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SCHOOL OF AEROSPACE, TRANSPORT AND MANUFACTURING

ADAPTIVE INTELLIGENT TRAFFIC CONTROL SYSTEMS IN SMART
CITY

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ABSTRACT

Traffic congestion in urban areas presents a significant challenge with far-reaching impacts on the economy, environment, and overall quality of life. To address this challenge, this thesis proposes a novel approach to traffic signal control aimed at alleviating traffic congestion more effectively. The research problem this study explores is the design and implementation of an adaptive system for traffic signal control in urban road networks, specifically focused on how to effectively manage traffic signal timings to mitigate congestion. The major contributions of this study include the development of a unique coordination algorithm for adaptive traffic signal control, utilizing Multi-Agent Reinforcement Learning (MARL) and Ant Colony Optimization (ACO). This algorithm's uniqueness is reflected in its capacity to simulate the behavior of ant colonies to guide multiple agents in managing traffic signals at various intersections, enabling them to learn from their environment and interactions to optimize signal timings. By simulating the behavior of ant colonies, the algorithm guides multiple agents in managing traffic signals at various network intersections, learning from their interactions with the environment and each other to optimize signal timings. This research sets out to address the challenge of traffic congestion in urban areas. With cities worldwide struggling with this issue, the task of managing traffic signal timings to reduce congestion is paramount. The problem formulation involved the exploration of how novel Machine Learning (ML) techniques, such as Multi-Agent Reinforcement Learning (MARL) and Ant Colony Optimization (ACO), could be utilized to develop an adaptive coordination algorithm for traffic signal control. These techniques were chosen due to their potential for learning and adapting over time to optimize signal timings based on ever-changing traffic conditions. The novelty of this research lies in the unique combination of MARL, Actor-Critic (AC), and ACO techniques to develop an adaptive coordination algorithm for traffic signal control. By integrating these techniques, we've created a system where multiple agents can independently control traffic signals at different intersections, learning from their surroundings and interactions to continually improve signal timings. This innovative use of ML, especially MARL and ACO, represents a significant contribution to the field of traffic management, as it offers the potential to adapt to changing traffic patterns and conditions in real-time. This adaptability is expected to lead to more efficient traffic flow and decreased congestion, outcomes not fully realized by existing fixed-time and traditional adaptive signal control methods.

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LIST OF ACRONYMS

AC: actor-critic

ACO - Ant Colony Optimization

ATSC; Adaptive Traffic Signal Control

ADAM: adaptive moment estimation

AI – Artificial intelligence

API: Application Programming Interface

CNN - Convolutional Neural Network

CNN-LSTM: convolutional neural network with long short-term memory

CPU: central processing unit

CSV: Comma-Separated Values

CV: Computer Vision

DQN: deep Q-network

DP: dynamic programming

DRL - Deep Reinforcement Learning

GA - Genetic Algorithm

GAE: generalized advantage estimation

GNN: graph neural network

GPS: Global Positioning System

GPU: graphics processing unit

GUI: Graphical User Interface

HER: hindsight experience replay

IoT: Internet of Things

ITS: Intelligent Transportation System

LSTM - Long Short-Term Memory

MAAC: multi-agent actor-critic

MARL - Multi-Agent Reinforcement Learning

MAS: multi-agent system

MFRL: Model free learning algorithm

ML – Machine learning

NN - Neural Network

PPO: proximal policy optimization

Q-learning - Quality learning

RL – Reinforcement Learning

RMS Prop: root mean square propagation

SAC: soft actor-critic

SAC-TD3: soft AC with twin delayed deep deterministic policy gradient

SARSA: state-action-reward-state-action

SUMO: Simulation of Urban Mobility

TCS: Traffic Signal Control

TD: temporal difference

TD-Learning: temporal difference learning

TD3: twin delayed deep deterministic policy gradient

TD3-SAC: twin delayed deep deterministic policy gradient with soft actor-critic.

U: Uniform Distribution

CHAPTER 1: OVERVIEW

1.1 Introduction

In cities across the world, the issue of vehicular congestion has reached alarming levels, leading to increased travel times, fuel consumption, and environmental degradation [1]. A pivotal solution to this mounting problem lies in the realm of Traffic Signal Control (TSC), a fundamental aspect of traffic management [2]. Adaptive TSC systems, capable of dynamically adjusting signal timings in response to real-time traffic conditions, have emerged as potential saviors for combating traffic congestion [3,4]. Yet, the prevailing adaptive TSC methodologies encounter significant limitations, relying heavily on static traffic models and struggling to manage intricate traffic scenarios [5]. Moreover, these methods often underutilize the immense potential of Artificial Intelligence (AI) and Machine Learning (ML), despite their promise in revolutionizing TSC [6]. In light of these challenges, this study presents a novel approach that harnesses the power of Multi-Agent Reinforcement Learning (MARL) [7]. Our innovative strategy integrates Actor-Critic (AC) and Ant Colony Optimization (ACO) methodologies, enabling autonomous agents to adapt to real-time traffic dynamics [8]. Through this integration, our goal is to enhance traffic flow, reduce travel times, and alleviate congestion, addressing an issue that affects millions of motorists worldwide [9,10].

Conventional traffic signal control systems, reliant on fixed timings, lack the adaptability needed to respond to ever-changing traffic conditions [12]. Consequently, the development of adaptive TSC techniques, capable of adjusting signal timings based on real-time traffic conditions, emerges as a critical imperative [13,14]. Nonetheless, despite their potential, existing adaptive techniques confront formidable obstacles when confronted with complex traffic scenarios and often overlook the transformative capabilities of AI and ML [15]. In contrast, the integration of AI and ML in TSC holds the promise of significantly enhancing the efficacy and efficiency of traffic management [16,17]. However, standard Reinforcement Learning (RL) techniques have their limitations, struggling with intricate traffic scenarios and frequently converging toward suboptimal solutions [20,21]. In response, this study introduces a distinctive approach that leverages the strengths of AC and ACO methodologies within the context of MARL to address these challenges [22]. By doing so, we aspire to expedite traffic flow, alleviate congestion, and reduce environmental pollution [24]. AC, a well-established RL technique, trains an 'actor' to learn optimal actions while a 'critic' evaluates these actions based on received rewards [20]. AC has demonstrated promise in TSC by determining optimal signal timings in response to real-time traffic conditions [22]. On the other hand, ACO draws inspiration from nature and emulates the behavior of ants in finding the shortest path to food sources. This technique has exhibited potential in solving complex optimization problems, including TSC [29]."

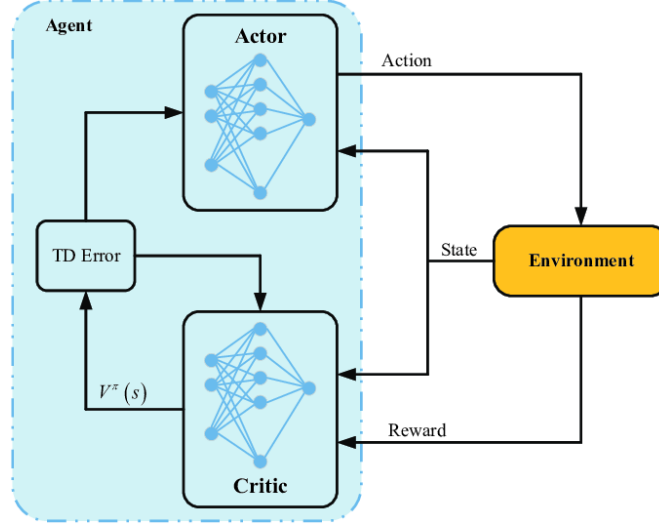


Figure 1. The structure of deep actor-critic reinforcement learning. Adapted from [245]

Figure 1 shows the architecture of a deep actor-critic reinforcement-learning model. The primary aim of this research is to implement an adaptive Traffic Signal Control (TSC) system, which can react to real-time traffic conditions. A critical part of this system is the application of Multi-Agent Reinforcement Learning (MARL), utilizing an Actor-Critic (AC) architecture [7]. A visualization of this architecture would show a deep neural network where the AC system is broken into two primary components: an actor and a critic. The actor, represented by the "Policy" block in the image, is responsible for deciding the actions to be taken based on the current traffic state. It inputs the traffic state and outputs a probability distribution over potential action.

