improve the smoothness of drives can drop fuel intake by 6%. Adamski et al. (2021) also presented an eco-driving model for selecting appropriate gear CDBs with the help of bus speed and the gradient of the road. From the actual study, there was a possibility of achieving fuel savings of 3-6 percent, thus showing that small changes in driving habits and the operation of a car can greatly contribute to fuel consumption.

(iii) Automated and smart buses

Integrating ICTs such as V2X, V2I, and V2V on CDBs has a substantial impact. Enabling real-time info exchange among vehicles and their surroundings could considerably lower energy utilization and exhaust emissions. From the bus energy-saves strategy by Zhang et al. (2019), there was an overall 2.47% in energy demand by the time the bus was through the route passing by signalized crossroads. Similarly, in the field of transportation, a Driver Advisory System (DAS) aims to provide each of the bus drivers with a preferred travel speed alongside idling time that will allow the vehicle to cross the following junction with green signals to reduce energy utilization. The numerical model of DAS was able to cut energy use by 15% - 20%. Similarly, the next authors, Ji et al. (2024), suggest a method of selecting the right speed profile of Automated and Connected BEBs that operate in Rapid Bus Transit (RBT) lines to minimize energy consumption through the application of an established nonlinear model. It is suggested that applying the influence of the speed and the road parameters to the predictions of energy utilization could increase the average engine efficiency by 2.11%. The research also corroborates the fact that the optimization of the speed of the energy-efficient profile enhances the Automated and Connected BEBs as well as the management of signal timing at the junctions. Meanwhile, a research manuscript introduces the eco-driving approach to reduce CDB energy demand passing by the signalized crossroads with bus stations while pairing V2X. One of the suggested eco-driving techniques is up to 13.8 percent fuel usage and emission level reduction. J. Hu et al. (2022) also propose a speed-planning module to drop fuel intake and energy expenditure during the management of buses with an interest in signalized intersections. For practicality, using the suggested method of convergent iterative planning, the total fuel usage and exhaust could decrease by approximately 18.4%.

Furthermore, based on the Cooperative Adaptive Cruise Control (CACC), X. Wang et al. (2024) proposed a new method to reduce fuel demand and experimented with it. It also proved that the developed CACC algorithm can work for the approximate reduction in total fuel intakes, varying within 6.8%.

(iv) Reinforcement Learning and Machine Learning for Buses Eco-Driving approaches

Both Machine Learning (ML) and RL have improved the factors related to eco-driving strategies used in buses and integrated more sustainable solutions in city transportation systems. With the help of such important data sources as real-time data from predictive analytics, the modern algorithms of ML may determine specific driving profiles that eliminate energy utilization and reduce the emissions related to idling, deceleration, and acceleration. This is because RL allows buses to modify their eco-driving approaches based on the current conditions of the actual environment and the road's topography to enhance efficiency. Vignarca et al. (2024) proposed a B-GLOSA using DRL in order to evaluate its effectiveness in delivering optimal driving modes to decrease energy consumption. Thus, the changes made in the research brought the drop in energy demand in electric buses to 26%. The cases for the developed approach have limitations, in that the interactivity of the traffic is missing, and adequate simulation testing scenarios are also missing. In a similar research, L. Yang et al. (2024) created an eco-driving approach within the DRL framework to minimize the energy utilization of BEBs. The model involves road properties, which include slope fixture or road steepness, passengers, load or passenger number in the vehicles, and proactively from signal interconnects. The results presented in the paper evidence that the purpose of the proposed algorithm is to bring energy consumption to a lower level; in particular, it has decreased by 40.69%. The CDBs have also been associated with multiple uses of ML and DRL, which have led to the development of an eco-driving approach for environmentally friendly transport. Meanwhile, Ma et al. (2018) introduced an ecological driving model considering environmental conditions, infrastructures, and vehicles. The study also established that using the proposed approach affects energy demand and its related emission levels in conventional city buses, and it showed a reduction of 6.25%. Kim et al. (2021) also considered an eco-driving method based on the ML approach to offer speed advice and the most suitable time for gear shifting to lighten the vehicle burden on the environment. According to the inference of the model, the potential benefits included an estimated 12.1 percent improvement in fuel efficiency for buses.

This subsection focused on the eco-driving approach adopted in the public transport sector. The next subsection will detail the studies' limitations and challenges.

4.1.2 Challenges and opportunities

In the prior studies, the focus has been placed on energy demand estimation for eco-driving of BEBs under various study cases, which gives an insight into energy-saving possibilities. Summing up, previous studies have the above-listed drawbacks:

- Other related studies are required to determine the effectiveness of certain eco-driving methodologies and measures appropriate for BEBs and CDBs.
- Previous studies involve mostly a single BEB in his or her research. They have not addressed traffic and communication technology; therefore, more extensive research is appealing to adequately embrace the critical analysis of eco-driving behaviors.
- Some of the identified eco-driving approaches and techniques for energy optimization discussed above are not similar. Each method considers factors such as the route, the passenger number, traffic, and traffic indicators (remaining time and distance). Since these factors depend on each other, no method or model currently provides a complete bus eco-driving plan.

According to the above limitations, therefore, this chapter aims to propose Fuzzy Logic eco-driving to determine the optimal speed for a BEB and CDB that serves a large city. The main contributions are illustrated as follows:

- The developed Fuzzy Logic model is for a short-term decision-making approach, namely real-time, and aims to find the right speed level for the bus's reduced energy demand. By using coupled FL control with V2X, the model can control the speed and fulfill its performance with better energy efficiency. It makes great sense to apply buses with more practicality and feasibility in daily use.

- As stated in this chapter model, for a better decision, the model will include traffic status, traffic lights, routes, and the passenger load. This will lead to the enhancement of the eco-driving system for energy consumption in conventional and electric bus fleets. This innovative approach has the potential of taking a new system into broad use for operating buses, and it has the desired effects of minimizing energy wastage, emissions, and expenses.

- This research will be done on a large scale in the city of Sousse in Tunisia, with multiple routes, signalized crossroads, and traffic conditions, to test the model's effectiveness in a real-world situation. The outcome of this chapter will go a long way in encouraging the use of the FL Eco-Driving approach in BEBs and CDBs for PTS in urban centers.

- This chapter will also examine the advantages of BEBs compared to CDBs regarding energy consumption.

Finishing up with the state of the art, limitations, and opportunities that can be handled in this chapter. The following section focuses on the Fuzzy Logic Eco-Driving model design and implementation.

4.2 System design and implementation

The objectives are to minimize traffic density, enhance driver safety, and increase the use of appropriate driving practices. These objectives correspond with current calls to convert cities into smart cities and encourage the usage of effective PTS. Therefore, we present a Green Light Optimized Speed Advisory, also known as GLOSA, to improve city traffic circulation by informing a vehicle about its necessary speed to get a green light before the traffic signal (Othmani, Boubaker, Rehimi, Halawani, et al., 2024). Hence, it eliminates or minimizes idling vehicle numbers at the intersection, and, as a result, it drops fuel intake and exhaust, besides traffic circulation optimization. While GLOSA has benefits, it also has drawbacks that need to be addressed (Chaudhry et al., 2024; A. Shafik, Eteifa, Rakha, et al., 2024).

In this regard, as discussed earlier in this section, there are a number of studies that address different means and methods of environment-sensitive bus driving systems. These can be categorized into three broad categories, namely: learning-based approaches, optimization-based approaches, and rule-based approaches (Mazouzi et al., 2024). The FL is a subcategory of the rule-based control approaches that have attracted much attention and been implemented in various fields due to the following advantages: It is easy to develop and implantation as compared to other complex algorithms that require several computational resources to be used in real-time control systems (Mazouzi et al., 2024). Additionally, the FL mimics human thought processes and favors the incorporation of human expertise into control strategies via fuzzy rules, particularly non-linear relationships and network uncertainties (Mazouzi et al., 2024). Also, Fuzzy Logic is flexible in coping with volatilities in EVs, PTs, EDAs, and other such systems relying on fuzzy sets and MFs capable of dealing with various degrees of ambiguity or uncertainty of real-life data since it does not require accurate applications with difficult and inadequately describable systems (Mazouzi et al., 2024; Namoun et al., 2021; Pulugurta et al., 2015).

This makes the approach more natural and prone to producing better results, especially in ever-changing environments and conditions that require the handling of more than two variables or propositions. Hence, by using fuzzy logic, the system can deal with different levels of uncertainty and imprecision, leading to control and optimization (Baturone et al., 2018, 2018; Mazouzi et al., 2024). The following subsection will detail the needed model development.

4.2.1 Fuzzy Logic Green Light Optimal Speed Advisory algorithm development (FL-GLOSA)

This work proposes a control system implemented with Type-1 Fuzzy Logic and provides an ecological driving pattern. The primary goal is to adaptively control vehicle speed based on seven factors: the speed limit of the road, the traffic signal allocation, either green or red, the time remaining on any current phase signal, vehicle speed, the slope of the roadway, and passenger number. The system then analyzes these inputs for the best speed at which the energy-efficient mode can be achieved (a snippet of the FL-Bus-Eco-Driving code is presented in Annex C). A depiction of the system's input and output arrangement, along with the FL diagram, are shown below in Figure 4.1.

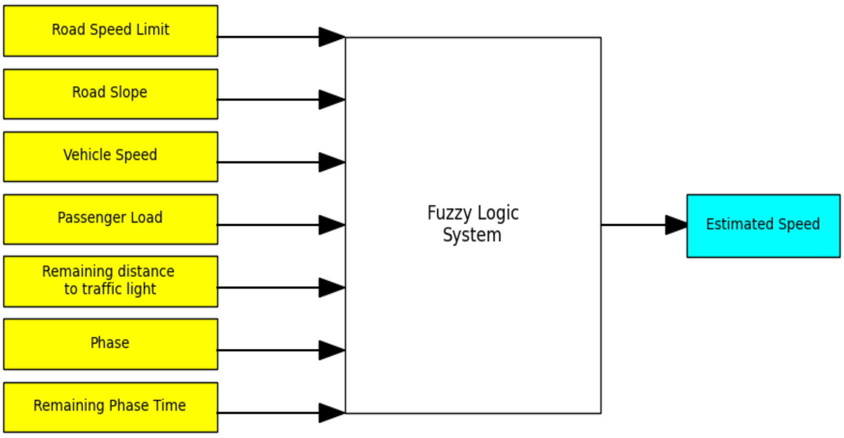

Figure 4.1. Fuzzy Logic Eco-driving system diagram

As depicted in Figure 4.1, the FL system incorporates seven key inputs to enhance speed estimation accuracy. The first input, the road speed limit, must be integrated to ensure that the right speed does not surpass the legally permitted maximum, thereby maintaining both regulatory compliance and safety standards (Gressai et al., 2021). Additionally, including road gradients and the estimated load of passengers is crucial for refining the speed calculation process within the Fuzzy Logic system. Road slope directly affects the vehicle dynamics, including the vehicle's power demand and braking force, influencing fuel demand (L. Gao et al., 2024; Lee et al., 2023). Similarly, passenger load plays a significant role in determining optimal deceleration and acceleration rates, as heavier loads necessitate speed adjustments to maintain efficiency (Barreno et al., 2024; Flores et al., 2023). Moreover, the standard Green Light Optimal Speed Advisory (GLOSA) algorithm inputs include the distance to the traffic signal (measured in meters), the traffic light phase (red or green), the remaining time in the current phase (in seconds), and the vehicle's current speed (in km/h). These parameters are essential for estimating the appropriate speed required to minimize unnecessary stops and fuel consumption (Jayasinghe, 2019; Wágner et al., 2023b). By integrating these inputs, the FL system can provide precise and context-aware speed recommendations, optimizing energy efficiency while adapting to varying traffic and road conditions. The vehicle's target Speed (u_{Target}) is calculated based on the mentioned factors, as illustrated in Equation 4.1:

$$u_{Target} = f \left\{ \begin{array}{c} Road\ Speed\ Limit\ (u_{max}) \\ Road\ slope\ (\emptyset) \\ Vehicle\ Speed\ (S_{Vehicle}) \\ Passenger\ load\ (P_{Load}) \\ Remaining\ Distance\ to\ TL\ (d) \\ Phase\ (Ph) \\ Remaining\ Phase\ Time\ (T) \end{array} \right. \quad (4.1)$$

To allow buses to control seamlessly the interactions between their speed and the environment, including traffic signals and surrounding traffic, an improved Fuzzy Logic Eco-driving system was developed and integrated with the Vehicle-to-Infrastructure (V2X) communication system. This system forecasts the best velocity the bus should take by giving attention to the remaining distance as well as the time to get to the traffic signal, the phase of the signal (red, green, yellow), the time left in the phase, and the velocity of the bus at that particular time and moment, passengers many on the bus at that time, the slope and speed limit of the road.

However, the following must be done to identify the correct speed: Identifying key factors defining GLOSA, including minimum ($u_{min} = 0.5 \times u_{max}$) and maximum ($u_{max}$= Road speed limit in m/s, velocity, and acceleration limits (γ = [-3.5 m/s^2 to 1.2 m/s^2]). Therefore, it is required to calculate d in s, Ph, T_{TL} and T in s along with GLOSA speed (A_S). These calculations are made based on the equations that have been described in Chapter 2, Section 2.2.1.

When approaching an unsignalized intersection, the bus's current speed is utilized to determine the right speed. However, upon examining the previously discussed speed equations and GLOSA, it becomes evident that these formulations do not account for two critical factors: road gradient and passenger number. As highlighted in the state of the art, both parameters considerably influence vehicle energy utilization and exhaust levels. To achieve eco-friendly driving, it is necessary to incorporate an equation that adjusts the speed calculation by considering the mentioned factors. In this context, Chen and Rakha (2022) proposed an equation (Eq. 4.2) designed to refine vehicle speed adjustments, thereby promoting more energy-efficient driving (H. Chen & Rakha, 2022):

$$u_{Target} = u_i + (\frac{F-R}{(M_{Vehicle} + P_{Load})}) \tag{4.2}$$

Where in R, and N are the combination of grade, rolling resistance, and aerodynamic forces in Newtons, u_{Target} represents the GLOSA target speed, u_i is the case speed (u_{GLOSA}, $S_{Vehicle}$) in m/s, and F represents the vehicle tractive force in N, illustrated in Equation 4.3 (H. Chen & Rakha, 2022):

$$F = \min\,(3600 \times f_p \times \beta \times \eta_d \times \frac{P_{required}}{S_{Vehicle}}, m_{ta} \times g \times \mu) \tag{4.3}$$

β is the gear reduction factor, f_p is the throttle level, m_{ta} represents the mass along the tractive axle in kg, μ is the road adhesion coefficient parameter, and η_d is the efficiency of the driveline.

Figure 4.2 outlines the developed study's Fuzzy Logic Eco-driving model that seeks to increase the bus speed efficiency by taking into account several gathered factors, in particular those stated earlier. The FL Eco-Driving Model determines the ideal speed to modify the bus's velocity smoothly within set limits. The intention is to maintain the bus's lower energy demand and air pollution while moving, promoting efficient and eco-friendly driving.

Algorithm Fuzzy Logic Eco-Driving Algorithm

Require: Road speed limit (u_{max}), road slope ($\emptyset$), bus speed ($S_{Vehicle}$), and passenger load (P_{Load});
▷ $\boldsymbol{u_i}$ is set to $\boldsymbol{S_{Vehicle}}$ when no intersection is ahead.
Locate the relevant intersection (int) ahead;
If there is no intersection (int) ahead Then
    Set the case speed (u_i) $\leftarrow S_{Vehicle}$;
Else if There is an intersection (*int*) ahead Then
    Require: Remaining distance to intersection (d), current signal phase (Ph), and remaining signal phase time;
    Compute the remaining time to reach the traffic light (T_{TL}) based on d;
    If Ph is Green Then
        ▷ $\boldsymbol{u_i}$ is set to $\boldsymbol{S_{Vehicle}}$ when Ph is Green
        Set $T \leftarrow 0$;
        Set $u_i \leftarrow S_{Vehicle}$;
    Else if Ph is Red Then
        Require: Remaining red light time ($Tred$);
        Calculate the total time until the next green light $T \leftarrow T_{TL} + Tred$;
    Else if Ph is Yellow Then
        Require: Remaining yellow light time ($Tyellow$);
        Set $T \leftarrow T_{TL} + Tyellow + Tred$;
    End if
    Estimate the GLOSA speed (u_{GLOSA}) $\leftarrow Max(u_{GLOSA}, u_{min})$ and $u_{GLOSA} \leftarrow Min(u_{GLOSA}, u_{max})$;
    Set $u_i \leftarrow u_{GLOSA}$;
    Estimate the resistive force (R) and the tractive force (F);
    Estimate the target speed (u_{Target}) $\leftarrow Max(u_{Target}, u_{min})$ and $u_{Target} \leftarrow Min(u_{Target}, u_{max})$;
    ▷ $\boldsymbol{u_{Target}}$ is adjusted based on $\boldsymbol{u_i}$, R, F, and $\boldsymbol{P_{Load}}$
End if

Figure 4.2. Proposed FL Eco-Driving algorithm

By integrating the mentioned factors, the FL system enhances eco-driving efficiency by offering a dynamic and effective approach to vehicle control across various driving conditions. The developed Fuzzy Logic model utilizes specific input variables and corresponding output Membership Functions (MFs), as depicted in the corresponding figures.

As depicted in Figure 4.3, the u_{max} is classified mainly into three classes: slow (ranging from 30 km/h to 60 km/h), moderate (between 30 km/h and 90 km/h), and high (starting from 60 km/h to 90 km/h).

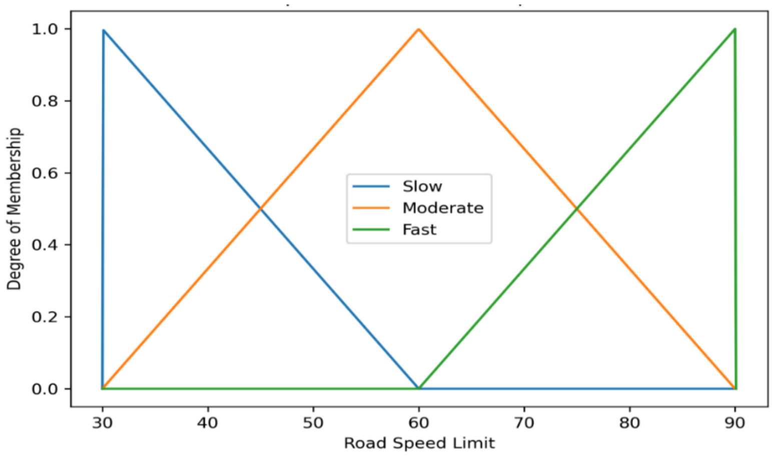

Figure 4.3. Road Speed Limit Membership Functions

$\emptyset$ is also categorized into 3 MFs: Downhill (-10% - 0%), Flat Road (-10% - 10%), and Uphill (0% - 10%), as shown in Figure 4.4.

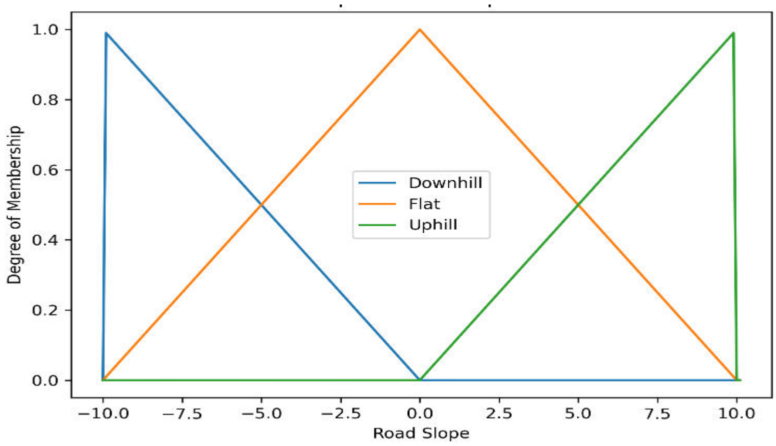

Figure 4.4. Road slope Membership Functions

Also, Figure 4.5 illustrates the $\mathbf{S_{Vehicle}}$ MF: also classified into 3 MFs: Slow (0 - 45km/h), Moderate (0 - 90km/h), and Fast (45 - 90km/h).

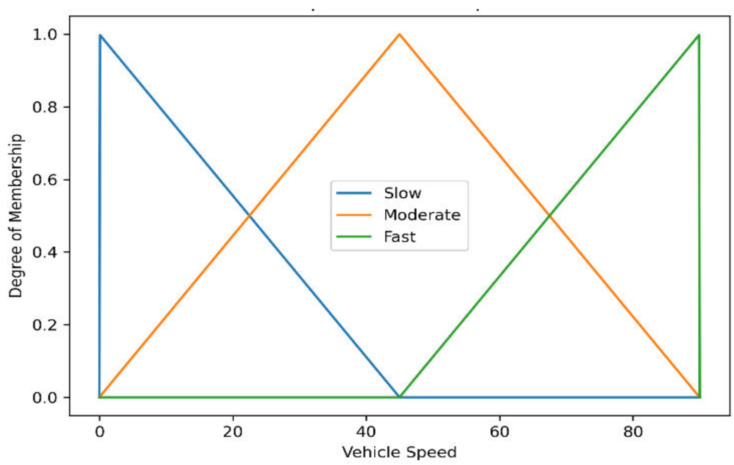

Figure 4.5. Vehicle Speed Membership Functions

Meanwhile, $\mathbf{P_{Load}}$ MFs are the following: light (0 - 50%), Medium (0 - 100%), and Heavy (50% - 100%), as shown in Figure 4.6.

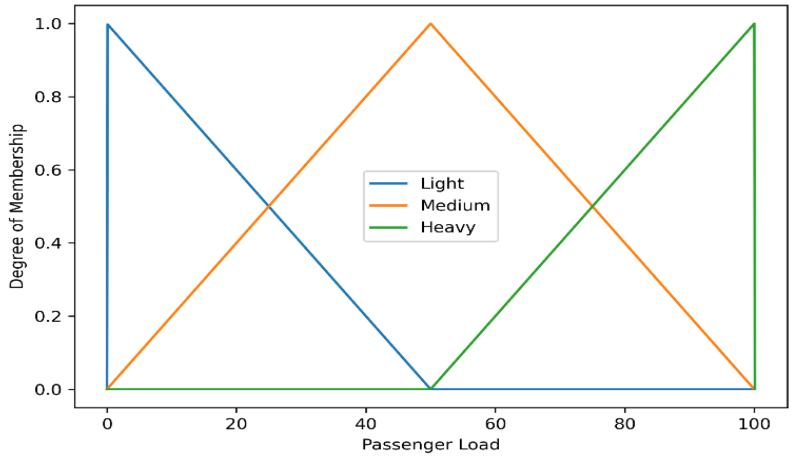

Figure 4.6. Passenger Load Membership Function

$\boldsymbol{d}$ MF is also categorized into three classes: Close (0m - 70m), medium (0m - 150m), and Far (70m - 150m), as illustrated in the Figure. 4.7.

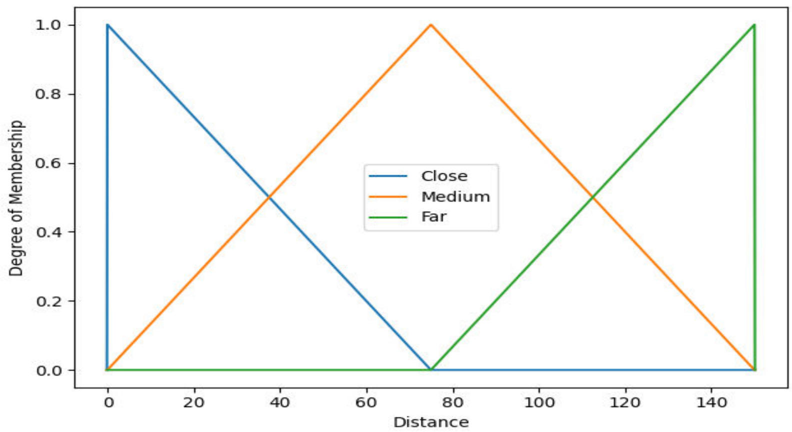

Figure 4.7. Remaining distance to traffic lights Membership Functions

As already mentioned in the previous chapter, based on Wágner et al. (2023) In this study, amber light is considered red light. So, as shown in Figure 4.8, the Ph MF is categorized into 2 categories: the blue line stands for the Green MF, and the orange line stands for the red-light MF.

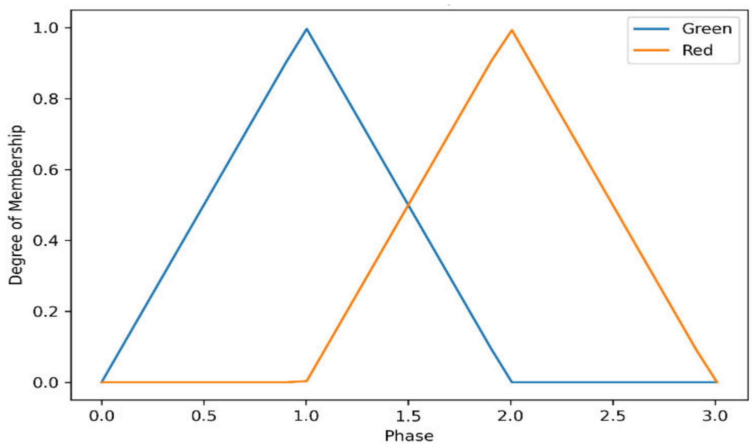

Figure 4.8. Traffic light phase Membership Functions

Lastly, the T MF is presented as follows: short (0s - 60s), medium (0s - 120s), and Long (60s - 120s).

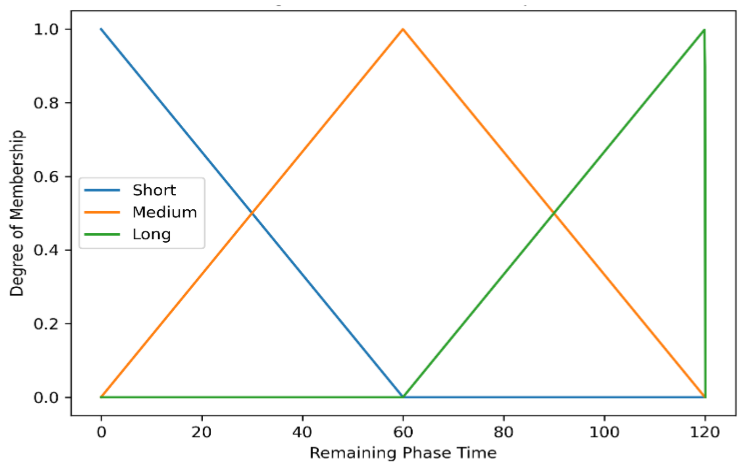

Figure 4.9. Remaining phase time Membership Functions

Thus, as per the specified input variables, the u_{Target} MF is flared by 1,458 output values; Out 1 to Out 1,458, referring to the following figure.

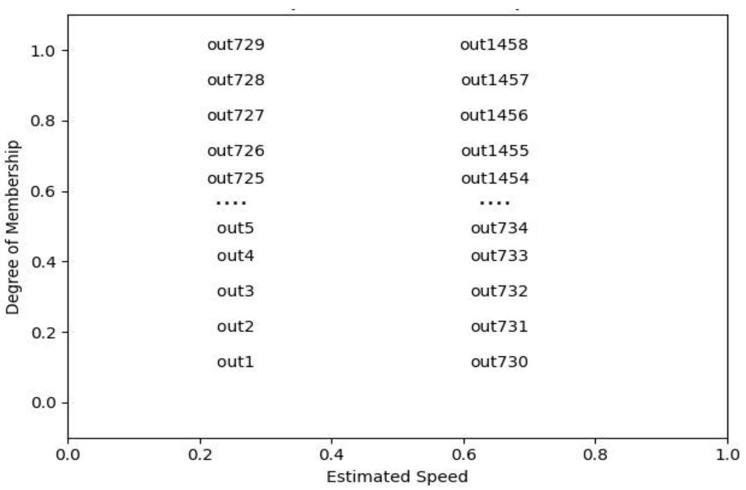

Figure 4.10. Estimated speed (u_{Target}) Membership Functions

The values derived from the fuzzification phase will be utilized for recalculations within the system. A selection of the applied rules is presented in Figure 4.11.

Rule N°	If Road speed Limit	And Distance	And Phase	And Remaining Phase Time	And Vehicle Speed	And Road Slope	And Passenger Load	Then Estimated Speed
	is	is	is	is	is	is	is	
1	Slow	Close	Green	Short	Slow	Downhill	Light	Out 1
2	Slow	Close	Green	Short	Slow	Downhill	Medium	Out 2
3	Slow	Close	Green	Short	Slow	Downhill	Heavy	Out 3
4	Slow	Close	Green	Short	Slow	Flat	Light	Out 4
5	Slow	Close	Green	Short	Slow	Flat	Medium	Out 5
::	::	::	::	::	::	::	::	::
1454	Fast	Far	Red	Long	Fast	Flat	Medium	Out 1454
1455	Fast	Far	Red	Long	Fast	Flat	Heavy	Out 1455
1456	Fast	Far	Red	Long	Fast	Uphill	Light	Out 1456
1457	Fast	Far	Red	Long	Fast	Uphill	Medium	Out 1457
1458	Fast	Far	Red	Long	Fast	Uphill	Heavy	Out 1458

Figure 4.11. linguistics Rules

This subsection focused on FL-Eco-Driving development and justified its use while proposing its core algorithm. The following subsection will introduce the selected study zone and its related data.

4.2.2 Study zone characteristics and data acquisition

This study area encompasses an operating bus route forth and back from Sousse to Kalaa Kbira, an adjoining urban zone located at 35.83° N and 10.6334° E and 35.87° N and 10.56° E, respectively. As displayed in the figure (Fig. 4.12), Kalaa Kbira is a growing town recognized by growing residential growth and industrial activities. Meanwhile, Sousse is acknowledged as a vital transportation point in Tunisia due to its thriving economy and rich historical culture.

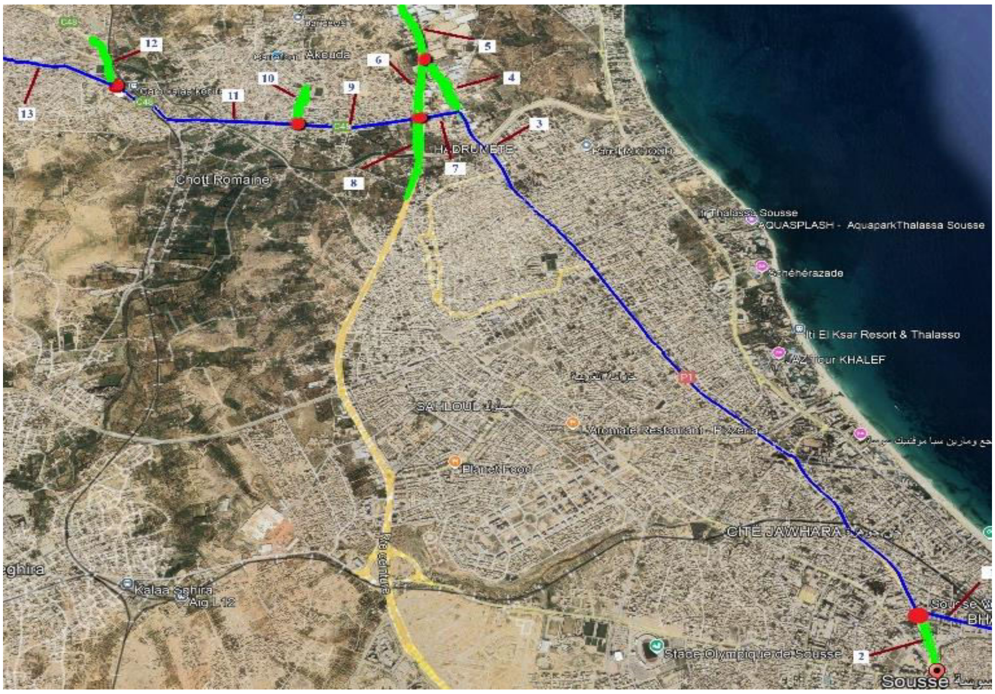

Figure 4.12. Google Earth View of the bus route between Sousse and Kalaa Kbira

This particular bus route includes 12.4 km of traffic area consisting of dense urban zones: residential and commercial areas; this means that it records high traffic circulation daily. There are traffic jams since it passes through many roundabouts and has a varying traffic flow throughout the day, particularly in the morning. The traffic patterns of the region obtained on Monday, March 24th, 2024, are presented in Figure 4.13.

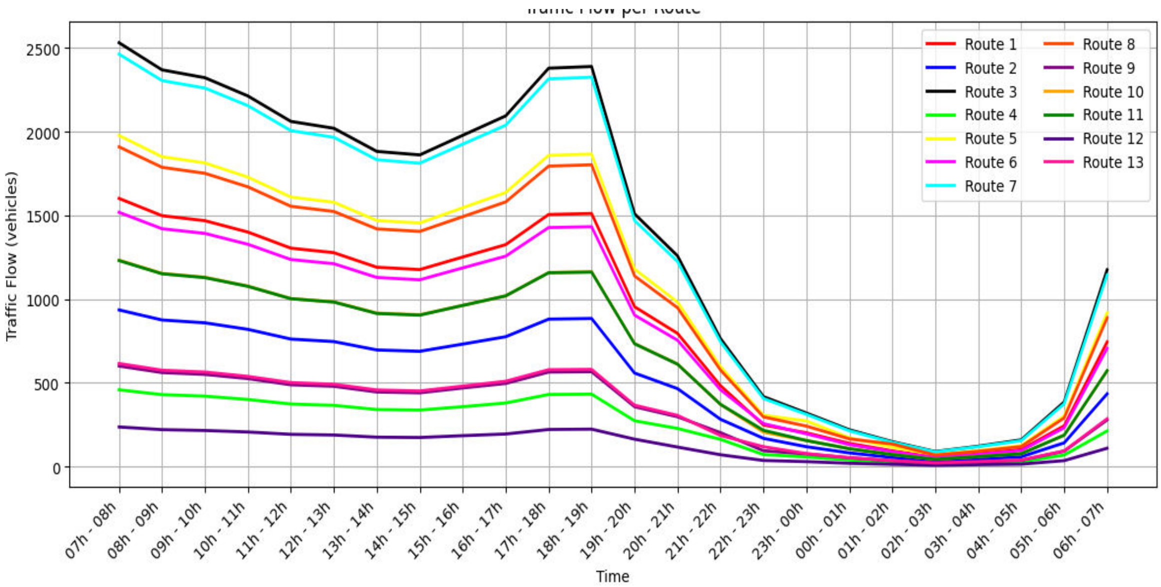

Figure 4.13. Hourly traffic circulation on each segment's

The bus path passes via the area directly, providing, on average, six round trips in their daily shift (7:05 A.M - 6:45 P.M) between the mentioned locations through 55 bus stops. In this chapter, we gathered the bus travel route slope along with the passenger number per meter, as shown in Figure 4.14.

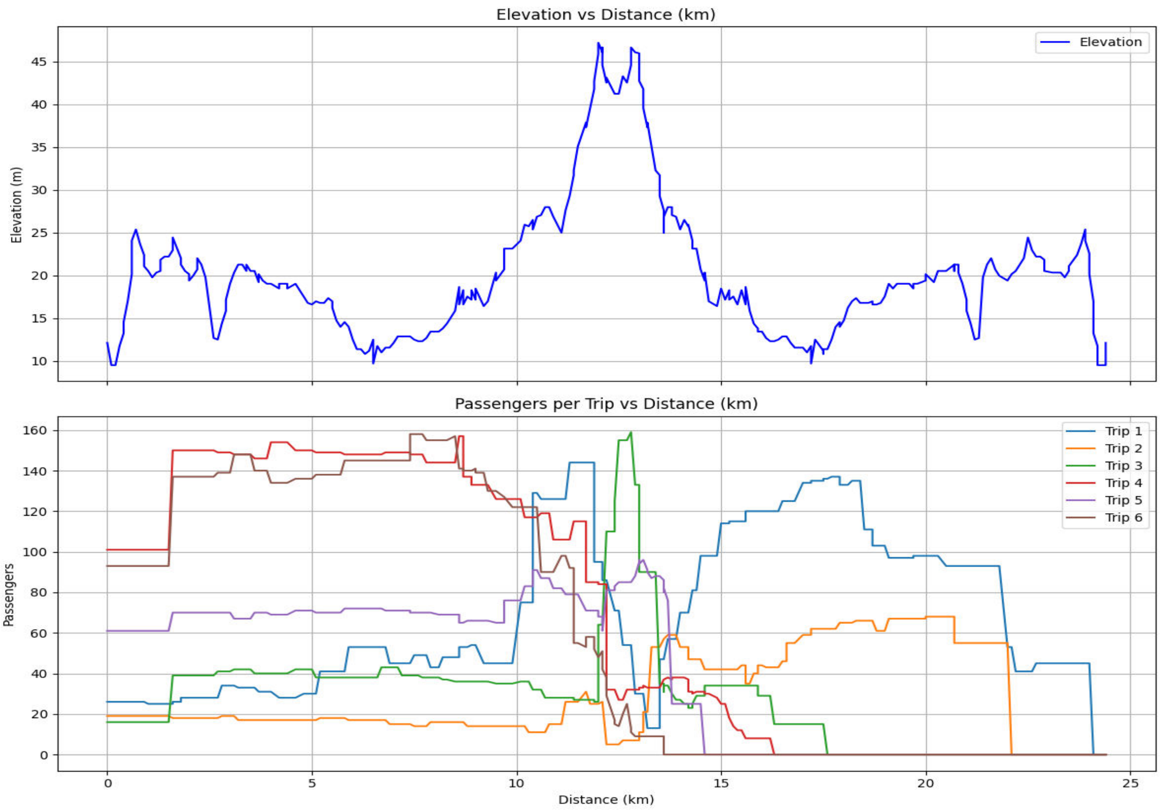

Figure 4.14. Route elevation and passenger number per distance

Finishing with this subsection about the study zone introduction and the gathered data presentation. We move to the following subsection, simulation setup and evaluation framework.

4.2.3 Evaluation framework and simulation setup

These factors include changes in road gradient and passenger number, along with traffic conditions on the route that make it possible to assess the interaction between the FL eco-driving model and V2X technology in terms of fuel demand and emissions. Therefore, the first process entails the establishment of an elaborate model of the study region and incorporating the obtained data into both SUMO and Python platforms. This model lets real-life driving conditions be recreated, with such an enriched simulation helping to determine the efficiency of the suggested study approach in dropping fuel intakes and exhausts, as illustrated in Figure 4.15.