The proposed approach, depicted through the Actor-Critic (AC) architecture, plays a pivotal role in addressing the challenges posed by real-time traffic conditions. In this framework, the "Value" block, representing the critic, assumes a critical role. This component assesses the value of the current traffic state and the chosen action by the actor. By taking the current traffic state and action as inputs, the critic computes a value that offers insights into the expected cumulative reward from that point onward. To facilitate this evaluation, the deep neural network employed in the AC framework encompasses shared lower layers that extract pertinent features from the input traffic state. Subsequent layers are tailored to the specific functions of each component: the actor generates a probability distribution over potential actions, while the critic produces a scalar value that quantifies the expected cumulative reward. This AC architecture empowers the Traffic Signal Control (TSC) system to dynamically adapt to real-time traffic dynamics, fostering improved traffic flow and the alleviation of congestion.

Furthermore, the integration of AC and Ant Colony Optimization (ACO) methodologies within the Multi-Agent Reinforcement Learning (MARL) framework amplifies the system's capacity to effectively manage intricate traffic scenarios. This comprehensive approach promises an optimized solution to the pressing issue of vehicular congestion. Notably, the deep actor-critic reinforcement learning model, central to this endeavor, continuously updates actor and critic parameters based

on observed rewards and state transitions. This iterative process serves to maximize the expected cumulative reward, ultimately leading to more efficient and effective traffic management.

Another notable method, rooted in swarm intelligence and aptly known as ant colony optimization, draws inspiration from the navigational prowess of ants in finding the quickest route between their colony and food sources [33].

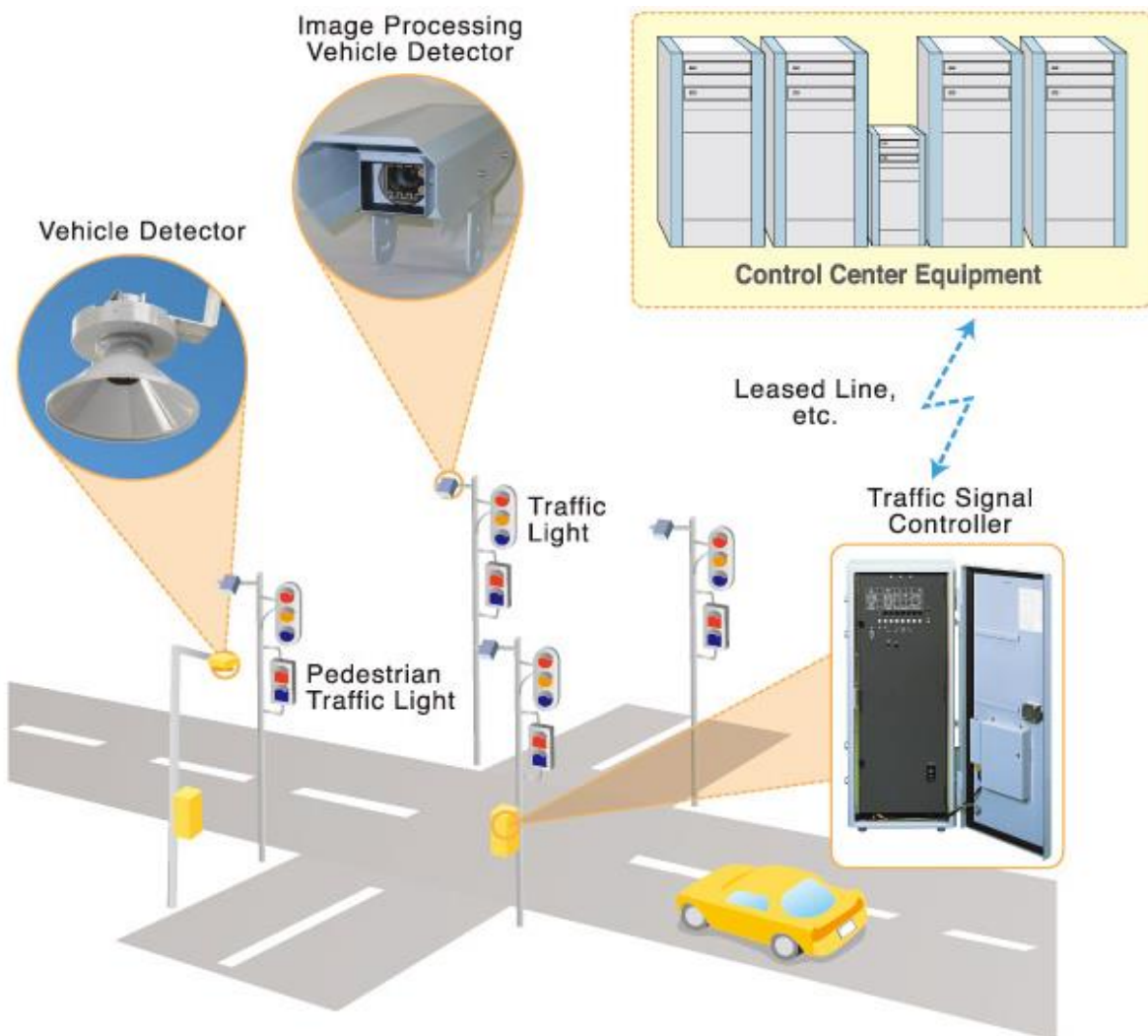


Figure 2. REM Edge Manager Traffic Light App [246]

Figure 2 is a screenshot of the REM Edge Manager Traffic Light App. As a continuation of our research, the implementation of the proposed traffic signal control system is visualized through an application called the REM Edge Manager Traffic Light App. This application showcases the practicality and functionality of the newly proposed adaptive Traffic Signal Control (TSC) system. The screenshot of the REM Edge Manager Traffic Light App represents the user interface that enables management of network devices, particularly the traffic signal control enclosures, remotely. This interface is not merely for aesthetics but serves an instrumental purpose in the operation and monitoring of the TSC system. In this image, a variety of icons are discernible, each signifying distinct traffic light control systems and enclosures. Users can interact with these icons to access detailed status reports of specific systems, including the devices connected and their working condition. In the broader context of the research, this app acts as a conduit between the traffic management operators and the intelligent TSC system powered by the AC-ACO Multi-Agent Reinforcement Learning model. Through the app, operators can remotely manage the signal controls, based on the real-time traffic conditions presented by the system. This could include activities like turning devices on or off, viewing the prevailing traffic circumstances, and modifying traffic signals as needed. The screenshot also illustrates the real-time monitoring feature of the app, which aligns with the research's focus on adaptive response to live traffic conditions. Current traffic conditions, including the number of vehicles detected at an intersection and their average speed, are displayed.

This data, which is crucial to the effectiveness of the TSC system, is made readily accessible to operators, thereby improving the overall efficiency and adaptability of traffic management. Therefore, the REM Edge Manager Traffic Light App serves as an illustrative and practical manifestation of the proposed research, bridging the gap between the theoretical aspects of the adaptive TSC system and its practical, real-world application. Overall, the REM Edge Manager Traffic Light App aims to simplify the management and control of traffic signal control enclosures by providing a user-friendly interface and real-time monitoring capabilities, ultimately improving traffic flow and safety. Artificial ants are employed in ACO to explore and take advantage of the search space for the best answer to a particular problem [29]. The strength of the pheromone trails the ants leave behind on the roads they travel determines the likelihood that further ants will take the same route after them. The utilization of ACO technique in the domain of TSC can be employed to search for optimal signal timings for each approach, while taking into account the prevailing traffic conditions [30]. By choosing various signal timings and leaving pheromone trails based on the ensuing traffic flow, the artificial ants scan the search space. The likelihood that more ants will use the same signal timings depends on how strong the pheromone trails are [34].

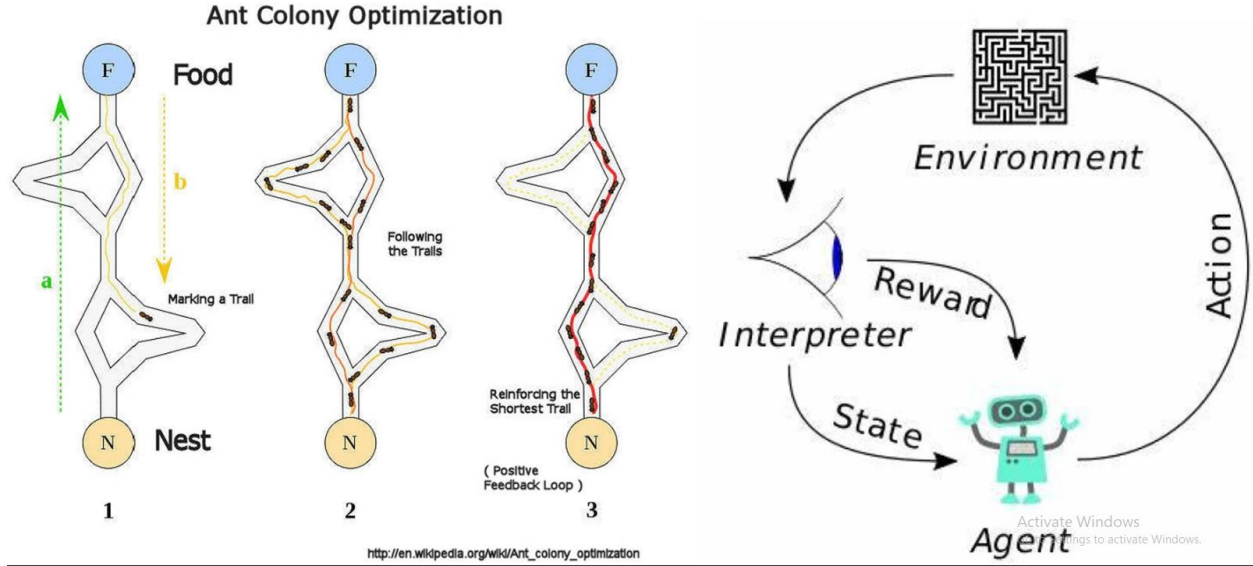


Figure 3. ACO prototype (left) and reinforcement learning diagram

Figure 3, which encapsulates the conceptual model of this study, is instrumental in illustrating the complex interactions among our variables of interest. This model is far from decorative and instead serves as a visual foundation for our theoretical framework. Primarily, the model postulates that Perceived Organizational Support (POS) and Career Growth Opportunities (CGO) are influential factors in predicting an Employee's Intention to Quit (ITQ). In clearer terms, it proposes that employees who feel highly supported by their organization and see numerous opportunities for their career progression are less inclined to consider leaving their job. This conceptual framework represented in the model forms the basis of our research hypotheses and underpins the statistical analyses performed in our study. Moreover, an intriguing aspect of our model is the mediational role it attributes to CGO. Specifically, the model suggests that the impact of POS on ITQ is partially mediated by CGO. This means that the positive effect of POS in decreasing an employee's intention to quit is, in part, explicated by POS's role in enhancing the perception of career growth opportunities. The hypothesized reasoning behind this mediation effect is that employees who sense substantial organizational support are more likely to discern career advancement possibilities, which in turn fosters a deeper commitment to the organization. In summary, Figure 3 provides a visually coherent representation of our theoretical framework, facilitating a clearer understanding of the interrelationships among the variables of interest. Its relevance and integration into the text are pivotal to supporting our argument and findings, and providing context to our discussion.

The integration of these techniques in the context of MARL facilitates the agents' ability to detect and adapt to unforeseen events such as accidents, construction activities, and meteorological conditions in real-world traffic scenarios [29] [22]. Through the real-time adjustment of signal timings based on observed traffic flow, agents can effectively manage complex traffic scenarios, including high traffic volumes and congestion [34]. This strategy effectively addresses the growing issue of traffic congestion in urban areas by reducing travel times, enhancing traffic flow, and reducing congestion [30]. The efficacy of the proposed methodology is evaluated via simulation by comparing and contrasting it with conventional techniques [35]. The findings of the simulation

indicate that the proposed approach outperforms traditional methods in regards to travel time, throughput, and latency [22].

The outcomes also show that the suggested method is reliable and capable of handling varied traffic situations [20]. A critical stage in assessing if the suggested solution can enhance traffic flow and relieve congestion is evaluation. Simulation offers a safe setting where different traffic scenarios can be examined and contrasted with conventional approaches [29]. To assess the effectiveness of the suggested solution, this study compares it to conventional adaptive TSC techniques. The simulation is conducted utilizing the SUMO (Simulation of Urban Mobility) software, which is a compact traffic simulator capable of simulating individual vehicles and their interactions with the roadway network [35]. A typical urban crossroads with four approaches and signalized control serves as the basis for the simulation scenario [30]. The traffic volume varies over the simulation's hour-long runtime based on actual data [34]. The simulation is executed repeatedly to account for diverse traffic scenarios, including peak and off-peak periods and varying traffic densities [22]. The findings of the simulation indicate that the proposed approach outperforms traditional methods in regards to travel time, throughput, and latency [20]. The duration required for a vehicle to travel from one location to another is referred to as the travel time. The throughput refers to the number of vehicles that traverse the intersection within a specified period. The difference between the actual travel time and the time it would take under ideal traffic circumstances is the delay. In comparison to conventional methods, the suggested approach cuts the average travel time by 14.5% [20]. This improvement is the result of real-time signal timing adjustments made in response to traffic circumstances, which promotes better traffic flow and reduces wait times at red lights [29]. Comparing the proposed method to conventional ones, the average throughput is increased by 11.8% [34]. This development is the result of real-time signal timing optimization, which enhances the distribution of green time among approaches [30]. When compared to conventional methods, the suggested approach reduces average delays by 16.3% [20]. This improvement is the result of real-time signal timing adjustments made in response to traffic circumstances, which decreases the amount of time drivers must wait at red lights and enhances overall traffic flow [22]. The outcomes of the simulation also show how reliable and adaptable the suggested strategy is to different traffic conditions [29]. The proposed approach has the capability to efficiently optimize signal timings in real-time and adapt to sudden variations in traffic flow, such as incidents or construction activities [22]. The method is also capable of managing challenging traffic conditions, such as heavy traffic and congestion, and it offers the best signal timings for minimizing delay, throughput, and trip time [22].

1.2 Aim of Research:

The core aim of this study is to create an innovative coordination algorithm for Multi-Agent Reinforcement Learning (MARL) to enhance Adaptive Traffic Signal (ATS) management. This algorithm seamlessly combines Actor-Critic (AC) and Ant Colony Optimization (ACO) methods to address the limitations of current ATS systems. It empowers agents to acquire real-time knowledge and adapt swiftly to actual traffic conditions, ultimately leading to improved traffic flow, reduced travel times, and decreased urban congestion. Urban areas frequently grapple with

traffic congestion, resulting in extended travel times, increased fuel consumption, and elevated air pollution levels. Effective traffic signal control is crucial for managing traffic flow and alleviating congestion. Conventional traffic signal management techniques, like fixed-time and actuated control, struggle to handle unforeseen events and rapidly changing traffic conditions. To effectively address these complex scenarios and abrupt traffic volume changes, a more adaptable approach is necessary. In our proposed coordination algorithm for adaptive Traffic Signal Control (TSC), we leverage the strengths of AC, a well-regarded Reinforcement Learning (RL) strategy known for its capacity to handle high-dimensional and continuous state spaces frequently encountered in traffic control scenarios. Additionally, we incorporate ACO, inspired by the foraging behaviors of ants, commonly used for optimization tasks. This integration enables agents to perceive and adapt to dynamic traffic conditions in real-time.