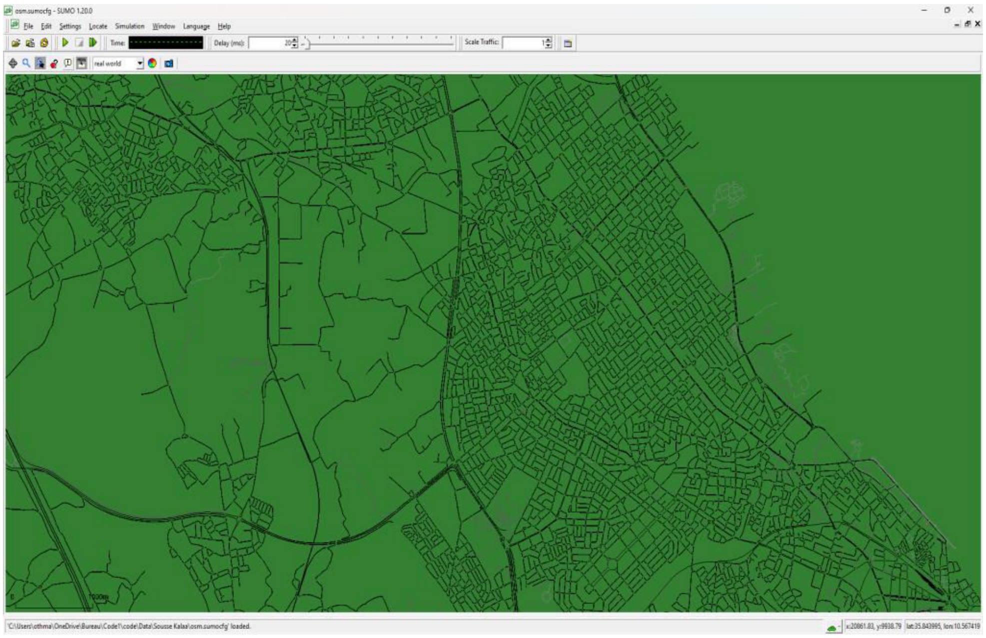

Figure 4.15. Modeling Bus route data on SUMO

The following step pertains to developing the simulation cases after building up simulations. Sixteen specific simulation runs will be implemented to test the FL Eco-Driving model. The model will be deployed to compare fitted buses to non-fitted buses and establish whether the model may be applied in BEBs as well. Furthermore, conventional and electric buses will be evaluated concerning the effect of the model on signalized and unsignalized roundabouts. Additionally, the investigation will determine the efficiency of the approach in the traffic environment that is congestion and the free flow of traffic by using V2X technology.

Since no signalized roundabouts exist in the chapter-selected area, interfering with the Webster approach, along with the hourly average traffic flow data, we can obtain signalized roundabouts for this study. As stated in Equations 4.4 - 4.7, this approach should be implemented for each of the roundabouts that consist of one or more roundabout segments (J. Wang et al., 2023):

$$C_{opt} = \frac{1.5 \times L + 5}{1 - Y} \tag{4.4}$$

$$Gr_e = C_{opt} - L \tag{4.5}$$

$$L = n \times (l + r_{e,i}) \tag{4.6}$$

$$gr_{e,i} = G_e \times \frac{y_i}{Y} \tag{4.7}$$

Where Y represents the study's total traffic flow ratio, n represents the phase's number, C_{opt} , L, Gr_e , $r_{e,i}$, and $gr_{e,i}$ define the optimal signalized junction cycle length, each junction's total lost time, and the junction's effective green time period, with the phase red time and the effective green period in s, while y_i represents each phase's maximum observed flow ratio of the intersection's direction.

To assess the FL-Eco-Driving Approach, we used the energy usage for CDBs and BEBs, represented using Equations 2.8 to 2.13 mentioned in Chapter 2, section 2.2.3. As for CDBs and gasoline vehicles' emissions, we adopted Equation 2.15, which is mentioned in the same chapter, section 2.3.2. The following table presents the vehicles deployed in this chapter.

Table 4.1. Selected study city vehicles Key parameters (Hjelkrem et al., 2021; Koroma et al., 2023; X. Yang & Liu, 2022)

Vehicle type / Parameters	Gasoline PCU	CDB	BEB
$M_{Vehicle}$ [kg]	1350	11200	13210
C_d	0.29	0.72	0.7
A_x [m²]	2.3	7.78	8.42
ρ [kg/m³]	1.29	1.29	1.29
g[m/s²]	9.81	9.81	9.81
η_T [%]	95	90	97
Battery capacity, B_{Cap}[kWh]	-	-	200
Maximum passengers' number, N_p	5	98	95
Average passengers' mass, $\overline{m}$[kg]	65	65	65

This subsection provides the chapter simulation setup and the adopted evaluation framework. The following section will fully assess the FL-Eco-Driving model's obtained results regarding emissions and energy demand levels their impacts on traffic.

4.3 Results and discussion: key findings and insights

This section outlines and evaluates the findings from adopting the FL system paired with V2X for BEBs and CDBs. It also focuses on vital performance metrics, like energy utilization and emission levels, under various traffic settings and route configurations.

4.3.1 Energy efficiency achievements and emissions reduction: key findings

Commencing with the FL-Eco-Driving application on BEBs and CDBs in no-traffic-flow and no-traffic-lights scenarios, the following figure (Fig. 4.16) shows the achieved energy utilization levels along with the obtained exhaust of every bus type alongside the FL model adoption.

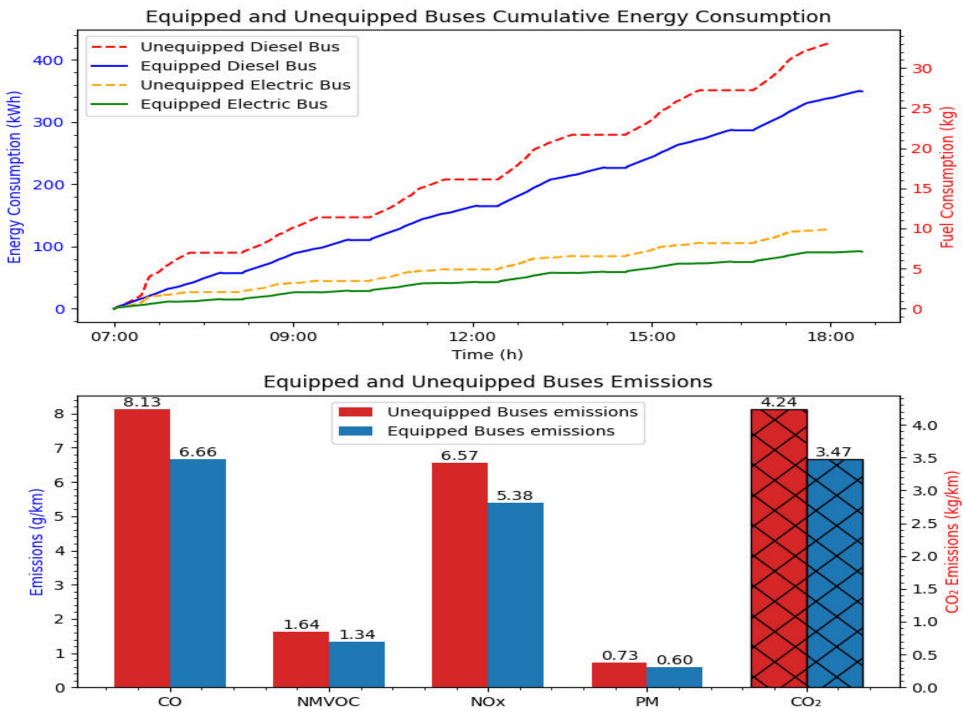

Figure 4.16. No traffic circulation and traffic lights cases: energy consumption and emissions

The above figure also shows that the amount of energy consumed and emissions potential of buses is higher than those that use the FL Eco-Driving model successfully. In particular, unequipped conventional diesel buses (CDBs) reach 426 kWh and release

4.24 km/CO_2, 8.13 km/CO, 1.64 km/NMVOC, 6.57 km/NO_x, and 0.73 km/PM. Equally, unequipped BEBs take about 127 kWh; this is much less than that of the conventional diesel ones. Hence, they have a 70% energy saving.

Also, the buses coupled with the FL Eco-Driving model had a drop in energy utilization and air pollution, wherein the CDBs and BEBs had a variation of 18% and 28%, respectively. In general, equipped CDBs required around 349 kWh, and their emissions were expressed as 3.47 CO_2 per km, 6.66 CO per km, 1.34 NMVOC per km, 5.38 NO_x per km, and 0.60 PM per km. In the same way, equipped BEBs recorded interesting results in terms of energy utilization, where 92 kWh were consumed, which implied that equipped BEBs were 74% less than unequipped CDBs. These findings can validate the usefulness of the FL Eco-Driving model in enhancing energy usage and reducing the adverse effects on the environment in PTS.

Based on such insights and findings of the literature, it may be concluded that the FL Eco-Driving model acts as a feasible and efficient approach to supporting the sustainability of the PTC. Compared with the results of other research, the identified cuts in bus energy utilization and pollutants employing this model are higher. In particular, for CDBs, the proposed model also reveals more remarkable energy-saving improvement than the results shown by Bakibillah et al. (2018), the improvement reaches 10%; in this case, the results of Adamski et al. (2021) and Bakibillah et al. (2024) are also surpassed by the proposed model. In addition, the FL Eco-Driving model provides better fuel savings outcomes than the ML approaches for Eco-Driving, which are 6% higher than Kim et al. (2021) and 12% higher than Ma et al. (2018). Moreover, the energy reduction of this model for the BEBs is higher, identified to be 28%, which is higher than the study conducted by Xue et al. (2024) 23%, Heuts et al. (2024) 16%, Fang et al. (2024) 8%, and Vignarca et al. (2024) 2%. These comparisons show that the designed FL-Eco-Driving model can enhance PTS's energy efficiency and environmental concerns. Proceeding to the traffic light incorporation cases, the subsequent Figure. 4.17 indicates the estimated simulation energy utilization and exhaust.

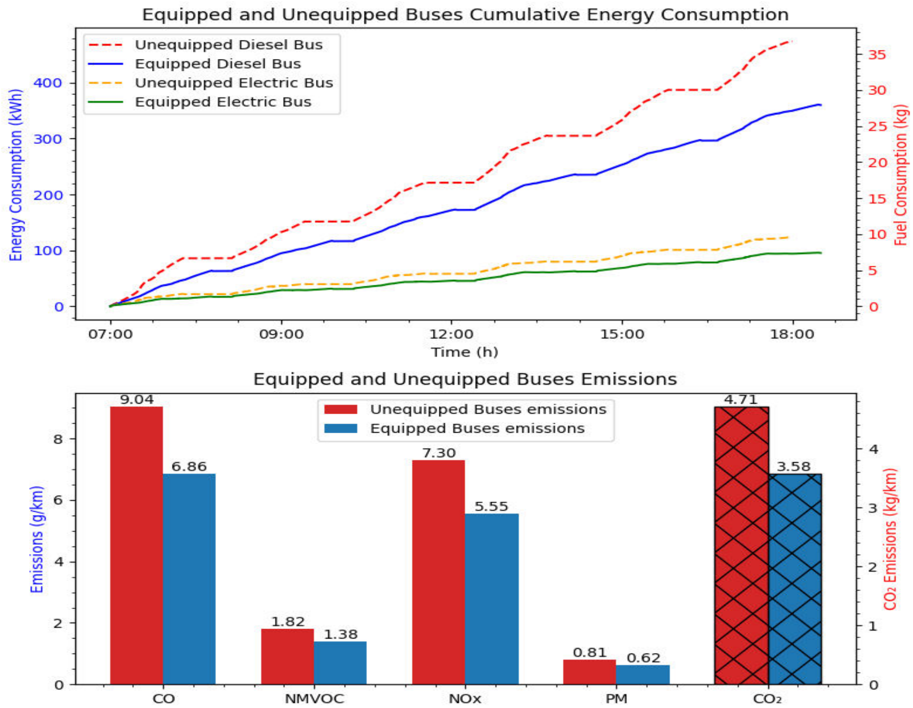

Figure 4.17. Traffic lights and traffic circulation cases: energy consumption and emissions

As the figure above indicates, traffic lights impacted the energy demand and exhaust levels, where BEBs and CDBs registered an increase of 3% and 1%, respectively. In the scenario where BEBs did not use the FL-Eco-Driving model, 129 kWh was used, while CDBs used approximately 474 kWh. In addition, CDBs were emitting 4.71 kg/km CO_2, 9.04 g/km CO, 1.82 g/km NMVOC, 7.3 g/km NO_x, and 0.81 g/km PM.

This study also showed that buses applying the FL Eco-Driving model may drop fuel intake and exhaust considerably. Specifically, BEBs' energy utilization was lowered by 26.4% and amounted to approximately 95 kWh. In the same way, CDBs' energy utilization and emissions case were improved by -24% with a new value of 360 kWh. The corresponding emissions for CDBs were lowered to 3.58 kg/km of CO_2, 6.86 g/km of CO, 1.38 g/km of NMVOC, 0.62 g/km of PM, and 5.55 g/km of NO_x. That is why, while comparing the energy-saving ability of BEBs in non-coupled and coupled scenarios, an overall enhancement of energy saving of 73% was revealed. Their energy utilization has risen to this level, thus indicating that electric buses possess the capacity to form part of the public transport system for sustainability in the future.

In this regard, the FL Eco-Driving model performed better than other models, including those proposed by Othman et al. (2024) and Zhang et al. (2019), by 6.4% and

23.93%, respectively. However, even so, the models developed by Vignarca et al. (2024) and L. Yang et al. (2024) are more efficient as they surpass the effectiveness of the FL Eco-Driving model by about 2% and 13%, respectively. Concerning fuel intake and pollution in conventional buses, this paper has found considerable contributions in previous literature. The obtained FL-Eco-Driving model is 5.6%, 17.2%, 18%, and 12% better than the methodologies of J. Hu et al. (2022), X. Wang et al. (2024), Ma et al. (2018), and Kim et al. (2021), respectively. These findings prove that the proposed model can be immensely useful in public transport applications, increasing fuel efficiency and decreasing emissions.

To fairly and systematically examine the FL Driving model named above, we proceed with the following scenario to assess the system's efficiency with no signalization regarding traffic flow. The following figure (Fig. 4.18) depicts energy utilization and emitted exhaust of coupled and uncoupled buses with FL in no-traffic-light and traffic circulation cases.

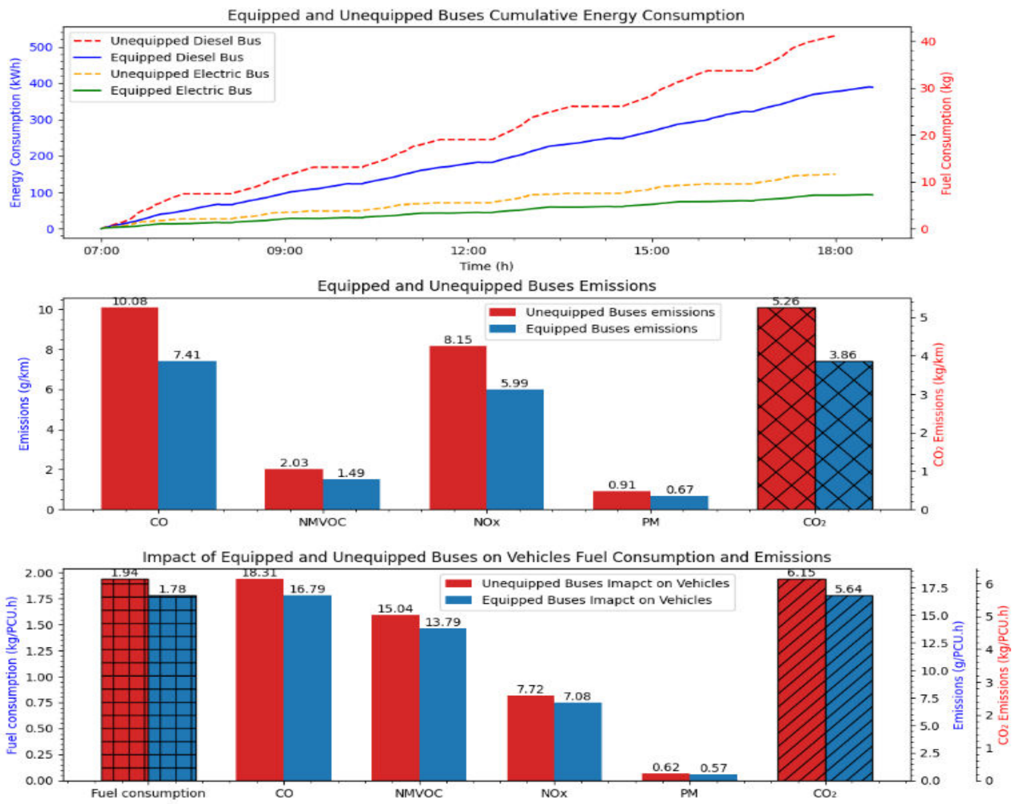

Figure 4.18. No traffic lights and Traffic circulation cases: energy consumption and emissions

The graph above illustrates both air pollution and energy utilization, and uncoupled buses with the FL model and their combined effects on traffic. Notably, traffic with coupled buses caused the overall energy and emission levels to decrease:

CDBs were up to 24%, while BEBs were up to 17% juxtaposed to the outcomes of the simulations with no traffic circulation and traffic lights. The CDBs increased by 12%. If there was no traffic flow but traffic lights existed, the increase was 16% for BEBs. The energy demand associated with traffic circulation was about 1.94 l PCUh of fuel and led to the emissions of 6.15 kg CO_2/PCUh, 18.31 g CO/PCUh, 15.04 g NMVOC/PCUh, 7.72 g NO_x/PCUh, and 0.62 g PM/PCUh. While the uncoupled BEBs consumed 149 kWh, which reduced utilization compared with unequipped CDBs that utilized and expelled 5.26 kg/km CO_2, 2.03 g/km NMVOC, 10.08 g/km CO, 0.91 g/km PM, and 8.15 g/km NO_x.

This study indicates that adopting FL-Eco-Driving technology on buses will reduce the energy and traffic implications for both buses and general traffic. Similarly, BEBs consumed 38% of the energy used by CDBs, which was only 93 kWh. CDBs saw a 27% drop in energy demand; the new energy utilization figure is roughly 387 kWh. The emission reduction levels for CDBs for CO_2, CO, NMVOC, NO_x, and PM were around 3.86 kg/km, 7.41 g/km, 1.49 g/km, 5.99 g/km, and 0.67 g/km, respectively. Moreover, the equipped buses had clean energy consumption, reducing traffic density and improving traffic circulation by 8%.

The FL model demonstrates substantial advancements compared to earlier studies, showcasing superior performance in reducing BEB energy demand. Specifically, it surpasses the models developed by Xue et al. (2024) by 33%, Heuts et al. (2024) by 26%, Fang et al. (2024) 18%, and Vignarca et al. (2024) by 1%, respectively. Furthermore, the noted gap between our model and the approach proposed by L. Yang et al. (2024) has been narrowed to approximately 3%, highlighting notable progress. As for CDBs, the FL-based model also excels, outperforming the frameworks of Bakibillah et al. (2018) by 18.76%, Adamski et al. (2021) by 21%, Bakibillah et al. (2024) by 15%, and Kim et al. (2021) and Ma et al. (2018) by 21%, respectively. These results underscore the model’s performance in minimizing energy utilization and emissions, solidifying its position as a leading solution in this domain.

Figure 4.19 shows the energy utilization and emission levels of both buses, along with traffic circulation under both traffic and traffic lights, facilitating the assessment of the FC Ecological Driving model's effectiveness.

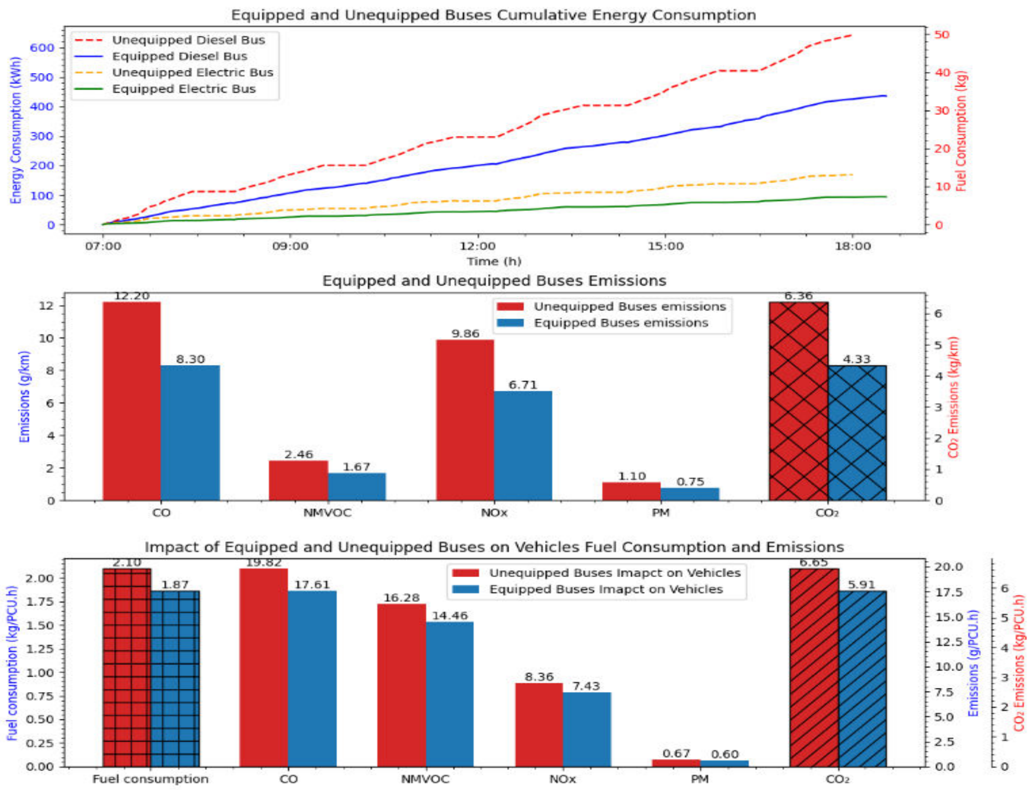

Figure 4.19. Traffic light and traffic circulation cases: energy consumption and emissions

The figure shows substantial energy and pollutant emission increases for both CDBs and BEBs and all traffic flow conditions when traffic lights exist: 13% CDBs, 21% BEBs, and 8% overall fuel usage and emissions. This model improves traffic operations, whereas environmental pollution and power usage decrease for all-electric bus types.

The FL Eco-Driving model reduction strategy decreased BEBs' energy use by almost 44%, reducing the usage to reach 94 kWh, which is remarkably lower than the previous value, which was 168 kWh. Through this method, the buses conserved between 74% and 78% more energy than CDBs and diesel buses adopted with FL-Eco-Driving technology. The implementation of FL-Eco-Driving technology on CDB led to significant reductions of 32% in fuel intake and emission levels because these buses used 640 kWh before FL-Eco-Driving but settled at 435 kWh afterward.

In regard to emission levels and energy usage, the model was able to minimize air pollution and energy usage effectively. From this data, the emissions of CO_2 reduced from 6.36 to 4.33 kg/km. Also, the NMVOC dropped from 2.46 to 1.67 g/km; meanwhile, the NOx was lowered, reaching 6.71 g/km, in addition to the PM being from 1.1 to 0.75 g/km. Finally, the CO was from 12.2 to 8.3 g/km. Additionally, the total traffic energy utilization and emissions were cut down by 11% while the fuel energy fell from 2.1 to 1.87 kg/PCUh. Further enhancements made were in emissions, such as CO_2 at 6.65 kg/PCUh, reduced to 5.91 kg/PCUh. Next, CO at 19.82 g/PCUh reduced to 17.61 g/PCUh, followed by NMVOC at 16.28 g/PCUh reduced to 14.46 g/PCUh, the NOx at 8.36 g/PCUh reduced to 7.43 g/PCUh, and finally the PM at 0.76 g/PCUh reduced to 0.6 g/PCUh. Such changes seek to illustrate the applicability of the model in order to improve environmental performance.

It can be inferred that the FL-based model is better juxtaposed to prior works in electric buses' efficiency, surpassing the models indicated by Vignarca et al. (2024) by 3.3%, Othman et al. (2024) by 24%, Zhang et al. (2019) by 41.53%, and Fang et al. (2024) by 14%, correspondingly. For CDBs, the FL-based model also has a good improvement over J. Hu et al. (2022), X. Wang et al. (2024), Bakibillah et al. (2018), Ma et al. (2018), and Kim et al. (2021) models by 13.6%, 25.2%, 23.76%, 26%, and 20%, respectively.

In the examination, we did not consider either the time or the prevailing climate (winter or summer). For instance, we do not use lights during the day; buses employ front and interior night lights. Heating devices are preferred in the cold season, while coolers are used more in the summer season. After thoroughly assessing the FL-Eco-driving findings and comparing them with previous studies in this section, the next one will focus on this chapter's limitations and prospects.

4.3.2 Challenges in real-world implementation and future directions

This research can be said to cover some extent, but it does not focus on policymakers' concerns. Still, the findings obtained in this chapter contain relevant information about encouraging sustainable accessibility. It promotes the FL-Eco-Driving systems for the concerned stakeholders and appeals to the public, along with commercial bus organizations, to adopt these models along with electric bus services to address greener modes of transportation. This will enhance the transportation capacity and go a long way toward achieving the goal of attaining sustainable mobility with the lowest effects on the environment of the existing PTS. Despite the improvements the given results show, several noticeable drawbacks and some recommendations for further studies were noted: This chapter has not concentrated on various traffic assessment metrics, which include bus waiting time, travel time, and queue lengths. Also, it neglected the deployment and maintenance expenses of the FL-based Eco-driving model and the safety of data exchange. Meanwhile, in the examination, we did not consider either the time or the prevailing climate (winter or summer). For instance, we do not use lights during the day; buses employ front and interior lights at night. Heating devices are preferred in the cold season, while coolers are used more in the summer season. Additionally, the study did not consider wind speed or air temperature, both of which significantly impact energy consumption. Higher wind speeds increase aerodynamic drag, leading to greater energy demand, while air temperature affects fuel effectiveness and battery performance. These factors should be considered in future analyses to improve both kinds' accuracy in estimating wasted energy.

Additionally, another critical limitation of this study is the absence of consideration for secure data transfer protocols in the FL-Eco-Driving system implementation. This limitation is particularly crucial given the system's reliance on continuous communication between vehicles, infrastructure, and central servers. Without robust security measures, the system becomes vulnerable to various cyber-attacks, including man-in-the-middle (MITM) attacks that could manipulate eco-driving recommendations, denial-of-service (DoS) attacks that could disrupt system operations, and data poisoning attacks that could corrupt the federated learning model with malicious training data. These vulnerabilities could lead to serious consequences such as increased energy consumption, compromised passenger safety, degraded system performance, and privacy breaches. Future research must prioritize the integration of secure communication protocols, encryption mechanisms, and intrusion detection systems to ensure safe deployment of FL-based eco-driving solutions in real-world public transportation systems. Next, we move to the chapter closure conclusion in the following section.

Conclusion

This chapter developed a Fuzzy Logic approach coupled with V2X communication in order to effectively represent the uncertainty in the vehicle, road, and traffic data and enhance BEBs and CDBs energy usage. The energy utilization of this study’s buses was enhanced by selecting the right speed, relying on multiple factors. V2X communication enables the model to capture data on real-time traffic and roadway conditions and make dynamic adjustments to optimize energy use. A case study was done to test the model using an urban traffic model and real-world traffic data to verify the strategy. The obtained findings highlight the FL-Eco-Driving model's efficiency by estimating public buses' speed relying on various factors, showing a remarkable drop in energy utilization and emission levels.

The following chapter will focus on developing a large language model capable of reasoning and acting to select driving speed patterns for various public buses, considering the factors discussed in this chapter and some of its limitations.

Chapter 5 : Smart and sustainable public transportation: ReAct LLM Eco-Driving Model

Introduction

Smart cities are one of the most prominent trends in contemporary urban development. This technology enhances existing processes, promotes environmentally friendly initiatives, and improves people's quality of life. Another feature of SCs is the way public transportation functions, as it is crucial for the mobility of people in urbanized regions. This has been due to the gradual implementation of affordable new transportation technologies, such as BEBs and Plug-in Hybrid Electric Buses (PHEBs), among others, resulting from the increased adoption of environmentally sustainable transportation systems worldwide (Biswas et al., 2025). This change is necessary to reduce greenhouse gases and help address city air pollution, which is integral to the SC vision of sustainable resource utilization. To address these challenges, ITS utilizes V2X technology, which enables the bus to communicate harmoniously and effectively with traffic signals, charging infrastructure, and other vehicles, making it safer and more efficient (Anderson, 2025). Additionally, it uses AI in SC applications, which encompasses knowledge management, decision-making tools, simulations, and mathematical modeling that ensure ITS operates transport systems efficiently like LLMs and RL, to reduce energy use, to function effectively in congested urban areas, and adapt to changing traffic patterns and conditions (Wen et al., 2025). Finishing with the chapter background in this section, we move to the second, where we explore how LLMs and RL have evolved to optimize driving behavior, reduce energy use, and emissions.

5.1 State of the Art of Ambient Temperature Influence on Energy Efficiency and Eco-Driving Innovations

The environmental effects, as well as the energy efficiency, of various bus technologies rely on several operational factors and environmental conditions. A significant amount of research has been conducted on this topic in recent studies. This section examines these factors from two perspectives. The first part examines how road slope, temperature, passenger numbers, and traffic lights impact a bus's energy use and related emissions, as well as how these factors alter the power requirements of major bus systems. The second part reviews eco-driving techniques applied to buses, focusing on methods used in various situations to reduce energy utilization and emissions.

This section contains three subsections. The first discusses the impact of ambient temperature and traffic lights on buses' energy consumption, while the second and third subsections focus on LLMs and DRL driving models.

5.1.1 Impact of ambient temperature and traffic lights on bus energy utilization and emissions

Factors influencing the energy utilization and direct and indirect emissions of Public Transport Buses (PTBs) include road gradient, passenger counts (as discussed in chapter 4, section 4.1), meanwhile, temperature variations, and interactions with traffic signals. Each of these elements affects different kinds of buses in unique ways. For instance, temperature significantly influences vehicle performance, as it restricts engine power output and battery capabilities, while also increasing the demand on auxiliary systems. When temperatures dip below zero degrees Celsius, the emissions of conventional buses rise by 10%-20%. Additionally, inadequate after-treatment systems can worsen fuel intakes, and elevated temperatures can stress cooling systems, ultimately decreasing fuel efficiency (Abediasl et al., 2023; Othmani, Boubaker, Rehimi, & Alimi, 2024). Electric buses experience a 20%-60% drop in range at sub-zero temperatures due to power inefficiencies, which are exacerbated when heating systems demand extra energy (Abediasl et al., 2023). When the temperature surpasses the average, rising to a warmer level, BEB's energy utilization increases(McGrath et al., 2022). PHEB performance of PHEBs varies with temperature; cooler conditions enhance combustion, leading to higher emissions, yet yield only slight efficiency gains in electric mode (Ansari et al., 2024).

It has also been observed that, in their routine movement through traffic light control, various types of buses consume more energy and emit more emissions by the time they complete their daily activities. Kumar (2023) states that the amount of energy loss in buses operated on regular fuels is even higher; therefore, CO_2 emissions increase when the vehicle is idling at red signals or when the brakes are suddenly applied. Nevertheless, the advantages of engine regeneration of power while stopped are essential, as energy usage increases significantly during charging and discharging through frequent stops, which is common in urban areas (Dong et al., 2022; Jayson et al., 2024). PHEBs use electric power at the stops and in other ways, and the authors underscore that energy demand increases significantly due to the shift within the hybrid system (Dahmane et al., 2018). It is for this reason that efficiency in terms of energy saving largely depends on how well traffic signals are coordinated within the transport system. Finishing with the impact of traffic lights and ambient temperature on buses' energy use in this subsection, we move on to the application of LLMs in autonomous and ecological driving in the next section.

5.1.2 LLMs for autonomous and eco-driving

Nowadays, LLMs have become a revolutionary trend in the development of autonomous and eco-driving systems, which enhance a vehicle's ability to perceive its environment and make informed decisions in real-world scenarios. Despite being able to generate and map extraordinary real-life big data flows from sensors and live traffic information to environmental conditions, such as weather and road configurations, LLMs help strike the right balance of safety, performance, and environmental impact in Autonomous driving (Gan et al., 2024b; Mahmud et al., 2025). Some of these models can easily translate traffic reports based on natural language understanding, predict changes in traffic conditions, and adapt driving strategies to enhance energy efficiency in standard vehicles and extend battery life in electric vehicles (Abraham et al., 2025; Moraga et al., 2025). In addition to their capacity to process signals, LLMs enhance Vehicle-to-Everything (V2X) interaction by interpreting and synthesizing instructions that are coherent to a human being, allowing vehicles, other structures in the immediate environment, and passengers to communicate effectively. This capability facilitates less risky and more natural interactions with other actors on the same road, in addition to promoting the concept of sustainable driving, which entails avoiding unnecessary acceleration, braking, or idling behaviors that lead to increased emissions and wasted energy (Jiang et al., 2024; Sohail et al., 2024). Moreover, integrating self-driving cars into intelligent transportation systems not only enhances the degree of accuracy and reactivity but also enriches their overall performance. This integration serves the primary societal goal of preserving the environment and combating climate change, making LLMs the cornerstone of optimizing next-generation mobility.

Having discussed in detail how LLMs can help improve aspects of autonomous and eco-driving, the focus now turns to different eco-driving applications within the bus transport sector. The next subsection further discusses how such systems are integrated and designed for different types of buses, including conventional diesel buses, electric buses, and plug-in hybrid electric buses, to minimize energy consumption and emissions. This transition will pave the way for zooming into even more practical scenarios, with analysis on top of the foundational capabilities to meet the demands that lie within sustainable bus fleet management.

5.1.3 Advanced buses eco-driving models based on Machine and Reinforcement Learning

By utilizing eco-driving models, buses in public transportation improve their energy efficiency and reduce their environmental impact. These systems apply computer-based methods to optimize driving operations by understanding the differences between CDBs, BEBs, and PHEBs. This analysis examines new scientific findings that inform eco-driving patterns for various bus types, including their development strategies and the impact on energy utilization and model requirements.

Early research mainly looked at eco-driving models for CDBs, Bakibillah et al. (2024) deployed an FL model, reducing energy use by 6%, by integrating the road slope factor. Meanwhile, focusing on the same factor, Kim et al. (2021) created a Learning Path Planning model, aka LPL, resulting in a 12.1% reduction in fuel intakes. Through their work applying ML to CDBs, Naskali & Şen (2021) applied ML to CDBs by incorporating the temperature factor, and achieved a 2% drop in fuel. Another ML approach developed by H. Ma et al. (2018) that incorporates passenger numbers, traffic lights, and road slope to predict trip fuel needs, resulting in a 6.25% energy reduction. Studies by various researchers suggest that DASs can enhance buses' operations. Still, most studies have focused on just a few factors and specific bus types.

Today, considerable attention is being paid to PHEBs and BEBs, as the population is increasingly concerned with eco-friendly transportation options. Therefore, walking is a viable solution for dynamic environments, as DRL performs well in such scenarios. Beginning with BEBs, we note that an eco-driving model developed by Pan et al. (2025) utilizes DRL while considering the impacts of city traffic, traffic signals, and road slope. the model demonstrated a 31.19% drop in energy utilization. Additionally, a study conducted by Wu et al. (2025) assessed DRL capability by integrating ambient temperature, resulting in a 14.71% reduction in energy use. Meanwhile, L. Yang et al. (2024) reduced the energy utilization of BEBs by 40.69% by adopting DRL, which involved five extensive attributes: temperature, road slope, traffic signalization, traffic flow, and passenger numbers. Similarly, Jin et al. (2023) have also applied DRL to enhance BEBs operations by reducing the cut-off energy by 40% in relation to traffic lights with passenger loads.

Moving PHEBs, considering traffic flow and passenger load, along with temperature, in DRL eco-driving models for PHEBs, also reduced the percentages to 34.1% by Yu et al. (2023). According to the findings from the surveys conducted by Ruiz et al. (2023) and Hu et al. (2023), energy consumption on the PHEB decreased by 22.5% and 9.6%, respectively, with the help of DRL. Ruiz addressed the road slope and the traffic light, and Hu could not give up any of the parameters in her study. Han et al. (2022), demonstrates that employing their DRL algorithm, with a focus on dynamic changes in passenger loading, can achieve a 12.92% energy savings in PHEBs' driving strategy.

Having outlined the results of the buses' eco-driving models subsection, we now transition to an analysis of the gaps in existing literature. The following subsection discusses how these observations align with or differ from the existing literature on LLMs and RL in this context. These gaps define the need and possibilities for further research and development of the eco-driving approaches in bus transportation.

5.1.4 Eco-driving challenges and opportunities for sustainable buses

Recent advancements in eco-driving technologies have significantly enhanced the energy efficiency and environmental sustainability of public transport buses. By leveraging ML and DRL, researchers have developed innovative models to optimize driving strategies for various bus types as mentioned in the previous subsection. These studies provide critical insights into reducing energy consumption and emissions while establishing performance benchmarks for next-generation bus systems. Figure 5.1 presents a list of selected studies on eco-driving applications in BEBs, PHEBs, and CDBs. The majority of these studies employ ML or DRL techniques, and all of them have demonstrated some level of energy savings and established important performance benchmarks. They serve as a basis to evaluate the impact and efficiency of the proposed LARBEM system, taking into account sustainable bus transport.