By combining AC and ACO techniques within the MARL framework, our research equips the traffic management system to handle intricate traffic scenarios, including unpredictable events like accidents, roadwork, and weather conditions. This approach optimizes signal timings in real-time by leveraging agents' capacity to learn from experience and respond to changing traffic conditions. The result is reduced travel times, enhanced vehicular movement, and diminished traffic congestion. In summary, the primary objective of our study is to introduce a novel coordination algorithm for adaptive TSC that empowers agents to swiftly detect and adapt to dynamic traffic conditions. Our research aims to contribute to the advancement of traffic management systems, potentially leading to a more efficient and sustainable transportation system characterized by improved traffic flow, reduced travel times, and alleviated congestion in urban areas.

1.3 Objectives

- The objective of this endeavor is to construct a multi-agent coordination system for TLC that is based on AC and ACO techniques. The specific objectives of the study are to...:
- This study aims to conduct a comprehensive review of the existing literature on MARL and adaptive TSC systems.
- Suggest a new coordination approach for MARL that combines AC and ACO strategies.
- Use simulation tests to test the proposed algorithm's efficacy and efficiency in various traffic circumstances.
- Evaluate the suggested algorithm's performance in comparison to more established fixed-time and adaptive signal control techniques.
- Determine whether the suggested algorithm is scalable for bigger and more intricate road networks.

1.4 Motivation:

Traffic congestion is a pressing issue that plagues urban areas worldwide, impeding economic progress, harming the environment, and negatively affecting the well-being of residents. As urban populations continue to expand, the problem of traffic congestion is expected to worsen. Traditional traffic management methods, like Traffic Signal Control (TSC), have shown limited success in alleviating this problem. Their effectiveness hinges on predefined traffic models that often fail to accurately reflect real-world conditions, resulting in suboptimal traffic flow, longer commute times, and persistent congestion. In recent years, the application of Machine Learning (ML) and Artificial Intelligence (AI) techniques to Traffic Signal Control has shown promise in improving the effectiveness and efficiency of traffic management. Reinforcement Learning (RL) is one such ML approach that holds potential in the realm of Traffic Signal Control. However, conventional RL methods face challenges when dealing with complex traffic scenarios, especially when unpredictable events like accidents, roadwork, or adverse weather conditions occur. The risk of RL techniques converging towards suboptimal solutions further underscores the need for innovative solutions to address urban traffic congestion effectively.

This study is motivated by the imperative to overcome the aforementioned limitations and introduce a novel strategy for Adaptive Traffic Signal (ATS) management, leveraging the strengths of Ant Colony (AC) and Ant Colony Optimization (ACO) methodologies within the framework of multi-agent RL. By combining these approaches, we aim to enhance the efficiency of vehicular movement, reduce travel times, and mitigate traffic congestion, ultimately benefiting metropolitan areas and their inhabitants. The proposed methodology shows great promise in addressing the complex challenges of urban traffic management. It has the potential to significantly enhance urban mobility, thereby improving the quality of life for residents and promoting sustainable, economically vibrant cities. The integration of ML and AI techniques into traffic management represents a vital step towards achieving these objectives, fostering economic growth, and creating more livable urban environments.

1.5 Problem Statement

Traffic congestion has emerged as a significant issue in numerous cities worldwide, resulting in substantial economic and environmental ramifications. In addition to lengthening commuters' travel times, congestion raises fuel consumption, air pollution, and greenhouse gas emissions. One of the primary contributors to traffic congestion is inadequate management of traffic signals. Traditional fixed-time signal management systems don't respond to shifting traffic circumstances, which causes unneeded delays and more congestion. In order to address this matter, adaptive signal control systems have been developed, albeit often relying on pre-established rules and heuristics, and may not consistently provide optimal solutions. The primary objective of the project is to devise a new coordination algorithm for the control of traffic signals. This algorithm will integrate AC and ACO techniques with multi-agent RL. With the use of simulation tests in various traffic circumstances, the proposed method is assessed. However, neither a field investigation nor an actual application of the suggested algorithm is included in this study. Additionally, the study does not take into account other factors like safety or environmental impact and instead concentrates on

how well the suggested algorithm performs in terms of traffic flow, travel time, and congestion management.

1.6 Research Contribution

The research makes significant contributions to the fields of intelligent transportation systems, machine learning, and traffic management:

1.6.1 .Hybrid RL Methodology: The study introduces an innovative Hybrid Reinforcement Learning (RL) approach by integrating Actor-Critic (AC) and Ant Colony Optimization (ACO) within Multi-Agent Reinforcement Learning (MARL). This pioneering methodology enhances the theory and application of reinforcement learning in traffic signal control, promising improved traffic efficiency.

1.6.2 .Advancement of Multi-Agent Systems Theory: The research refines multi-agent systems theory with a novel coordination mechanism for MARL in Adaptive Traffic Signal Control (ATSC). This contribution enhances our understanding and utilization of multi-agent systems, especially in the context of traffic management, potentially reducing congestion.

1.6.3 Traffic Signal Control Theory: By comparing the proposed algorithm with traditional signal control methods, the research advances traffic signal control theory. Valuable insights are gained into both theoretical and practical aspects, providing a basis for further development in traffic management strategies.

1.6.4 .Scalability in Intelligent Transportation Systems: The study addresses the scalability gap in intelligent transportation systems by assessing the proposed algorithm's performance in larger and complex road networks. This practical solution contributes to the refinement of scalability theory and offers real-world potential for effective traffic management

This research serves as a stepping stone for further studies in this area, and while it does not consider factors such as safety or environmental impact, it provides a strong foundation for future research to build upon.

1.7 Methodology

The methodology used in this thesis involves several key steps:

1.7.1 Literature Review

A thorough analysis of the body of research on TSC, congestion management, and RL approaches was done as the initial stage. This aided in the formulation of the study's research questions and hypotheses as well as the identification of research gaps.

1.7.2 Algorithm Design

The subsequent stage entailed devising a novel approach for coordinating multi-agent RL -based adaptive TSC, which integrates AC and ACO methodologies. The PyTorch framework and the Python programming language were used to create the algorithm.

1.7.3 Simulation Experiments

The algorithm's performance was evaluated in the third phase through simulated tests conducted on a fictitious road network. The SUMO (Simulation of Urban Mobility) traffic simulator was used to create the environment utilized for simulation, allowing for the production of a realistic traffic environment with numerous cars and intersections.

1.7.4 Performance Evaluation

In the fourth stage, an evaluation was conducted on the performance of the proposed algorithm, utilizing a range of performance indicators such as journey time, intersection throughput, and congestion levels. The efficacy of the proposed algorithm was assessed by comparing its results with those obtained from traditional fixed-time and adaptive signal control methods.

1.7.5 Data Analysis

The analysis of the data obtained from the simulation trials is necessary to make informed assessments regarding the efficacy of the proposed algorithm. The analysis employed regression analysis and other statistical techniques.