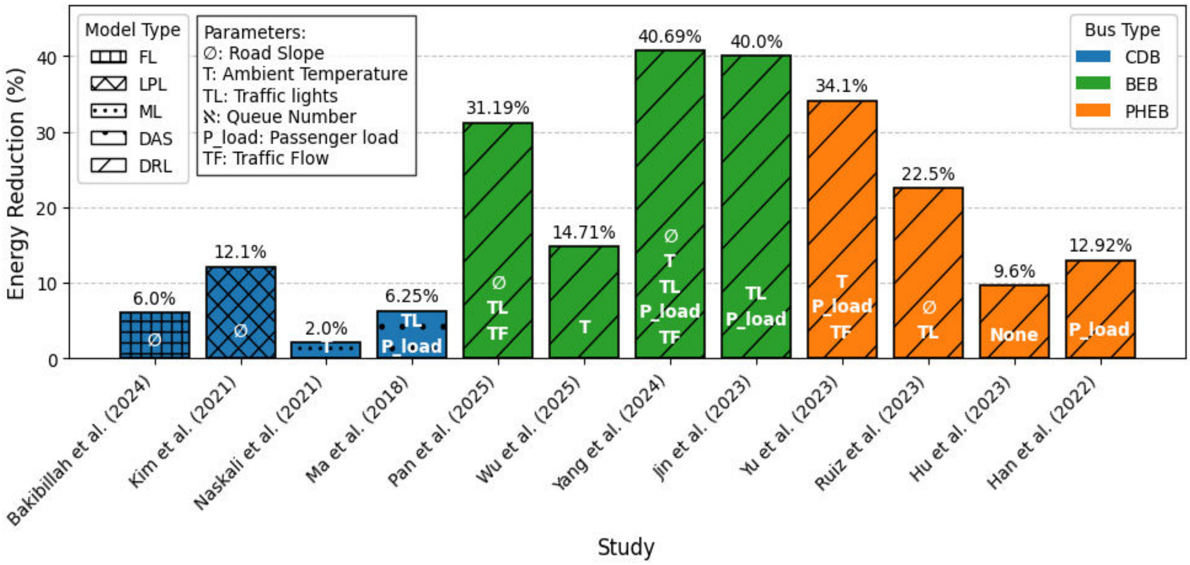

Figure 5.1. Summary of the literature on eco-driving models

To address the literature challenges, this chapter introduces a novel eco-driving model for buses through the development and adoption of LARBEM, an LLM-based model that optimizes energy efficiency and reduces emissions across diverse bus types, including PHEBs, CDBs, and BEBs. Unlike previous research, which often focused on a unified eco-driving model accounting for multiple variables like passenger count, temperature, road slope, queue length, traffic signals, and urban traffic flow, this work combines the reasoning and decision-making strengths of the LLM with RL's adaptive capabilities via the ReAct (Reasoning and Acting) framework, offering a robust approach for managing mixed public bus fleets in SC environments. The LARBEM model will be tested on Sousse and Kalaa Kbira bus route in Tunisia, combined with collected traffic data on March 24, 2024 including road gradient, traffic patterns, passenger loads, and weather conditions to evaluate its ability to dynamically adjust driving strategies for reduced energy utilization and emissions, filling key literature gaps and providing practical insights for transit agencies in Tunisia and globally to advance AI-supported smart city transportation.

The data discussed in the reviewed studies suggests that eco-driving models are relatively successful in reducing fuel consumption, with a specific emphasis on BEBs and PHEBs, and knowledge of DRL solutions. However, a gap is revealed: there is no single study that has estimated an eco-driving model for PHEBs, CDBs, and BEBs to support the variability of bus fleets that is characteristic of current urban environments. Moreover, the variance in parameters selected by the researchers overlooks essential factors for predicting energy use, such as queue length; hence, the application of the indicated models becomes limited, as outlined in the section. The shortage of a more comprehensive approach, based on numerous factors such as queue length, temperature, passenger load, road slope, traffic signals, and traffic density, does not allow for designing an elaborate eco-driving assistant system tailored to the needs of SCs.

Having explored the strengths and limitations of eco-driving models for various bus types, we now turn our attention to the development of the LARBEM system. The following section presents a new solution to fill the outlined gaps, which involves the application of sophisticated computing to improve eco-driving for heterogeneous fleets of buses. Therefore, to expand on the findings from the underlying models, LARBEM will attempt to provide a broader approach towards a sustainable urban mobility system.

5.2 System design and implementation

The analysis is presented in the LLM-based Agentic ReAct Bus Eco-Driving Model section, which elaborates on the model's concept using advanced modeling methods to enhance the energy efficiency of bus traffic and reduce emissions. It also includes the LARBEM Development section, which outlines the steps for developing a LARBEM, as well as the RL Agent subsection that explains the process of creating an RL agent to optimize bus operations adaptively. Finally, we have a study zone, collected data, a simulation framework, and evaluation subsections to provide the adopted methodology for assessing LARBEM efficiency.

5.2.1 LARBEM development

In this subsection, we present the LARBEM, which is equipped with V2X communication, an enhanced communication technology that supports flexible systems, such as ADAS for buses, as depicted in Figure 5.2. This particular model utilizes large language models to make adjustments during the decision-making stage, with the ultimate goal of reducing energy intensity and greenhouse gas emissions for various types of buses. Utilizing advanced computational intelligence with real-time connectivity, LARBEM represents a novel approach to enhancing eco-driving strategies for sustainability improvement in the public transportation sector, thereby reducing environmental impact and improving operational efficiency.

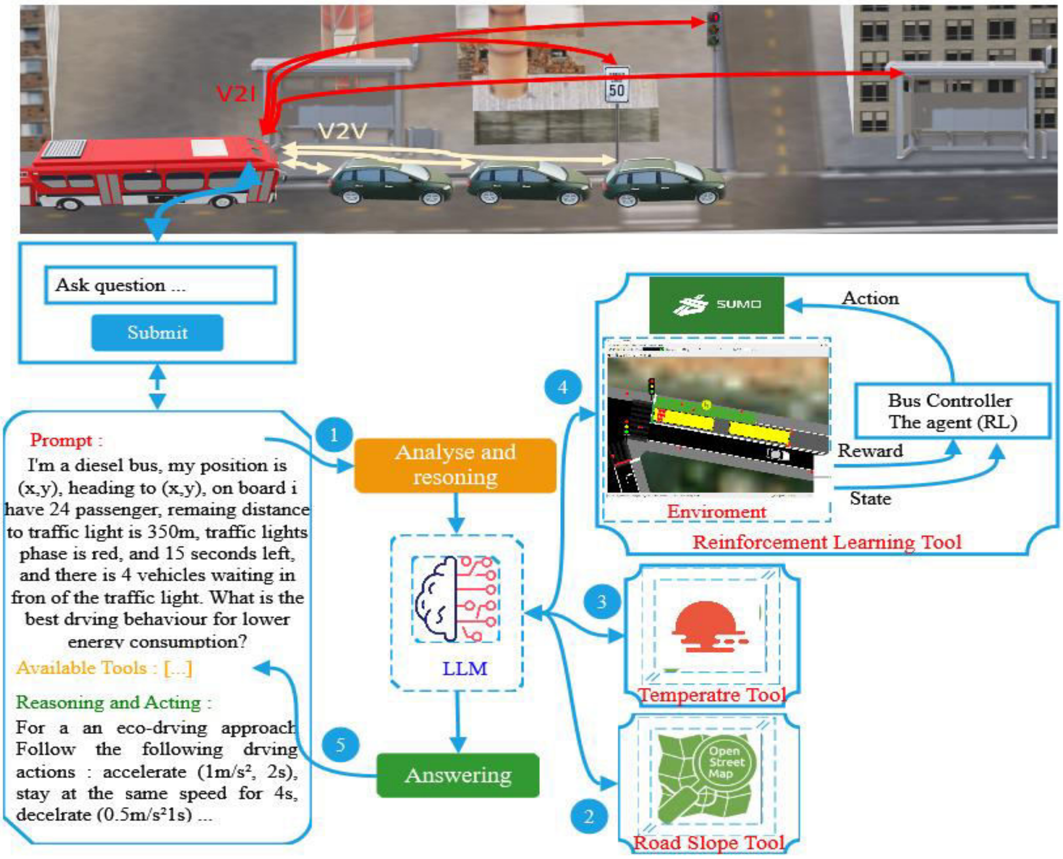

Figure 5.2. LARBEM

The study integrated LLM as the core decision-making component of the LARBEM system to generate optimized driving recommendations for buses. These recommendations are tailored to real-time traffic conditions, road characteristics, passenger load, and environmental factors, enhancing overall efficiency and adaptability.

The primary reasons for adopting large language models can be outlined as follows: recent advancements have highlighted their value in the transportation field, notably in improving autonomous driving systems and providing support (Y. Li et al., 2025; Murtaza et al., 2025). Additionally, cutting-edge LLMs can mimic human-like reasoning by continuously processing environmental data and evaluating possible actions, as seen in ReAct agent LLMs (Dyachenko et al., 2025; Sezgin, 2025).

Moreover, integrating LLMs with specialized agents enhances their efficiency and decision-making capabilities, leading to more effective outcomes (Y. Sun & Liu, 2025; Yuan, 2025).

For this study, we utilized Qwen 2.5-1.5B as the central reasoning component to develop an LLM-based Agentic ReAct Bus Eco-Driving Model, constructed with the LangChain and LangGraph libraries in Python 3.12 (Chase, 2022/2022; William, 2023/2025). This model was chosen for its superior ability to manage intricate, real-time decision-making processes while offering scalability and efficiency, requiring minimal reliance on high-end Graphical Processing Units (GPUs) compared to alternative models (Ahmed et al., 2025; Aydin et al., 2025).

Figure 5.2 illustrates how the bus employs V2X (V2I + V2V) to determine the remaining distance (D) to the nearest bus stop or traffic light, prioritizing the closer of the two. When the bus is nearer to a traffic light than a bus stop and D falls within a 300-meter range, as noted by Lee & Wang (2022) and Chowduri et al. (2024), it retrieves the road speed limit (v_{max}), the entire sequence of the upcoming traffic light phases (φ_i), the queue length ($\aleph$), the current traffic light state (ɝ), and the remaining time in that state (τ). If the bus stop is closer, these parameters (φ_i, $\aleph$, ɝ,τ) are assigned a value of zero, and the collected data, alongside the bus type ($Type$), actual speed (v_i), and passenger load (P_{load}) which are transmitted to the LARBEM system via a prompt for further processing.

Upon receiving a prompt, LARBEM initiates its reasoning process and determines the appropriate tools to formulate a response, as illustrated in Figure 5.2. The large language model (LLM) is integrated with three specialized tools, each serving a distinct purpose. Initially, the LLM utilizes OpenStreetMap (OSM), an open-source platform with a freely accessible Application Programming Interface (API), to retrieve road slope information ($\emptyset$) (OpenStreetMap contributors, 2017). Next, it employs Open-Meteo, a tool offering a complimentary API, to collect temperature data (T) (Zippenfenig, 2025). Finally, the LLM channels this information into the reinforcement learning (RL) tool, which determines optimal driving patterns that are relayed back to the LLM, enabling LARBEM to deliver a practical and accurate response. Table 5.1 outlines the LARBEM process for enhancing bus driving patterns using real-time traffic and environmental inputs.

Table 5.1. LARBEM algorithm

Algorithm 1: V2X-Enabled Eco-Driving with LARBEM
1. **Require**: Bus type (Type), actual speed (v_i), passenger load (P_{load}), road speed limit (v_{max});
2. **Locate** the nearest bus station and traffic light ahead;
3. **Compute** the remaining distance (D) to the closest entity; ▷ Bus station or traffic light
4. **If** there is no traffic light within 300 m ahead **then:**
5. **Set** D ← bus station distance;
6. **Set** traffic light program (φ_i) ← 0; ▷ No traffic data needed if the bus station is closer.
7. **Set** queue number (ℵ) ← 0;
8. **Set** current signal phase (ঌ) ← 0;
9. **Set** remaining phase time (τ) ← 0;
10. **Else:**
11. **Require**: ঌ, τ, φ_i, ℵ;
12. **Set** D ← Distance to next traffic light;
13. **end if.**
14. **Prepare** prompt with collected data: Prompt ← (Type, D, v_{max}, φ_i, ℵ, ঌ, τ, v_i, P_{load});
15. **Send** Prompt to the LLM within **LARBEM**; ▷ LLM receives the prompt and begins reasoning.
16. **Retrieve** road slope (∅) using the LLM road slope tool; ▷ LLM calls the OpenStreetMap agent using its free API.
17. **Retrieve** temperature (T) using the LLM temperature tool; ▷ LLM calls the Open-Meteo agent using its free API.
18. LLM call Reinforcement Learning (RL) tool;
19. RL ← (Type, D, v_{max}, φ_i, ℵ, ঌ, τ, v_i, P_{load}, ∅, T);
20. **Compute** the optimal driving pattern (DP) using RL Agent; ▷ RL optimizes driving behavior.
21. LLM ← DP;
22. **Output** the recommended DP obtained from the LLM within **LARBEM**;
23. Bus applies the obtained DP;

The study carefully chose input data grounded in existing literature to mirror real-world driving scenarios and enhance eco-driving decision-making. Parameters such as D, φ_i, ℵ, ঌ, and τ were adopted from A. K. Shafik & Rakha (2024) and A. Shafik et al. (2024) to fine-tune vehicle speed optimization at signalized intersections.

Additionally, variables like $Type$, $\emptyset$, T, and P_{load} were included based on their influence on different bus types, as detailed in the literature review, enabling LARBEM to adapt to diverse real-world conditions and bus categories. Lastly, v_i and v_{max} were incorporated, following Kampitakis et al. (2024) and L. Yang et al. (2024b) to replicate realistic driving behaviors while ensuring compliance with road speed limits.

With the LARBEM system's framework established in this subsection, we now proceed to the development of its reinforcement learning (RL) agent in the next section.

5.2.2 Reinforcement Learning agent development

This study develops a reinforcement learning (RL) bus agent integrated into the SUMO platform to identify optimal driving strategies that mitigate environmental impacts. As illustrated in Figure 5.3, the agent functions within a closed-loop simulated traffic environment, learning to reduce energy consumption for PHEBs, BEBs and CSBs.

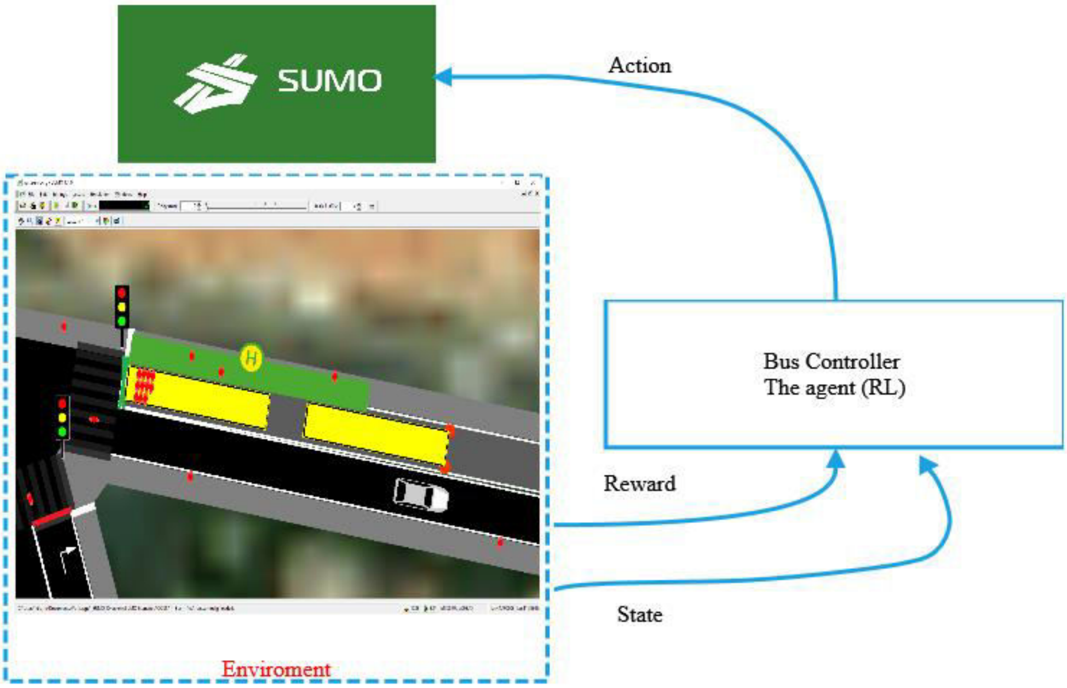

Figure 5.3. Bus RL agent

Figure 5.3 illustrates the reinforcement learning (RL) framework operating within a closed-loop system, linking an RL agent to the SUMO environment. SUMO generates realistic urban traffic scenarios that incorporate road networks, traffic signals, vehicle dynamics, and environmental variables. Central to RL is its reliance on the Markov Decision Process (MDP), defined by a discount factor (∂) between 0 and 1, transition Probabilities (P), a finite structure comprising States (S), Actions (A), Reward function (R). The agent learns about its surroundings through state Observations (O), selects actions accordingly, and receives rewards as detailed in Equation 5.1 (Y. Wang & Vittal, 2023):

$$O \in (S, A, P, R, \partial) \tag{5.1}$$

The Reinforcement Learning framework begins with the state space, denoted as S, which is represented by an 11-dimensional vector encapsulating key environmental and operational conditions, as detailed in Equation 5.2:

$$S = [Type, v_i,\ v_{max}, \emptyset, T, P_{load}, D, \varphi_i, \aleph, \text{ɝ}, \tau] \tag{5.2}$$

Transitioning to the action space A is defined as a discrete set comprising 10 possible actions (A_i), which governs the bus's speed through controlled deceleration or acceleration, as articulated in Equation 5.3:

$$A = -2.5 + A_i \times 0.5 \tag{5.3}$$

Regarding the reward function R in the step method, the goal is to minimize energy consumption ($energy$) based on each bus type, while penalizing excessively long travel times (TT). This can be formulated using Equation 5.4:

$$R = -\,(energy + TT) \tag{5.4}$$

In the final stage, the Reinforcement Learning tool uses a Q-learning algorithm to train the RL agent across 100 episodes. The agent follows an epsilon-greedy exploration strategy, where epsilon decays exponentially. The Q-values are then updated according to the Q-learning equation (Y. Wang & Vittal, 2023):

$$Q(S, A) = Q(S, A) + \varepsilon \times \left\{R + \partial \times Max_{\acute{A}}[Q\big(\acute{S}, \acute{A}\big) - Q(S, A)]\right\} \tag{5.5}$$

Where $\acute{S}, \acute{A}$ are the next state and action, and ε: the learning rate. The RL agent determines the most efficient driving strategy by choosing actions that reduce energy usage while keeping travel times low. The optimal actions are selected based on the lowest reward provided to the LLM, enabling it to generate the best driving pattern. As shown in Table 5.2, the RL agent operates using a Q-learning algorithm in a SUMO simulation environment to identify an energy-efficient driving pattern that minimizes bus energy consumption.

Table 5.2. RL agent algorithm

Algorithm 2: RL Agent for Bus Eco-Driving Optimization

1. **Require**: Simulation of Urban MObility (SUMO) environment, initial state (S), action Space (A), reward (R), learning and exploration rates (ε), discount factor (∂) (0 to 1), number of episodes (100), initial Q-table $Q(S, A)$;
2. **Set** $S \leftarrow$ [Type, D, v_{max}, φ_i, ℵ, з-, τ, v_i, P_{load}]; ▷ State space S is an 11-dimensional vector obtained from the LLM within **LARBEM**
3. **Set** recommended driving pattern (DP) ← [ ]; ▷ empty list
4. **Set** $A \leftarrow (-2.5 + A_i \times 0.5)$; ▷Action space ($A$) is a discrete set with 10 actions (Ai)
5. **Set** $Q(S, A) \leftarrow 0$;
6. **For** each episode from 1 to 100 **do**
7.   **Reset** SUMO environment to initial state S;
8.   **While** episode not terminated:
9.   **Observe** current state S from SUMO environment;
10.   **If** with probability ε **then**
11.   **Select** random Ai from A; ▷ Exploration using epsilon-greedy strategy
12.   **Else**:
13.   **Select** $A \leftarrow Max_{\acute{A}}\ Q(S, A)$; ▷ Exploitation
14.   **End If**
15.   **Execute** A_i in SUMO environment;
16.   **Observe** next state S' and reward R;
17.   **Compute** reward $R = -(\,energy + TT)$; ▷ Energy consumption plus penalty on travel time
18.   **Update** Q-value using Q-learning: $Q(S, A) = Q(S, A) + \varepsilon \times \{R + \partial \times Max_{\acute{A}}[Q(\acute{S}, \acute{A}) - Q(S, A)]\}$;
19.   **Set** S ← S'; ▷ Transition to next state
20. **End While**
21. **End For**
22. **Identify** optimal driving pattern;
23. **Set** DP ← A* = $Max_{\acute{A}}\ Q(S, A)$; ▷ with highest reward (lowest negative value)
24. **Send** DP to LLM within **LARBEM**;
25. **Output** DP;

Having detailed the RL agent's development in this subsection, we now explore the study zone characteristics and data acquisition process in the following.

5.2.3 Study zone characteristics and data acquisition

To assess the effectiveness of the LARBEM model, real-world data were gathered to ensure the simulation accurately reflects actual conditions. The bus route from Sousse to Kalaa Kbira was chosen as the study area, providing a detailed representation of the transportation path, including road slope and hourly traffic patterns; this analysis draws on the input data detailed in Chapter 4, subsections 4.2.2 and 4.2.3. Additionally, Figure 5.4 presents the hourly ambient temperature variations within the study zone.

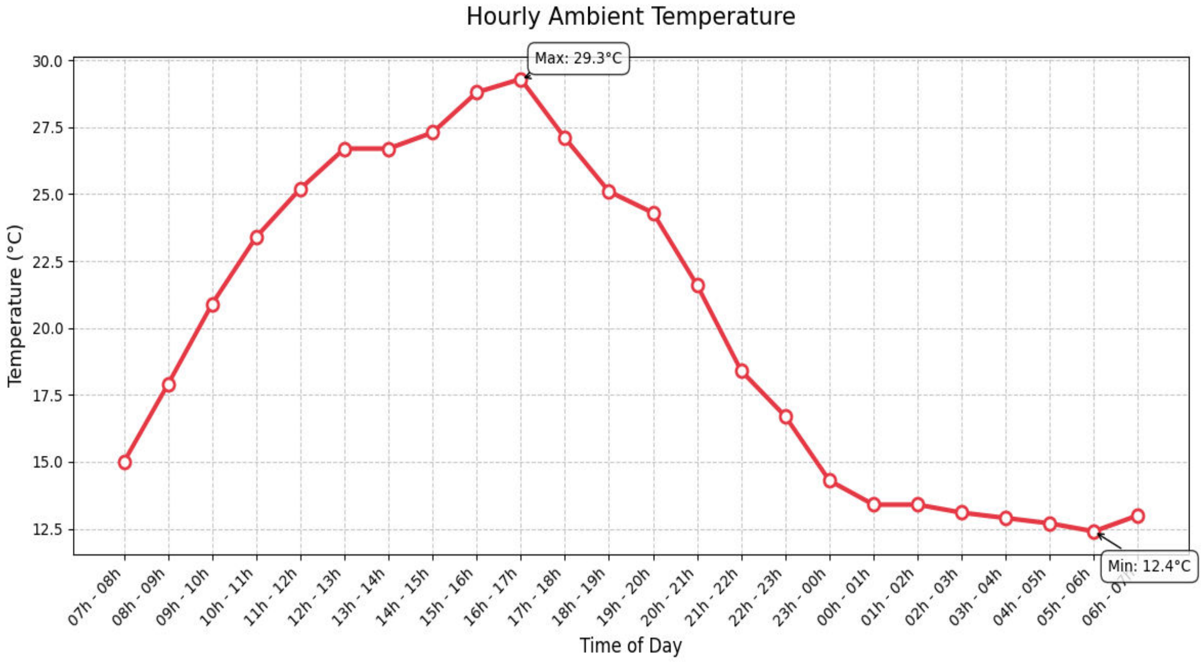

Figure 5.4. Hourly Study zone ambient temperature

Figure 5.1 depicts the line graph of the hourly ambient temperature over a twenty-four-hour cycle. The horizontal axis scale represents the period from 07:00 to 07:00 the following morning, while the vertical axis scale represents temperature in Celsius, ranging from a minimum of 12.5°C to a maximum of 30.0°C. There is a regular increase in temperatures, starting with the lowest temperatures at around 06:00, which range from 12.4°C, and culminating at 29.3°C at about 14:00 and 15:00 before it starts to drop gradually in the evening and at night, reaching a relatively low value at around 06:00.

Having detailed the study zone characteristics and data acquisition process in this subsection, we now move to the next, which outlines the evaluation framework and simulation setup. This subsection describes the methodology used to assess the

LARBEM system's performance under various conditions, leveraging the collected data to simulate real-world eco-driving scenarios. This transition sets the stage for understanding the practical implementation and testing of the proposed system.

5.2.4 Evaluation framework and simulation setup

To evaluate the efficiency of the LARBEM system across diverse simulation scenarios, we utilized SUMO version 1.22 alongside Python version 1.12, harnessing V2X connectivity to model and analyze its effectiveness. This approach enabled us to measure reductions in energy utilization, along with the emitted CO_2 in the atmosphere, for various bus types under different conditions, as illustrated in Figure 5.5.

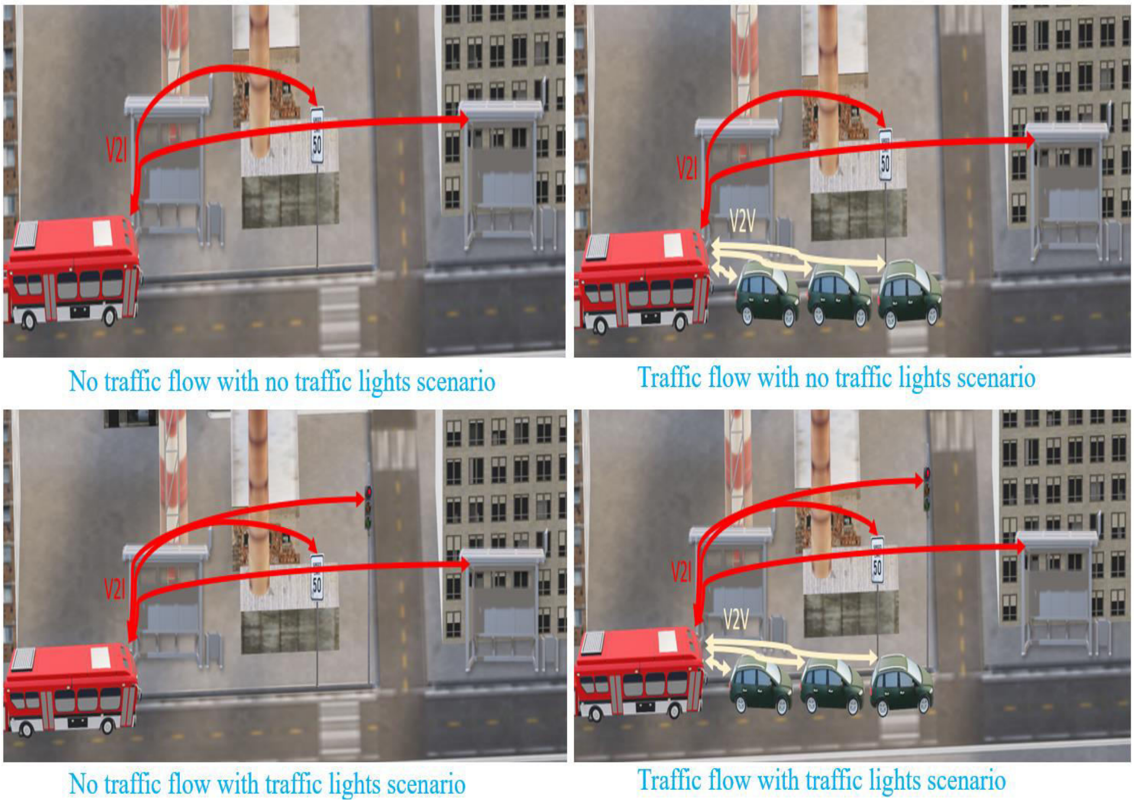

Figure 5.5. Simulation scenarios

Figure 5.5 outlines the evaluation of 24 simulations designed to assess three bus types: Conventional Diesel, Battery Electric, and Plug-in Hybrid Electric buses, while focusing on their energy use and emissions with and without the LARBEM system. These simulations span four distinct scenarios to test LARBEM's adaptability across different conditions: a baseline with no traffic or traffic lights to gauge essential bus performance; a scenario with traffic flow but no lights to study vehicle interaction effects; a setup with traffic lights but no traffic to analyze stop-and-go impacts; and a realistic urban scenario combining traffic and signalized intersections. Together, these scenarios provide a comprehensive view of how LARBEM enhances the efficiency of various bus technologies in diverse settings.

Given that the bus route features only roundabouts without signalized intersections, we adapt these roundabouts into signalized versions using equations 4.4–4.4 from Chapter 4, subsection 4.2.3, to align with the simulation framework.

This study also adopted PHEBs, which combine the benefits of both conventional internal combustion engines ICEs and electric propulsion systems, offering a flexible and efficient solution for public transportation (M. A. S. H. Mohamed, 2024; Sens, 2023). BEBs, which rely solely on large battery packs, or CDBs, which depend entirely on fossil fuels, PHEBs utilize a dual powertrain architecture that integrates an electric motor and a combustion engine as illustrated in Figure 5.6.

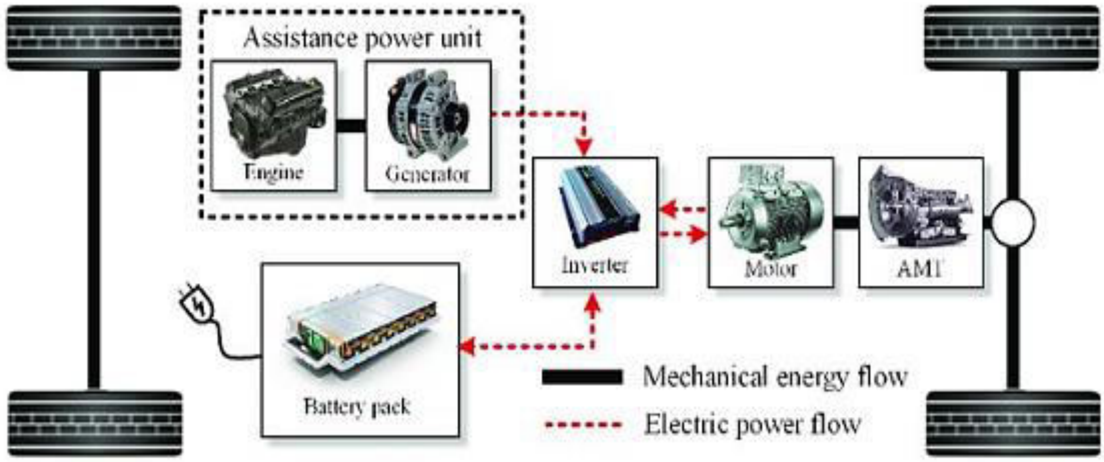

Figure 5.6. PHEBs architecture (Z. Chen et al., 2020)

The hybrid design enables PHEBs to operate in all-electric mode for short distances, thereby reducing emissions and fuel consumption in urban areas. For longer trips or when battery levels are low, the vehicle switches to its combustion engine, ensuring extended range and operational reliability. The ability to recharge the battery via plug-in charging further enhances energy efficiency, making PHEBs a cost-effective transition technology for cities moving toward full electrification (Ashkezari et al., 2024). Their lower upfront costs drive their widespread adoption worldwide compared to BEBs, reduced dependency on charging infrastructure, and adaptability to varying route demands. Additionally, regenerative braking in PHEBs recaptures kinetic energy, further improving efficiency. While not as emission-free as BEBs, PHEBs significantly reduce greenhouse gases and fuel costs compared to CDBs, making them a practical intermediate solution in the shift toward sustainable urban transportation.

The growing emphasis on sustainable urban bus transportation highlights the need to assess the energy and emission profiles of various bus technologies. The chapter outlines models for CDBs, BEBs, and PHEBs, examining their energy consumption and emissions across various factors, including passenger loads, road gradients, temperatures, acceleration rates, and idling periods. Figure 5.7 depicts the forces acting on a city bus, providing a visual foundation for this analysis.

Figure 5.7. City bus applied forces

As presented in Figure 5.7, the bus is subjected to various resistive forces, as discussed in Chapter 2, Section 2.2.3. To integrate the ambient temperature into the equation, we need to modify the drag resistive force presented in equation 2.9 with Eq 5.6 (J. Ma et al., 2019b; Miri et al., 2021; Othmani, Boubaker, Rehimi, & Alimi, 2024):

$$Acc_{res} = \frac{1}{2} \times (\frac{P_a}{1+(R \times T)}) \times Cd \times Ax \times (v_{vehicle} - v_{wind})^2 \qquad (5.6)$$

P_a : air pressure (Pa), R : gas constant (8.314 J/molK), and T : ambient temperature (K). Moving to PHEBs, the following equations are used to calculate both fuel and energy utilization along with emitted CO_2 in kg (Othmani, Boubaker, Rehimi, & Alimi, 2024; Ruiz et al., 2023):

$$F_c = \begin{cases} \frac{P}{n_{ce}} \times ge, \ if \ P \geq 0 \\ \Delta \times T_{idle}, \ if \ P < 0 \end{cases} \qquad (5.7)$$

$$E_{bat} = \begin{cases} \frac{P}{n_T}, & if\ P \geq 0 \\ n_{rb} \times P, & if\ P < 0 \end{cases} \tag{5.8}$$

$$CO_2 = F_c \times \beta \tag{5.9}$$

Meanwhile, for BEBs we adopt the next equations to calculate both energy utilization and indirect CO_2 emissions (Basso et al., 2019; Mao et al., 2021; L. Yang et al., 2024a):

$$P_{HVAC}(T) = 0.0264 \times T^2 - 1.046 \times T + 11.13 \tag{5.10}$$

$$P_{HVAC}(n) = 0.064 \times n + 2.49 \tag{5.11}$$

$$E_{HVAC} = P_{HVAC}(T) + P_{HVAC}(n) \tag{5.12}$$

$$E_{bat} = E_{HVAC} + E_{bat} \tag{5.13}$$

$$CO_2 = E_{bat} \times \Omega \tag{5.14}$$

E_{HVAC}: the heating, ventilation, and air conditioning system (kW), $P_{HVAC}(T)$ and $P_{HVAC}(n)$ are the power consumption of the heating, ventilation, and air conditioning based on ambient temperature and the number of passengers, respectively, Ω: CO_2 emissions factor (kg/kWh), and T: ambient temperature (°C). Table 5.3 provides the PHEB parameters.

Table 5.3. PHEB key parameters (Ruiz et al., 2023)

Parameters \ **Vehicle type**	**PHEB**
Weight, w_b [kg]	19500
Air drag coefficient, C_d	0.7
Front area surface, A_x [m²]	8.2
Transmission efficiency, η_T [%]	96
Battery capacity, B_{Cap}[kWh]	470
Max passengers' number, n	95
Average passengers' mass, $\overline{m}$ [kg]	65

Having established the evaluation framework and simulation setup for assessing LARBEM's impact on bus eco-driving in this subsection, we now proceed to the results and discussions section, which presents the results and delves into key findings and insights derived from the simulations. It bridges the methodology with practical outcomes, offering a clear understanding of LARBEM's effectiveness across diverse scenarios.

5.3 Results and discussion: key findings and insights

The study's outcomes undergo an extensive evaluation through two primary subsections. The section first presents evaluation data from the LARBEM system, which reveals energy usage and CO_2 emission levels of buses under LARBEM-managed and unmanaged conditions. The section demonstrates how the system delivers measurable environmental improvements alongside efficiency benefits to the transportation system. In the following sections, we conduct a comparative analysis of LARBEM's findings against prior research, providing insights into how these results align with or diverge from existing literature and offering a broader context for understanding the system's impact and significance in advancing sustainable transportation solutions. These sections establish a connection between empirical evidence and interpretive analysis, thereby enhancing the value of the field.

5.3.1 Energy consumption and emissions reduction achievements: key findings

The subsection outlines the practical advantages of public transportation systems that incorporate adaptive regenerative braking, integrated with energy management technologies. The practical application of LARBEM on various bus types yields two key findings, comparing energy consumption and carbon dioxide emissions under different operational conditions. Figure 5.8 illustrates how LARBEM-tailored buses utilized energy under various conditions.

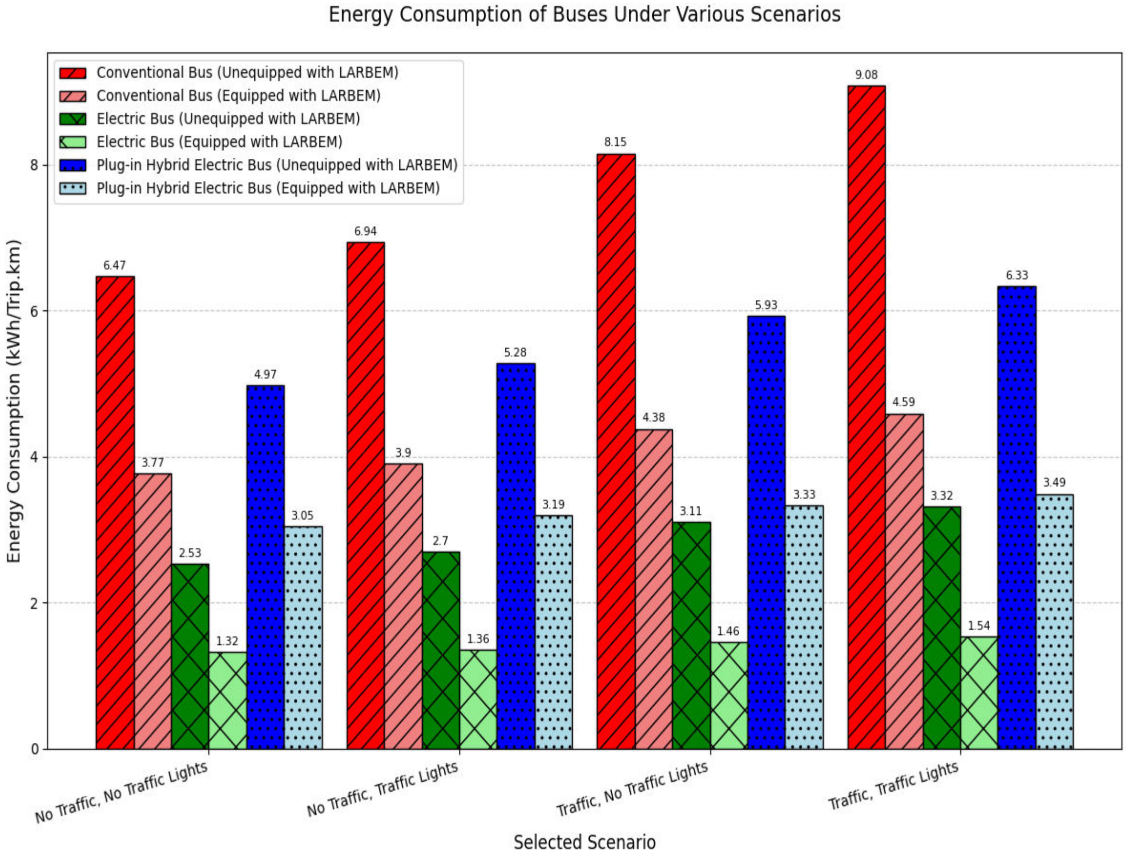

Figure 5.8. LARBEM impact on energy use under various conditions and bus types

Figure 5.9 supplements the prior one by showing CO_2 emissions levels, which illustrate the LARBEM system's performance compared to baseline scenarios.