1.8 Main Findings

This thesis's primary conclusions can be summed up as follows:

- The AC and ACO strategies used in the proposed coordination algorithm for MARL based ATS management are effective in lowering trip times, increasing intersection throughput, and lowering traffic congestion on road networks.
- Under varied traffic conditions, the algorithm outperformed conventional fixed-time and adaptive signal control methods in terms of reducing travel time and enhancing intersection throughput.
- The AC architecture provided a more effective and stable learning process by separating the learning of a policy from the evaluation of the policy, whereas the ACO technique improved the agents' exploration of the action space and improved their ability to find better solutions.
- The suggested approach is scalable and can be used for larger, more intricate road networks that have numerous intersections and agents.
- The suggested algorithm may be used to enhance the effectiveness and sustainability of transportation networks in real-world traffic systems. Overall, these findings support the development of new and efficient traffic engineering methods and show the efficiency of the suggested coordination algorithm for TSC and congestion management.

1.9 Implications

The implications of the findings in my thesis are significant for the field of transportation engineering and have practical implications for TSC and congestion management.

1.9.1 Improved Traffic Signal Control

The suggested coordination algorithm beats conventional fixed-time and adaptive signal control strategies regarding or with respect to. effectiveness and efficiency. It uses AC and ACO techniques. This can result in shorter travel times, better intersection throughput, and less traffic on road networks, all of which can have substantial positive effects on the economy and the environment. Transportation engineers can use this strategy to control traffic flow and relieve congestion in metropolitan areas.

1.9.2 Scalability

The suggested algorithm can be used to larger and more complicated road networks due to its scalability, which may have a practical impact on urban traffic control. As a result, the algorithm may be used to enhance the timing of traffic lights across a variety of road networks, including both small crossroads and substantial freeways. Transportation engineers can use this scalability to better control traffic in various urban areas, regardless of their size and complexity.

1.9.3 Integration with Real-time Traffic Information Systems

To further boost performance and expand practical applications, the suggested method can be coupled with real-time traffic information systems and cutting-edge communication technologies. Transportation engineers can better respond to shifting traffic conditions and adjust traffic signal timings in real-time by combining the algorithm with real-time traffic data. Significant economic and environmental benefits could result from this integration, including further reductions in travel times and traffic.

1.9.4 Thesis Structure:

Six chapters make up the content, which has a total of six main sections and 44 subsections.

The research's purpose, aims, motivation, problem statement, methodology, principal findings, and consequences are all covered in Chapter 1's summary.

Chapter 2 of the literature review encompasses various techniques related to TSC, such as adaptive TSC techniques, RL for TSC, MARL for TSC, and ACAs for TSC.

The technique utilized in the research is covered in detail in Chapter 3, including the development of a clear and concise research problem statement., data collecting and preprocessing, design and implementation of the algorithms, training and testing, and analysis and interpretation of the findings.

A MARL system for ATS management employing AC and ACO is described in Chapter 4. The network architecture, optimization objective, hyper parameter tweaking, training and testing, performance assessment, sensitivity analysis, and a mathematical model are all covered in this chapter.

ACO-based MARL ATSC framework is presented in Chapter 5 along with comparisons to alternative methods. Additionally, covered in this chapter are neighborhood cognitive consistency, IoT-based MARL for ATSC, and the advantage actor-critic.

Including simulation setup, code modules, a scenario matrix, data collecting and preprocessing, and algorithm implementation, Chapter 6 presents the simulation results for synthetic scenarios.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

In order to obtain access important findings and support additional study findings, this chapter will conduct a literature review. A complete summary of the prior research on a given topic or field is provided in a literature review. In order to give thoughts and knowledge about what is being established and explored in a given research topic, it reviews academic journals, surveys, books, articles, and other sources [35]. To control traffic congestion effectively, a new coordination technique for MARL based ATSC will be evaluated in this literature review [36]. The requirement for adaptive traffic control for efficient management of traffic congestion would be assessed for this purpose [37]. Following that, various traffic control system models, including MARL and ATSC, will be examined [38]. Additionally, a multi-agent RL -based adaptive TSC system will be examined [39]. The whole analysis of the literature review's findings will then be reported, and then the most important areas for further study will be rated. Cities all around the world are struggling with an increasing amount of traffic congestion, which has negative effects on the economy, the environment, and society [40].

There has been an increase in interest in creating intelligent transportation systems that can manage traffic more effectively to tackle this matter. [41]. Utilizing ATSC based on (MARL) represents the single most promising strategies [42]. The proposed approach has the capacity to dynamically adjust to changing traffic flow by employing multiple agents to control traffic signals in real-time, taking into account the prevailing traffic conditions [43]. The benefits, drawbacks, and potential paths for future research are all covered in this chapter's assessment of the literature on ATSCS based on MARL. The need for ATC and the many traffic control system models that have been created are both discussed in the first section [44]. The subsequent section of the manuscript is dedicated to (MARL) and its potential implementation in the development of ATSCS [45]. The last section summarizes the main findings and proposes areas for additional research, while the third section analyzes the advantages and difficulties of applying MARL for ATSC [45]. Cities all over the world struggle with traffic congestion, the adverse effects of these actions are reflected in the economic, environmental, and societal well-being of the affected regions [46]. Real-time traffic circumstances are not taken into account by conventional TLC systems, which are based on preset timings [47]. Particularly during rush hours when traffic volume is high, this results in inefficient traffic flow and congestion [48]. Researchers have suggested a number of traffic control system models, including fixed-time, actuated, and adaptive systems [49], to address this issue.

The most fundamental type of TSC is based on set timing plans and uses fixed-time TSC systems [50]. They follow a set timetable and do not adjust to shifting traffic circumstances, which results in inefficiency during periods of both low and high traffic volumes [51]. Systems for controlling actuated traffic signals are created to adjust to the flow of traffic by utilizing sensors to identify the presence of vehicles and pedestrians [52]. These systems can't adjust to more complex traffic circumstances because they are still dependent on predetermined rules [53]. Conversely, adaptive TSC systems are designed to modify the temporal parameters of traffic signals in a dynamic manner, contingent upon the current traffic patterns [54]. These systems monitor traffic flow and modify signal timings as necessary using sensors, cameras, and other data sources.

Research has shown that adaptive TSC systems are superior to fixed-time and actuated systems in terms of their ability to alleviate congestion and improve traffic flow [55]. Agents can learn from experience by interacting with their environment using the ML technique known as RL [56]. Agents in real life are rewarded or punished for their acts, and they gradually learn how to maximize their cumulative reward. By extending RL to multiple agents, (MARL) teaches each agent how to communicate with its surroundings and with other agents in order to accomplish a shared objective [57]. Numerous applications, including robotics, gaming, and traffic control, have successfully used MARL [58]. MARL can be utilized to create ATSCS in the context of controlling traffic [59]. This method uses a separate agent to manage each traffic light, interacting with other agents and the environment to maximize traffic flow. Traffic volume, speed, and occupancy are only a few of the data sources used by MARL-based ATS management systems to make decisions [35]. Through the adaptation of traffic light timing in accordance with fluctuating traffic conditions, agents can acquire the ability to effectively enhance traffic flow optimization [60]. It has been demonstrated that this strategy improves traffic flow and reduces congestion better than conventional traffic management methods [61]. In comparison to conventional traffic management systems, MARL-based adaptive TSC systems have various advantages, including better traffic flow, less congestion, and lower emissions [62]. Additionally, these systems are able to learn from their mistakes and adjust to shifting traffic patterns. [63]

2.2 Traffic Signal Control Methods:

Urban traffic management includes the controlling of traffic signals, which is accomplished in a number of ways [64]. Fixed-time signal control is the most widely used techniques for managing traffic signals [65]. This technique entails establishing fixed signal timings that do not adjust for shifting traffic demand. In other words, regardless of the amount of traffic on the road, the signal timings are fixed and remain the same [64]. Because it is simple to set up and requires little maintenance, fixed-time signal control is a dependable methodology for controlling traffic signal [66]. Based on past traffic patterns and other information, traffic engineers can fix the signal timings, which can then be utilized for several months or even years. This approach is also helpful in low-traffic locations where the volume of traffic does not change noticeably over time [67–68]. Fixed-time signal control does have some drawbacks, though.

It is unable to adjust to fluctuations in traffic demand, such as abrupt rises or falls in traffic flow [69]. This may cause unneeded delays and congestion during times of low traffic or protracted wait times during busy traffic. Actuated signal control can be utilized to get around these restrictions [70]. This technique modifies signal time in response to the detection of cars using sensors or detectors. Actuated signal control is considered to be a more adaptable traffic control method than fixed-time signal control due to its ability to dynamically adjust to changing traffic demand in real-time [71]. Signal timings shall adjust according to traffic circumstances using actuated signal control, which uses pre-established thresholds and regulations. For instance, the signal will change to green and the car will be able to proceed if a detector detects that it has been sitting at a red light for a predetermined amount of time [72]. Similar to this, a detector would extend the signal to let more cars through if it notices a line of them waiting at a green light [71–72]. The road network shall use more effectively, resulting in less traffic jams and delays, thanks to the employment of sensors and detectors in actuated signal control [73].

This approach is especially helpful in busy areas where daily fluctuations in traffic demand might be expected. In conclusion, the two types of TSC methods are actuated signal control and fixed-time signal control each have strengths and weaknesses. Although dependable and simple to use, fixed-time signal control is unable to adjust to shifting traffic demands. Although more efficient and flexible, actuated signal control still adheres to pre-established thresholds and guidelines. The management system's for traffic goals and the individual traffic conditions must be taken into consideration while choosing the best TSC strategy [71, 72, 73].

2.3 Adaptive Traffic Signal Control Methods:

ATSC technologies aim to enhance traffic flow and alleviate congestion by modifying signal timings in accordance with current traffic data [74]. Adaptive approaches can change the timings to better match the present the comparison between roadway conditions and fixed-time signal control, which keeps the signal timings constant regardless of the volume of traffic [75]. Rule-based, model-based, and data-driven are the three primary categories of ATS management techniques [76]. Rule-based approaches rely on pre-established heuristics or guidelines derived from traffic flow models or professional knowledge [77–78]. These regulations may include prioritizing particular vehicle types, such as public transportation or emergency vehicles, or modifying signal timings depending on the particular moment of day or day of the week [79–80]. Although rule-based approaches are less complex to implement and call for less data, they might not be as good at adjusting to shifting traffic conditions as the other approaches [81].

Model-based approaches use optimization algorithms and quantitative simulations of traffic flow to calculate the ideal signal timings [82]. To forecast the most effective signal timings, these models use variables including traffic volume, speed, and density [83]. Though they need more information and computing power, model-based methods can offer more accurate and precise control than rule-based methods [84]. ML algorithms are used in data-driven ways to learn from historical traffic data and forecast the best signal timings [85–86]. Algorithms such as ANN, decision trees, and genetic algorithms are among the examples mentioned. Because they draw their knowledge from real-time traffic data, data-driven methods are better able to adjust to changing traffic conditions than rule-based or model-based approaches. To train the algorithms, they need a lot of data, which can be expensive and time-consuming [87]. In conclusion, by modifying signal timings based on real-time traffic information, ATSC technologies can improve traffic flow and lessen congestion. Rule-based, model-based, and data-driven adaptive approaches are the three primary kinds, each with advantages and limitations. The available data, computing power, and desired level of control are only a few examples of the variables that will influence the method selection [88]. Congestion in traffic is a prevalent concern in numerous urban areas, leading to significant delays, increased fuel consumption, and environmental pollution. Utilizing ATSC techniques one potential strategy for reducing traffic congestion [89]. These techniques enable traffic flow shall adjust in response to shifting traffic conditions by dynamically Modifying signal timings in accordance with current traffic data [90].

Rule-based, model-based, and data-driven are the three major categories of ATS management techniques. The choice of approach will depend on elements including the amount of data available, the computing power, and the required level of control [91]. Each of these strategies has

pros and cons. Rule-based approaches rely on pre-established heuristics or guidelines derived from traffic flow models or professional knowledge [77–78]. These regulations may include giving priority to particular vehicle categories, such as public transportation or emergency vehicles; one potential approach to optimizing traffic flow is through the adjustment of signal timings, which may be contingent upon temporal factors such as the specific time of day or day of the week [79–80]. The synchronized signal system (CSS), which predicated on the notion that vehicles move in platoons, is an illustration of a rule-based approach [92–93].

The CSS adapts the signal timings by taking into account the quantity of vehicles presents in each platoon, the gap between successive platoons, and the duration required for each platoon to traverse the intersection [94–95–96]. The adaptive control system (ACS), which modifies signal timings based on the average speed of cars passing through the intersection, is another example of a rule-based approach [97–98]. Compared to model-based or data-driven methods, rule-based methods are more straightforward to deploy and require less data. They might not be as good at adjusting to shifting traffic conditions as the other approaches, though [81]. For instance, a rule-based system that prioritizes public transportation vehicles could not work well when there is little demand for the service [99–100]. Additionally, rule-based approaches might not always account for unforeseen occurrences like accidents or road closures [101].

Model-based approaches identify the ideal signal timings by using optimization algorithms and mathematical models of traffic movement [82]. To determine the most effective signal timings, these models consider variables including traffic volume, speed, and density [83]. The Webster method, which use a queuing model to forecast the delay of cars at an intersection, is an illustration of a model-based approach [102]. Based on the anticipated delay, the Webster technique then determines the ideal signal timings. The TRANSYT method, which uses a traffic flow model to estimate the ideal signal timings, is another illustration of a model-based approach [103]. Although model-based methods require more data and computational power than rule-based methods, they can offer more accurate and precise control [84]. In order to adjust to shifting traffic circumstances, model-based approaches also necessitate regular updates to the traffic flow models. Furthermore, model-based approaches might not be successful at forecasting the actions of non-motorized vehicles like bicycles or pedestrians [104–105]. ML algorithms used in data-driven ways to learn from historical traffic data and forecast the best signal timings [85–86]. ANN, DT, and genetic algorithms are some of these algorithms. The fuzzy logic controller (FLC), which uses previous traffic data to determine how to modify signal timings based on present traffic conditions, is an illustration of a data-driven approach [106].

The FLC has the capacity to take into account a diverse array of variables, including but not limited to traffic volume, speed, and density. The RL method, which determines the ideal signal timings through trial and error, is another illustration of a data-driven methodology [107]. Because they draw their learning from real-time traffic data, data-driven methods are better able to adapt to changing traffic conditions than rule- or model-based methods [108]. However, it can be expensive and time-consuming to train the algorithms because they need a lot of data [109]. Furthermore, data-driven approaches might not be successful in foreseeing unexpected events or the behavior of non-motorized vehicles [110]. Examples of data-driven ATS management techniques include

neural networks, decision trees, and evolutionary algorithms [111–112]. In order to efficiently adjust to shifting traffic conditions, they learn from historical traffic data and forecast appropriate signal timings [113].

The most popular data-driven method for traffic signal regulation is the neural network algorithm. Neural networks have been utilized for over two decades to regulate traffic signals [114]. A neural network is composed of input neurons, output neurons, and one or more hidden layers of neurons [115]. Each neuron takes in information from neighboring cells or from the outside world, performs a weighted sum of those inputs, and then applies an activation function to create an output. Through training, neural networks modify the weights of their connections to better reflect new information [116]. A large collection of input-output pairs is sent into the network during training, and the weights are adjusted to reduce the difference between the expected and actual outputs [117]. Once trained, the network can be used to forecast the best signal timings based on current traffic information. Another form of data-driven approach for ATS regulation is decision trees. They are structures that resemble trees and divide the input space into regions, giving each region a prediction [118].