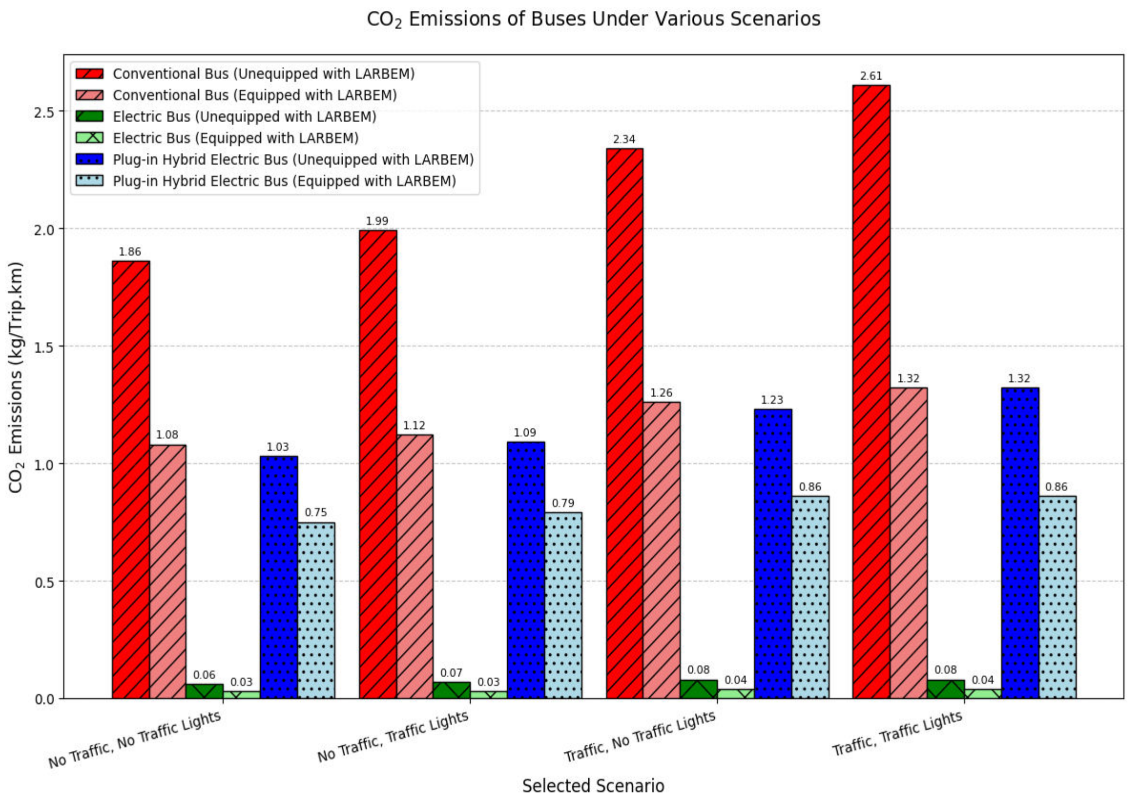

Figure 5.9. Various buses and scenarios impact on CO_2 emissions

The statistical data presented in these two figures demonstrate precisely how LARBEM operates as a powerful solution for energy conservation, alongside environmental protection, and showcases its ability to enhance bus performance. LARBEM operation with V2X systems yields significant energy conservation alongside environmental benefits across various operating conditions. The research analyzes CDBs, BEBs, and PHEBs with and without LARBEM to measure their energy use (kWh per trip per km) and the emitted CO_2 (kg per trip per km) under different operational conditions. In a scenario with no traffic or traffic lights, CDBs without LARBEM consume 6.47 kWh per trip per kilometer and emit 1.86 kg of CO_2 per trip per kilometer. With LARBEM, their energy consumption drops 42% to 3.77 kWh per trip per kilometer, reducing emissions to 1.08 kg per trip per kilometer. BEBs without LARBEM use 2.53 kWh per trip per kilometer and emit 0.06 kg of CO_2 per trip per kilometer, but with LARBEM, this improves to 1.32 kWh per trip per kilometer (a 48% drop) and 0.03 kg per trip per kilometer. For PHEBs without LARBEM, energy use is 4.97 kWh per trip per kilometer, with 1.03 kg of CO_2 per trip per kilometer. With LARBEM, energy use falls to 3.05 kWh per trip per kilometer, representing a 39% reduction, and CO_2 emissions decrease to 0.75 kg per trip per kilometer. The model makes BEBs the most energy-efficient, using 65% less energy than CDBs and 19% less than PHEBs, thanks to LARBEM optimizing electric power systems in these conditions.

Without traffic signals and traffic flow, the trials of CDBs using the LARBEM yield 6.94 kWh per trip per km and 1.99 kg of CO_2 per trip.km. With LARBEM, their energy use drops by 44% to reach a 3.9 kWh per trip.km, cutting emissions reaching 1.12 kg/trip.km. BEBs without LARBEM use 2.7 kWh per trip.km and emit 0.07 kg CO_2 per Trip.km, but with LARBEM, this improves to 1.36 kWh per trip. km (50% drop) and 0.03 kg/trip.km. For PHEBs without LARBEM, energy use is 5.28 kWh per trip.km, with 1.09 kg CO_2 per Trip.km, reducing to 3.19 kWh per trip.km (40% decrease) and 0.79 kg/trip.km when LARBEM is added. In this setup, the model makes BEBs the most energy-efficient option, using 65% less energy than CDBs and 18% less than PHEBs, as LARBEM optimizes powertrains, especially for BEBs, to handle the energy strain from frequent traffic light stops.

In a situation with no traffic lights but with traffic flow, CDBs without LARBEM use 8.15 kWh per trip.km and release 2.34 kg of CO_2 per trip.km. When fitted with LARBEM, their energy use drops by 46% to 4.38 kWh per trip.km, cutting emissions to 1.26 kg per trip.km. BEBs without LARBEM need 3.11 kWh per trip.km and produce 0.08 kg of CO_2 per trip.km, but with LARBEM, this improves to 1.46 kWh per trip.km (54% decrease) and 0.04 kg per trip.km. Meanwhile, PHEBs without LARBEM use 5.93 kWh per trip.km and emit 1.23 kg per trip.km, which falls to 3.33 kWh per trip.km (43% reduction) and 0.86 kg per trip.km with LARBEM. The model shows BEBs are the most energy-saving option, using 67% less energy than CDBs and 24% less than PHEBs, as LARBEM adjusts electric systems to cope with higher energy needs from traffic jams.

In the toughest scenario, marked by heavy traffic and frequent traffic lights, CDBs without LARBEM use 9.08 kWh per trip.km and release 2.61 kg of CO_2 per trip.km. With LARBEM, their energy drops by 50% to 4.59 kWh/trip.km, cutting emissions to 1.32 kg/trip.km. BEBs without the model use 3.32 kWh per trip.km and emit 0.08 kg of CO_2 per Trip.km, but with LARBEM, this improves to 1.54 kWh per trip.km (54% drop) and 0.04 kg/trip.km. Plug-in hybrid electric buses (PHEBs) without

LARBEM consume 6.33 kWh per trip and produce 1.32 kg per trip, which falls to 3.49 kWh per trip.km (65% reduction) and 0.86 kg per trip.km when equipped.

The model indicates that BEBs are the most energy-efficient option, using 66% less energy than CDBs and 24% less than PHEVs. LARBEM enhances electric power systems to handle the additional energy demands resulting from traffic congestion and frequent stops at traffic lights. Overall, the study demonstrates LARBEM’s value in enhancing energy efficiency and reducing CO_2 emissions for various bus types, whether operating under normal or challenging driving conditions.

Having presented the results of the LARBEM system’s performance in optimizing eco-driving behaviors, we now shift focus to a detailed discussion of these findings. The next section interprets the outcomes, highlighting key insights into how large language models and reinforcement learning contribute to energy efficiency and emission reductions. By comparing these results with existing literature, we aim to contextualize the system’s effectiveness and identify its contributions to the broader field of sustainable transportation.

5.3.2 Analysis and comparison of results: insights and alignment with previous studies

This subsection presents a detailed performance assessment of the LARBEM system, including an in-depth analysis that compares its data to recognized research within the field. A critical comparison can be found in Figure 5.9, which illustrates how the current research model performs in comparison to previous literature data on energy usage and emissions decreases. The figure serves as a vital visual representation, illustrating LARBEM's performance differences when compared to past research and displaying its efficiency as well as environmental impact values. The section illustrates the relationship between the present research and existing literature by combining comparative data to support study results, as well as highlighting progress and identifying points of agreement or disagreement for enhanced energy optimization and sustainability in the bus transportation system.

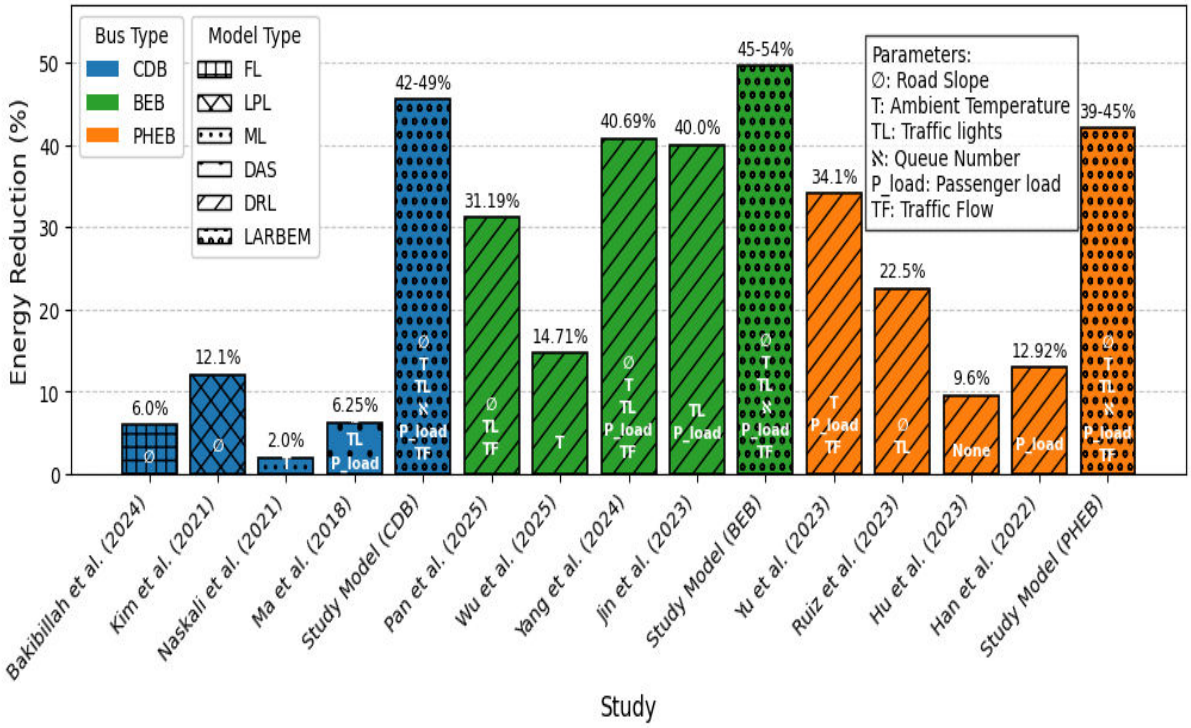

Figure 5.10. LARBEM versus literature review

The LARBEM model demonstrates energy utilization and CO_2 emission reduction performance in various simulation tests, achieving reductions of 42%-49% for CDBs, 48%-54% for BEBs, and 39%-45% for PHEBs, as shown in Figure 5.9. The energy conservation figures obtained from Kim et al. (2021) and Bakibillah et al. (2024) for CDBs operated with LPL and FL, respectively, were 12.1% and 6%, which were lower than the LARBEM by 36%-43% and 30%-37%, respectively. The reductions achieved by CDBs using ML and Driving Assistance Systems (DAS) amount to 2% and 6.25% according to Naskaki and Sen (2021) and Ma et al. (2018), while lagging behind LARBEM performance by 40% to 47% and 36.8% to 42.8% respectively, thus demonstrating LARBEM's superior effectiveness for standard buses.

For BEBs, Wu et al. (2025) and Pan et al. (2025) successfully reduced both energy utilization and CO_2 emissions by 14.71% and 31.19%, respectively, using DRL. However, these results fall short of the LARBEM model by 13.8%-22.8% and 30.3%-39.3%, respectively, in optimizing BEB energy. Meanwhile, Jin et al. (2023) and Yang et al. (2024) achieved reductions of 40% and 40.69% for BEBs with DRL, but LARBEM outperforms them by 5%-14% and 4.31%-13.31%, respectively. This demonstrates LARBEM's strength in enhancing BEB energy efficiency and reducing emissions in challenging urban settings.

For PHEBs, Ruiz et al. (2023) and Yu et al. (2023) demonstrated energy utilization and CO_2 reductions of 22.5% and 34.1%, respectively, using DRL. Meanwhile, Hu et al. (2022) and Han et al. (2022) achieved reductions of 9.6% and 12.9%, respectively. The study's results with LARBEM range from 39%-45% for PHEBs, outperforming these findings by 5%-11%, 16.5%-22.5%, 29.5%-35.5%, and 26%-32%, respectively. This highlights LARBEM's ability to effectively manage both electric and fuel modes, especially in challenging situations.

5.3.3 Challenges in real-world implementation and future directions

The study model effectively reduces energy utilization for all bus types, outperforming the results of previous research. This demonstrates the effectiveness of the study in developing eco-driving plans for various buses in real-world driving conditions. It works well because it combines reasoning and action decisions from the ReAct framework with the real-time decision-making power of RL. These handle factors like temperature, passenger numbers, road slope, traffic flow, and lights.

The study identifies specific issues that future investigations should address to enhance overall reliability. The study lacks an assessment of information security procedures within communication technology, as these standards are essential for real-time applications that link buses with traffic lights and other devices to exchange data. The research study fails to evaluate the impacts of different weather elements, including rainfall and snow, as these elements reduce visibility levels while raising resistance against tire roll and potentially requiring additional heating systems and defoggers. Road vehicles require reliable road friction and traction that remain unaffected by weather conditions, as they directly influence energy efficiency performance. The research fails to address essential factors regarding the implementation of eco-driving systems, as it overlooks necessary policies, regulations, and incentives for urban transit fleets to adopt these systems.

Another significant limitation is the absence of resilience testing for the LLM component within the ReAct framework against adversarial attacks and malicious inputs. The study does not evaluate the model's robustness against prompt injection attacks, where malicious actors could manipulate the system by inserting harmful instructions into user inputs or environmental data streams. Jailbreaking attempts could bypass safety mechanisms and cause the model to generate dangerous driving recommendations that compromise passenger safety. Additionally, the system remains vulnerable to adversarial examples and data poisoning through corrupted sensor inputs that could deceive the reasoning process and lead to suboptimal energy management decisions. Model extraction attacks pose risks to intellectual property, while denial-of-service attacks through resource-intensive prompts could overload the system during critical operations. These vulnerabilities could result in erratic driving behaviors, increased energy consumption contrary to eco-driving objectives, system failures during peak hours, and potential safety hazards for passengers and pedestrians. Future research must incorporate adversarial testing, implement input validation mechanisms, and develop robust safeguards to ensure the LLM's reliable performance under real-world adversarial conditions. Future researchers should focus on improving the real-world application and the resilience of the model by enhancing its performance and efficiency.

Conclusion

This chapter presents a novel eco-driving method for buses to tackle sustainable city transport challenges. It introduces the LARBEM, paired with Vehicle-to-Everything and Reinforcement Learning, to improve energy utilization and lower emissions for plug-in hybrid electric, conventional diesel, and battery electric buses. The model was simulated and tested on the Sousse–Kalaa Kbira bus route in Tunisia, incorporating real traffic data from March 24, 2024, along with weather and road details. This was accomplished using Python and SUMO to assess the effectiveness of the model in reducing energy use and CO_2 emissions in various scenarios. Results show LARBEM boosts energy efficiency and reduces CO_2 emissions by 48%-54% for BEBs, 42%-49% for CDBs, and 39%-45% for PHEBs, outperforming earlier models.

It proposes a solution for various bus fleets in SCs by developing a comprehensive index incorporating road slope, passenger numbers, traffic light status, temperature, and traffic line length. LARBEM helps buses make smart, adaptable choices for efficient and eco-friendly travel in changing conditions. However, the study identifies areas for improvement, including securing communication technology for data sharing, incorporating factors such as weather, road grip, and surface quality, and considering policy changes that haven't yet been implemented. Overall, this work lays a strong foundation for advancing intelligent transport systems, enabling transit agencies to meet sustainability goals, reduce high operating costs, and support the broader objective of building smarter, greener cities globally.

General conclusion

The impacts of dwindling space within cities due to increasing urbanization and the effects of climate change have underscored the need for smarter and environmentally sustainable transportation systems as a crucial concern in urban development for smart cities. In an attempt to meet these challenges, this thesis proposes and designs sophisticated Intelligent Transportation Systems (ITS) that can improve energy and emission consumption in urban mobility networks. In this context, four research studies were conducted using related subject areas to facilitate the effective implementation of dynamic traffic signal control, FL-GLOSA, and the proposed LARBEM eco-driving model, with two real-world Tunisian case studies.

The studies on sustainable transportation presented in this thesis show progress toward sustainability. In Chapter 3, the integration of adaptively coordinated traffic signals coupled with V2X, using FL-GLOSA at the Mouhamed V intersections, has demonstrated that the fuel consumption was cut down to 54% and that the emissions range between 36 and 54% at the coordination scenarios that offered a better performance of static systems by 25–48%. Similarly, in the public transport domain, the FL-Eco-Driving approach developed in Chapter 4 furthered these improvements, resulting in reductions of energy consumption by 18-44% for BEBs and 24-32% for CDBs, which were 5-41% more than those achieved by the prior eco-driving models. LARBEM from Chapter 5 progressed these benefits even further, bringing CDBs, BEBs, and plug-in hybrid electric buses (PHEBs) reductions of energy and CO_2 emission by 39 – 54% on the Sousse–Kalaa Kbira route, thereby implying significant interactions of AI-ITS to foster the traffic flow and efficiency of vehicles.

However, challenges persist. Some challenges include the high cost of developing the infrastructure necessary for V2X, questions about data security, and the absence of many critical factors that define any environment, such as temperature and wind speed, which restrain the real-world application of V2X. Another barrier responsible for early weariness is the reduction in the adoption rate due to monthly maintenance expenses, and the introduction of policy incentives further complicates the issue, particularly in a developing country like Tunisia with limited resources. Further research in this area should consider weather dynamics in terms of traffic density, Communication network security analysis, and cost-benefit analysis for deployment. It may also integrate all the thesis contributions into a single framework, analyzing its efficiency.

In conclusion, this thesis demonstrates that ITS, combined with adaptive traffic management and eco-driving tools, represents a possible pathway towards sustainable urban mobility. Due to this, such technologies work towards achieving the goal of low energy usage, less emissions, and increased traffic flow while creating smarter cities. The FL-GLOSA and LARBEM frameworks provide a roadmap that can be implemented in transit agencies and other policies, aiming to work cohesively to offer guidance on how to embrace dynamism and responsibility towards the environment. Thus, as cities evolve, these solutions pave the way for future cities where technology and sustainability work in tandem to enhance the quality of life in urban areas.