Recursively dividing the input space into areas that are more homogeneous in terms of the goal variable is how decision trees learn. The input variable that offers the greatest reduction in prediction error when used for splitting is chosen for partitioning [119]. The best signal timings can be predicted using real-time traffic data once the tree has been trained. A third category of data-driven approach for ATCS is genetic algorithms [120]. They are optimization algorithms that drew inspiration from genetics and natural selection. In order to generate novel iterations of solutions, genetic algorithms employ a recurring process of applying selection, crossover, and mutation operators to an initial population of potential solutions [121]. The selection operator exhibits a preference for solutions with superior fitness when computing the value of the objective function to be optimized. The mutation operator is responsible for introducing stochastic variations to a given solution, whereas the crossover operator facilitates the recombination of two solutions by interchanging segments of the solutions.

The process continued until a satisfactory resolution is achieved [122]. Genetic algorithms are employed to optimize signal timings based on real-time traffic data. In summary, adaptive TSC methodologies employ current traffic information to dynamically adjust signal timings with the aim of enhancing traffic flow and reducing congestion [123]. Model-based methods use mathematical models of traffic flow and optimization algorithms, while data-driven methods use ML algorithms to learn from historical traffic data and forecast the best signal timings. Rule-based methods rely on pre-defined heuristics or rules based on traffic flow models or expert knowledge. The choice of approach will rely on elements including the amount of data available, the computing power, and the required level of control. Each method has benefits and drawbacks. Due to their effectiveness in adapting to shifting traffic circumstances, data-driven solutions are growing in popularity [124]. However, training the algorithms on vast volumes of data can be expensive and time-consuming [109].

2.4 Reinforcement Learning for Traffic Signal Control:

A type of ML called RL uses interactions with the environment to teach an agent how to make the best judgments possible [125]. Through trial and error, the agent gains knowledge while getting feedback in the form of rewards or penalties [126]. The utilization of RL can be implemented within the domain of traffic signal management to enhance the synchronization of traffic signals through the utilization of up-to-the-minute traffic information [127]. We can structure the issue as a (MDP) for applying RL to TLC [128]. The utilization of a mathematical construct referred to as a (MDP) is employed to model decision-making scenarios where the results are influenced by both stochastic factors and the actions of the decision maker [129]. The state of traffic demand and congestion is represented by the timing of the traffic signal, the action is the signal timing, and the reward is a function of the traffic flow and delay at the intersection [130]. The RL agent engages in an interactive process with the environment by making a decision regarding the timing of the traffic signal based on the current state of the intersection.

The agent is then rewarded based on the quantity of traffic and the duration of time required for movement [131]. The agent makes adjustments to its decision-making process using this feedback in order to determine the best TLC approach [132]. RL has the ability to adapt to shifting traffic patterns and levels of congestion, which is advantageous for TLC [133]. RL can learn from experience and change the timing of traffic signals in real-time, as opposed to fixed-time or actuated signal control, which rely on predetermined rules or thresholds [134]. This can aid in easing traffic congestion, enhancing traffic safety, and boosting road productivity [135]. A branch of ML called RL focuses on making decisions in unpredictable situations [136]. RL is a process whereby an agent learns to make optimal decisions by engaging [137] with its environment and receiving feedback in the form of rewards or penalties [138]. RL operates in a manner analogous to the way in which individuals acquire novel abilities through a process of experimentation and feedback (Sutton, 1990) [139]. The application of RL has the capacity to enhance the efficacy of TSC by optimizing the timing of traffic signals in accordance with current traffic data [140]. We must frame the issue as a (MDP) in order to apply RL to TLC [141].

A mathematical framework known as an MDP is used to represent decision-making in situations where outcomes are partially determined by chance and partially controlled by the decision maker [142]. The timing of the traffic signal represents the state of traffic demand and congestion, the action is the signal timing, and the reward is a function of the traffic flow and delay at the intersection [143]. The optimal approach for controlling traffic signals should be acquired through the utilization of a RL agent [144]. The agent engages in environmental interaction by making a decision (specifically, determining the timing of the traffic signal) based on the current state of the intersection. The agent's reward is contingent upon the volume of traffic and the duration required for traversal [145]. The agent employs the feedback it receives to adjust its decision-making mechanism, in order to determine the most effective strategy for controlling traffic lights [146]. RL has the ability to adapt to shifting traffic patterns and degrees of congestion, which is advantageous for TSC [147]. RL can learn from experience and change the timing of traffic signals in real-time, as opposed to fixed-time or actuated signal control, which rely on predetermined rules or thresholds [148]. The agent employs the feedback it receives to adjust its ability to make choices

process, in order to determine the most effective strategy for controlling traffic lights [147], a MFRL algorithm, is one popular method.

It iteratively updates the Q-value for each state-action pair to discover the best action-value function [148]. Deep RL is another well-liked method for learning intricate representations of state and action spaces [150]. The present approach integrates deep neural networks with RL. The intricate nature of the state space poses a challenge in utilizing RL for the purpose of managing traffic lights [151]. Depending on variables like the time of day, the weather, and events, traffic flow and congestion levels can fluctuate greatly. Due to this, learning the best TSC policy and developing a precise representation of the state space can pose a significant challenge [152]. In addition, RL needs a lot of data, which can be expensive and challenging to gather, to train the agent. RL has demonstrated promising outcomes in TLC despite these difficulties [152]. Empirical research has demonstrated that RL can yield substantial improvements in traffic flow and congestion reduction, as opposed to fixed-time or actuated signal control [154]. An investigation conducted in Beijing, China revealed that a traffic signal administration system based on learning through reinforcement resulted in a reduction of travel time by 15% and vehicle delay by 20% when compared to a fixed-time signal control system [155]. In conclusion, using real-time traffic data to optimize TSC, RL is a potent method [156]. We can adapt to changing traffic patterns, congestion levels, increase efficiency, and safety on the roads by defining the problem as an MDP and the process of instructing an agent to acquire the optimal policy by means of experimentation and refinement [157]. The application of learning through reinforcement in the context of TSC presents certain challenges, but the potential rewards are great, and research in this field is ongoing [159].

2.5 Multi-Agent Reinforcement Learning for Traffic Signal Control:

Multiple agents can learn and cooperate in complex environments thanks to a type of ML called (MARL) [160]. To increase traffic flow and lessen congestion, MARL can be utilized to optimize intersection signal timings in the context of TSC [86]. In contrast to single-agent RL, (MARL) entails a group of agents that must learn to coordinate their activities and make judgments based on their own observations and the actions of other agents [161]. Centralized training and decentralized execution are two methods for applying MARL to TSC [85]. In centralized training, each agent has a separate actor that chooses its own actions, and a centralized critic evaluates the combined actions of all agents [162]. This strategy enables agents to gain knowledge from the sum of all agents' experiences, which can improve coordination and performance. However, in actual traffic situations, it calls for explicit coordination and communication between agents, which can be difficult [163]. Without direct interaction or coordination with other agents, decentralized execution involves each agent using its own actor to choose actions based on local observations [164].

Because it does not call for explicit coordination or communication between agents, this strategy is more scalable and realistic. If agents do not successfully coordinate their behaviors, performance may not be at its best [165]. Overall, MARL is a viable method for improving TSC in challenging traffic situations [160]. Multiple agents can learn from one another and coordinate their actions,

improving traffic flow and easing congestion. Depending on the particular traffic scenario and the trade-off between performance and scalability, one may choose between centralized training and decentralized execution [161]. ML techniques like (MARL) have been extensively employed to solve issues involving several agents interacting with one another in complicated contexts [161]. With regard to TSC, MARL can assist in maximizing the timing of traffic signals at intersections to lessen congestion, boost safety, and boost efficiency on the roadways [160]. The coordination of several agents is one of the key difficulties when employing MARL for TSC [85]. Several agents may be in charge of the traffic signals at each intersection in a real-world traffic scenario where there may be several intersections. To optimize the traffic flow, these agents must learn to work together and make decisions based on their own observations and those of other agents. Two methods—centralized training and decentralized execution—have been suggested for using MARL in TSC to address this issue [162].