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Annexes

1. Annexe A : dataset structure
2. Annexe B : shorten version of FL-GLOSA code
3. Annexe B : shorten version of FL-Eco-Driving Model

Annexe A : dataset structure

- Data Source and Simulation Details: The data was collected through simulations using the SUMO and Python, aiming to identify the optimal speed for vehicles by minimizing energy consumption and travel time under varying conditions by varying the inputs across different simulations to understand its impact on speed selection
- Objective: The simulations aimed to identify the optimal speed for vehicles by minimizing energy consumption and travel time under varying conditions

Format: The data is stored in CSV format.

Entries Number: 9463

Number of Features: 6

Data Type:

5 columns are of integer type (int64).

1 column is of floating-point type (float64).

Column	Name	Data Type	Example Values
1	Simulation ID	Int64	1, 1, …., 2, 2
2	Traffic Light Distance	Int64	0, 0, …., 100, 100
3	Phase	Int64	0, 0, …., 100, 100
4	Phase Remaining Time	Int64	5, 10, …, 25, 30
5	Road Speed Limit	Int64	4, 8, …., 20, 24
6	Estimated Speed	Float 64	4.72, 8.03,…,20.41,24.15

Annexe B : shorten version of FL-GLOSA code

```
from simpful import *

# Create a Fuzzy System object

FS = FuzzySystem(show_banner=False)

# Define fuzzy sets and linguistic variables for each input

FS.add_linguistic_variable("Phase",

   LinguisticVariable([FuzzySet(term="Green", function=Triangular_MF(1, 1, 2)),

                FuzzySet(term="Red", function=Triangular_MF(1, 2, 2))],

concept="Phase"))

FS.add_linguistic_variable("Remaining_distance",

   LinguisticVariable([FuzzySet(term="Low", function=Triangular_MF(0, 0, 50)),

                FuzzySet(term="Medium", function=Triangular_MF(0, 50, 100)),

                FuzzySet(term="High", function=Trapezoidal_MF(55, 100, 150, 150))],

concept="Remaining_distance"))

FS.add_linguistic_variable("Remaining_phase_time",

  LinguisticVariable([FuzzySet(term="Low", function=Triangular_MF(0, 0, 20)),

               FuzzySet(term="Medium", function=Triangular_MF(0, 30, 60)),

               FuzzySet(term="High", function=Trapezoidal_MF(40, 60, 90, 90))],

concept="Time"))
```

```
FS.add_linguistic_variable("Road_speed_limit",
   LinguisticVariable([FuzzySet(term="Low", function=Triangular_MF(0, 0, 15)),
                FuzzySet(term="Medium", function=Triangular_MF(0, 15, 30)),
                FuzzySet(term="High", function=Trapezoidal_MF(15, 30, 33, 33))],
concept="Speed"))
# Define consequents.
FS.set_crisp_output_value('Speed1',0)
FS.set_crisp_output_value('Speed2', 12.4)
FS.set_crisp_output_value('Speed3', 24)
FS.set_crisp_output_value('Speed4', 0.11)
FS.set_crisp_output_value('Speed5', 12.32)
FS.set_crisp_output_value('Speed6', 24)
FS.set_crisp_output_value('Speed7', 0.4)
⋮
 FS.set_crisp_output_value('Speed47', 13.03)
FS.set_crisp_output_value('Speed48', 25.18)
FS.set_crisp_output_value('Speed49', 0.21)
FS.set_crisp_output_value('Speed50', 12.6)
FS.set_crisp_output_value('Speed51', 24.35)
FS.set_crisp_output_value('Speed52', 0.114)
FS.set_crisp_output_value('Speed53', 12.479)
```

```
FS.set_crisp_output_value('Speed54', 24.15)

# Define fuzzy Rules.

Rule1 = "IF (Phase IS Green) AND (Remaining_distance IS Low) AND
(Remaining_phase_time IS Low) AND (Road_speed_limit IS Low) THEN
(Estimated_speed IS Speed1)"

Rule2 = "IF (Phase IS Green) AND (Remaining_distance IS Low) AND
(Remaining_phase_time IS Low) AND (Road_speed_limit IS Medium) THEN
(Estimated_speed IS Speed2)"

Rule3 = "IF (Phase IS Green) AND (Remaining_distance IS Low) AND
(Remaining_phase_time IS Low) AND (Road_speed_limit IS High) THEN
(Estimated_speed IS Speed3)"

Rule4 = "IF (Phase IS Green) AND (Remaining_distance IS Low) AND
(Remaining_phase_time IS Medium) AND (Road_speed_limit IS Low) THEN
(Estimated_speed IS Speed4)"

Rule5 = "IF (Phase IS Green) AND (Remaining_distance IS Low) AND
(Remaining_phase_time IS Medium) AND (Road_speed_limit IS Medium) THEN
(Estimated_speed IS Speed5)"

Rule6 = "IF (Phase IS Green) AND (Remaining_distance IS Low) AND
(Remaining_phase_time IS Medium) AND (Road_speed_limit IS High) THEN
(Estimated_speed IS Speed6)"

Rule7 = "IF (Phase IS Green) AND (Remaining_distance IS Low) AND
(Remaining_phase_time IS High) AND (Road_speed_limit IS Low) THEN
(Estimated_speed IS Speed7)"
```

Rule47 = "IF (Phase IS Red) AND (Remaining_distance IS High) AND (Remaining_phase_time IS Low) AND (Road_speed_limit IS Medium) THEN (Estimated_speed IS Speed47)"

Rule48 = "IF (Phase IS Red) AND (Remaining_distance IS High) AND (Remaining_phase_time IS Low) AND (Road_speed_limit IS High) THEN (Estimated_speed IS Speed48)"

Rule49 = "IF (Phase IS Red) AND (Remaining_distance IS High) AND (Remaining_phase_time IS Medium) AND (Road_speed_limit IS Low) THEN (Estimated_speed IS Speed49)"

Rule50 = "IF (Phase IS Red) AND (Remaining_distance IS High) AND (Remaining_phase_time IS Medium) AND (Road_speed_limit IS Medium) THEN (Estimated_speed IS Speed50)"

Rule51 = "IF (Phase IS Red) AND (Remaining_distance IS High) AND (Remaining_phase_time IS Medium) AND (Road_speed_limit IS High) THEN (Estimated_speed IS Speed51)"

Rule52 = "IF (Phase IS Red) AND (Remaining_distance IS High) AND (Remaining_phase_time IS High) AND (Road_speed_limit IS Low) THEN (Estimated_speed IS Speed52)"

Rule53 = "IF (Phase IS Red) AND (Remaining_distance IS High) AND (Remaining_phase_time IS High) AND (Road_speed_limit IS Medium) THEN (Estimated_speed IS Speed53)"

Rule54 = "IF (Phase IS Red) AND (Remaining_distance IS High) AND (Remaining_phase_time IS High) AND (Road_speed_limit IS High) THEN (Estimated_speed IS Speed54)"

```
FS.add_rules([Rule1, Rule2, Rule3, Rule4, Rule5, Rule6, Rule7, .., Rule47, Rule48,
Rule49, Rule50, Rule51, Rule52, Rule53, Rule54])


# Set input values, perform Sugeno inference and print estimated Speed values.
FS.set_variable("Phase", Phase value)
FS.set_variable("Remaining_distance", remaining distance value)
FS.set_variable("Remaining_phase_time", remaining phase time value)
FS.set_variable("Road_speed_limit", road speed limit value)
Speedput = FS.Sugeno_inference(['Estimated_speed'])
# Extract the value associated with the key 'Estimated_speed'
estimated_speed = Speedput['Estimated_speed']
print(estimated_speed)
```

Annexe C : shorten version of FL-Eco-Driving Model

```
# Import needed libraries
import sys
import io
from simpful import *

FS = FuzzySystem(show_banner=False)

# Define fuzzy sets and linguistic variables for each input
FS.add_linguistic_variable("Road_speed_limit",
  LinguisticVariable([FuzzySet(term="Slow", function=Triangular_MF(0, 30, 60)),
                FuzzySet(term="Moderate", function=Triangular_MF(30, 60, 90)),
                FuzzySet(term="Fast", function=Triangular_MF(60, 90, 120))],
      concept="Speed"))

FS.add_linguistic_variable("Distance",
  LinguisticVariable([FuzzySet(term="Close", function=Triangular_MF(0, 0, 75)),
                FuzzySet(term="Medium", function=Triangular_MF(0, 75, 150)),
                FuzzySet(term="Far", function=Triangular_MF75, 150, 150))],
      concept="Distance"))

FS.add_linguistic_variable("Phase",
  LinguisticVariable([FuzzySet(term="Green", function=Triangular_MF(0, 1, 2.)),
                FuzzySet(term="Red", function=Triangular_MF(1., 2, 3))],
      concept="Phase"))

FS.add_linguistic_variable("Remaining_phase_time",
  LinguisticVariable([FuzzySet(term="Short", function=Triangular_MF(0, 0, 60)),
                FuzzySet(term="Medium", function=Triangular_MF(0, 60, 120)),
                FuzzySet(term="Long", function=Triangular_MF(60, 120, 120))],
      concept="Time"))
```

```
FS.add_linguistic_variable("Vehicle_speed",
   LinguisticVariable([FuzzySet(term="Slow", function=Triangular_MF(0, 0, 45)),
                 FuzzySet(term="Moderate", function=Triangular_MF(0, 45, 90)),
                 FuzzySet(term="Fast", function=Triangular_MF(45, 90, 120))],
         concept="Speed"))

FS.add_linguistic_variable("Road_slope",
   LinguisticVariable([FuzzySet(term="Downhill", function=Triangular_MF(-10, -10,
         0)),
                 FuzzySet(term="Flat", function=Triangular_MF(-10, 0, 10)),
                 FuzzySet(term="Uphill", function=Triangular_MF(0, 10, 100))],
         concept="Slope"))

FS.add_linguistic_variable("Passenger_load",
   LinguisticVariable([FuzzySet(term="Light", function=Triangular_MF(0, 0, 50)),
                 FuzzySet(term="Medium", function=Triangular_MF(0, 50, 100)),
                 FuzzySet(term="Heavy", function=Triangular_MF(50, 100, 100))],
         concept="Load"))

# Define consequents.
FS.set_crisp_output_value('out1', 29.5)
FS.set_crisp_output_value('out2', 26.4)
FS.set_crisp_output_value('out3', 23.4)
FS.set_crisp_output_value('out4', 29.6)
FS.set_crisp_output_value('out5', 27.1)
FS.set_crisp_output_value('out6', 24.0)
FS.set_crisp_output_value('out7', 29.5)
FS.set_crisp_output_value('out8', 26.4)
FS.set_crisp_output_value('out9', 23.4
FS.set_crisp_output_value('out10', 29.5)
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FS.set_crisp_output_value('out1448', 35.4)
FS.set_crisp_output_value('out1449', 32.4)
FS.set_crisp_output_value('out1450', 37.6)
```

```
FS.set_crisp_output_value('out1451', 34.5)
FS.set_crisp_output_value('out1452', 31.5)
FS.set_crisp_output_value('out1453', 37.6)
FS.set_crisp_output_value('out1454', 35.1)
FS.set_crisp_output_value('out1455', 32.1)
FS.set_crisp_output_value('out1456', 37.6)
FS.set_crisp_output_value('out1457', 34.5)
FS.set_crisp_output_value('out1458', 31.5)

# Define fuzzy rules.
RULE1 = "IF (Road_speed_limit IS Slow) AND (Distance IS Close) AND (Phase IS
        Green) AND (Remaining_phase_time IS Short) AND (Vehicle_speed IS Slow)
        AND (Road_slope IS Downhill) AND (Passenger_load IS Light) THEN
        (Estimated_speed IS out1)"
RULE2 = "IF (Road_speed_limit IS Slow) AND (Distance IS Close) AND (Phase IS
        Green) AND (Remaining_phase_time IS Short) AND (Vehicle_speed IS Slow)
        AND (Road_slope IS Downhill) AND (Passenger_load IS Medium) THEN
        (Estimated_speed IS out2)"
RULE3 = "IF (Road_speed_limit IS Slow) AND (Distance IS Close) AND (Phase IS
        Green) AND (Remaining_phase_time IS Short) AND (Vehicle_speed IS Slow)
        AND (Road_slope IS Downhill) AND (Passenger_load IS Heavy) THEN
        (Estimated_speed IS out3)"
RULE4 = "IF (Road_speed_limit IS Slow) AND (Distance IS Close) AND (Phase IS
        Green) AND (Remaining_phase_time IS Short) AND (Vehicle_speed IS Slow)
        AND (Road_slope IS Flat) AND (Passenger_load IS Light) THEN
        (Estimated_speed IS out4)"
RULE5 = "IF (Road_speed_limit IS Slow) AND (Distance IS Close) AND (Phase IS
        Green) AND (Remaining_phase_time IS Short) AND (Vehicle_speed IS Slow)
        AND (Road_slope IS Flat) AND (Passenger_load IS Medium) THEN
        (Estimated_speed IS out5)"
RULE6 = "IF (Road_speed_limit IS Slow) AND (Distance IS Close) AND (Phase IS
        Green) AND (Remaining_phase_time IS Short) AND (Vehicle_speed IS Slow)
```

AND (Road_slope IS Flat) AND (Passenger_load IS Heavy) THEN (Estimated_speed IS out6)"

RULE7 = "IF (Road_speed_limit IS Slow) AND (Distance IS Close) AND (Phase IS Green) AND (Remaining_phase_time IS Short) AND (Vehicle_speed IS Slow) AND (Road_slope IS Uphill) AND (Passenger_load IS Light) THEN (Estimated_speed IS out7)"

RULE8 = "IF (Road_speed_limit IS Slow) AND (Distance IS Close) AND (Phase IS Green) AND (Remaining_phase_time IS Short) AND (Vehicle_speed IS Slow) AND (Road_slope IS Uphill) AND (Passenger_load IS Medium) THEN (Estimated_speed IS out8)"

RULE9 = "IF (Road_speed_limit IS Slow) AND (Distance IS Close) AND (Phase IS Green) AND (Remaining_phase_time IS Short) AND (Vehicle_speed IS Slow) AND (Road_slope IS Uphill) AND (Passenger_load IS Heavy) THEN (Estimated_speed IS out9)"

RULE10 = "IF (Road_speed_limit IS Slow) AND (Distance IS Close) AND (Phase IS Green) AND (Remaining_phase_time IS Short) AND (Vehicle_speed IS Moderate) AND (Road_slope IS Downhill) AND (Passenger_load IS Light) THEN (Estimated_speed IS out10)"

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RULE1447 = "IF (Road_speed_limit IS Fast) AND (Distance IS Far) AND (Phase IS Red) AND (Remaining_phase_time IS Long) AND (Vehicle_speed IS Moderate) AND (Road_slope IS Uphill) AND (Passenger_load IS Light) THEN (Estimated_speed IS out1447)"

RULE1448 = "IF (Road_speed_limit IS Fast) AND (Distance IS Far) AND (Phase IS Red) AND (Remaining_phase_time IS Long) AND (Vehicle_speed IS Moderate) AND (Road_slope IS Uphill) AND (Passenger_load IS Medium) THEN (Estimated_speed IS out1448)"

RULE1449 = "IF (Road_speed_limit IS Fast) AND (Distance IS Far) AND (Phase IS Red) AND (Remaining_phase_time IS Long) AND (Vehicle_speed IS Moderate) AND (Road_slope IS Uphill) AND (Passenger_load IS Heavy) THEN (Estimated_speed IS out1449)"

RULE1450 = "IF (Road_speed_limit IS Fast) AND (Distance IS Far) AND (Phase IS Red) AND (Remaining_phase_time IS Long) AND (Vehicle_speed IS Fast) AND (Road_slope IS Downhill) AND (Passenger_load IS Light) THEN (Estimated_speed IS out1450)"

RULE1451 = "IF (Road_speed_limit IS Fast) AND (Distance IS Far) AND (Phase IS Red) AND (Remaining_phase_time IS Long) AND (Vehicle_speed IS Fast) AND (Road_slope IS Downhill) AND (Passenger_load IS Medium) THEN (Estimated_speed IS out1451)"

RULE1452 = "IF (Road_speed_limit IS Fast) AND (Distance IS Far) AND (Phase IS Red) AND (Remaining_phase_time IS Long) AND (Vehicle_speed IS Fast) AND (Road_slope IS Downhill) AND (Passenger_load IS Heavy) THEN (Estimated_speed IS out1452)"

RULE1453 = "IF (Road_speed_limit IS Fast) AND (Distance IS Far) AND (Phase IS Red) AND (Remaining_phase_time IS Long) AND (Vehicle_speed IS Fast) AND (Road_slope IS Flat) AND (Passenger_load IS Light) THEN (Estimated_speed IS out1453)"

RULE1454 = "IF (Road_speed_limit IS Fast) AND (Distance IS Far) AND (Phase IS Red) AND (Remaining_phase_time IS Long) AND (Vehicle_speed IS Fast) AND (Road_slope IS Flat) AND (Passenger_load IS Medium) THEN (Estimated_speed IS out1454)"

RULE1455 = "IF (Road_speed_limit IS Fast) AND (Distance IS Far) AND (Phase IS Red) AND (Remaining_phase_time IS Long) AND (Vehicle_speed IS Fast) AND (Road_slope IS Flat) AND (Passenger_load IS Heavy) THEN (Estimated_speed IS out1455)"

RULE1456 = "IF (Road_speed_limit IS Fast) AND (Distance IS Far) AND (Phase IS Red) AND (Remaining_phase_time IS Long) AND (Vehicle_speed IS Fast) AND (Road_slope IS Uphill) AND (Passenger_load IS Light) THEN (Estimated_speed IS out1456)"

RULE1457 = "IF (Road_speed_limit IS Fast) AND (Distance IS Far) AND (Phase IS Red) AND (Remaining_phase_time IS Long) AND (Vehicle_speed IS Fast) AND (Road_slope IS Uphill) AND (Passenger_load IS Medium) THEN (Estimated_speed IS out1457)"

```
RULE1458 = "IF (Road_speed_limit IS Fast) AND (Distance IS Far) AND (Phase IS
        Red) AND (Remaining_phase_time IS Long) AND (Vehicle_speed IS Fast)
        AND (Road_slope IS Uphill) AND (Passenger_load IS Heavy) THEN
        (Estimated_speed IS out1458)"

# Define the rule sets
FS.add_rules([RULE1, RULE2, RULE3, RULE4, RULE5, RULE6, RULE7, RULE8,
        RULE9, RULE10, ... , RULE1448, RULE1449, RULE1450, RULE1451,
        RULE1452, RULE1453, RULE1454, RULE1455, RULE1456, RULE1457,
        RULE1458])

# define FL-Eco-Driving function
def speed(Road_speed_limit,Distance,Phase,Remaining_phase_time, Vehicle_speed,
        Road_slope, Passenger_load):

  # Set antecedent values, perform Sugeno inference and print output values.
  FS.set_variable("Road_speed_limit", Road_speed_limit)
  FS.set_variable("Distance", Distance)
  FS.set_variable("Phase", Phase)
  FS.set_variable("Remaining_phase_time", Remaining_phase_time)
  FS.set_variable("Vehicle_speed", Vehicle_speed)
  FS.set_variable("Road_slope", Road_slope)
  FS.set_variable("Passenger_load", Passenger_load)

  output = FS.Sugeno_inference(['Estimated_speed'])
  returnestimated_speed = output['Estimated_speed']
  return returnestimated_speed
```