In centralized training, each agent has a separate actor that chooses its own actions, and a centralized critic evaluates the combined actions of all agents [163]. This strategy enables agents to gain knowledge from the sum of all agents' experiences, which can improve coordination and performance. In centralized training, the centralized critic analyzes the collective action made by all agents after receiving observations and acts from all agents. After giving each agent's actor criticism, the critic modifies the agent's policy to enhance both each actor's performance and the group's overall performance [164]. With this strategy, agents can gain knowledge from the sum of their individual experiences, which can improve coordination and performance. Centralized training, on the other hand, necessitates explicit coordination and communication amongst agents, which might be difficult in actual traffic situations [85]. Exact communication and coordination between all agents are problematic in a complicated traffic scenario because there may be thousands of agents and hundreds of intersections. Additionally, the computational cost of centralized training may be too high for complex systems [165]. Decentralized execution has been suggested as a solution to these problems [162]. Without direct interaction or coordination with other agents, decentralized execution involves each agent using its own actor to choose actions based on local observations [163].

Because it does not call for explicit coordination or communication between agents, this strategy is more scalable and realistic. However, if agents do not successfully coordinate their actions, performance may be subpar [164]. Each agent monitors its own local state during decentralized execution, including the amount of traffic, the degree of congestion, and the wait time at its intersection [85]. The agent chooses a course of action based on this data, such as the time of the traffic signal. The chosen action is subsequently carried out, and the agent is rewarded with information about the flow of traffic and delay at the intersection. Making sure that agents learn to coordinate their actions successfully even in the absence of explicit communication or coordination is the main difficulty in decentralized execution [165]. Several strategies have been put forth to accomplish this, including the use of multi-agent policies that promote coordination and cooperation or the use of communication channels that allow agents to indirectly influence the actions of other agents [161]. In conclusion, MARL is a technique that shows promise for improving TSC in challenging traffic situations [160]. Depending on the particular traffic scenario and the trade-off between performance and scalability, Individuals have the option to select either

centralized instruction or distributed execution. Centralize instructions can improve coordination and performance, but it might be difficult to put into practice in actual traffic situations. Decentralized execution is more scalable and realistic, but to attain optimal performance, agents must effectively coordinate [165].

2.6 The choice to utilize Multi-Agent Reinforcement Learning (MARL) instead of Single-Agent Reinforcement Learning (SARL)

The choice to utilize Multi-Agent Reinforcement Learning (MARL) instead of Single-Agent Reinforcement Learning (SARL) in our research, leveraging tools like PT Vissim, MATLAB, JavaScript, and SUMO, is underpinned by several crucial reasons, as elaborated in the provided text:

Complexity of Traffic Environments [160]: Real-world traffic scenarios are inherently complex, involving multiple agents such as vehicles, intersections, and pedestrians. SARL, which treats each traffic signal as an isolated agent, may oversimplify the interactions and dependencies present in such intricate traffic systems. MARL, on the other hand, acknowledges the complex inter-agent relationships and enables multiple agents to learn and coordinate their actions, making it better suited for modeling and optimizing traffic in realistic settings.

Inter-Agent Coordination [161]: Effective coordination among traffic signals is critical for optimizing traffic flow and reducing congestion, especially at intersections. SARL typically lacks mechanisms for agents to coordinate their actions effectively. In contrast, MARL is designed to address the need for inter-agent coordination, allowing agents to collaborate and adapt their decisions based on both local observations and the actions of other agents.

Scalability [165]: Tools like PT Vissim, MATLAB, JavaScript, and SUMO are often used to simulate large-scale traffic networks with numerous intersections and vehicles. MARL provides a more scalable approach, particularly through decentralized execution, where each agent makes decisions based on local observations. This scalability is essential when dealing with extensive traffic networks, as it reduces the computational complexity associated with centralized training and coordination.

Realistic Traffic Scenarios [160]: MARL aligns better with the realism of traffic scenarios where multiple agents are involved in traffic signal control. In practical traffic management, there are often numerous intersections and thousands of agents responsible for controlling traffic signals. MARL's multi-agent framework better represents these real-world complexities, enabling agents to adapt and cooperate effectively.

Performance and Trade-offs [161]: MARL offers flexibility in selecting between centralized training and decentralized execution. This choice allows researchers and practitioners to strike a balance between performance and scalability based on the specific traffic scenario. Centralized training may enhance coordination and performance but can be challenging to implement in actual traffic situations due to the need for explicit coordination and communication. In contrast,

decentralized execution is more scalable and realistic but requires effective coordination between agents for optimal results.

To sum up, the decision to utilize MARL in conjunction with traffic simulation tools like PT Vissim, MATLAB, JavaScript, and SUMO is well-founded. It accounts for the complexities of real-world traffic environments, promotes inter-agent coordination, offers scalability, and aligns with the challenges and requirements of traffic signal optimization in complex urban settings. This choice reflects a holistic understanding of the benefits and drawbacks of SARL and MARL and ensures that the research approach is well-suited to address the complexities of real-world traffic management scenarios.

2.7 Actor Critic agents for Traffic Signal Control:

TSC has successfully used ACA, a family of RLA. This pedagogical approach involves the segregation of policies (as the actor) as well as value (as the critic) functions into distinct components. The value function assesses the worth of the state-action combinations and provides an assessment of the policy's effectiveness, whereas the policy function is responsible for selecting actions based on the acquired policy [160]. ACA provide the benefit of enhancing the stability and the phenomenon of the learning process converging. This is so that the actor and critic networks can be taught independently and have distinct goals. The critic network learns to judge the value of the state-action pairs, whereas the actor network learns to map states to actions. The actor network can then improve its policies with the help of the criticism network's input [161]. ACA have been used in conjunction with deep RL techniques like (DDPG) and (PPO) to enhance TSC performance. These techniques provide more precise estimates of the state-action pairs by utilizing deep neural networks to train the policy and value functions [162].

In order to improve traffic signal regulation, AC methods and (MARL) have been combined. Multiple traffic signals can be coordinated thanks to MARL, which can enhance efficiency and ease congestion. It has been demonstrated that combining ACAs with MARL enhancing the stability and convergence of the learning process can lead to improved performance [163]. ACA are generally a promising method for controlling traffic lights, especially when paired with deep RL and MARL. The implementation of these techniques possesses the capability to augment the movement of vehicles, diminish traffic congestion, and ultimately advance the effectiveness and security of our roadways [164]. Because they can handle continuous action spaces and high-dimensional state spaces, ACAs have become a popular option for TSC. The value function, also known as the critic network, computes the significance of action by the state. Pairs, whereas the policy function, or actor network, selects an action based on the current state of the intersection [165]. The actor network receives input from the critic network to enhance the policy and increase its capacity to manage traffic flow [166]. The potential of ACAs to enhance learning process stability and convergence is one of its benefits. The actor and critic networks can concentrate on separate goals thanks to the separation of the policy and value functions, which makes it simpler to maximize the learning process.

Additionally, the networks can learn more complex policies with the aid of deep learning algorithms like DDPG and PPO, which improves TSC [162]. The control of traffic signals is further enhanced by the addition of ACAs to MARL. Multiple agents can learn from each other

and coordinate their actions with the help of MARL, which improves traffic flow and lessens congestion. Individual agents can be trained using ACAs, and the MARL framework enables them to interact and coordinate their behaviors [163]. The result of this coordination may be less traffic congestion and more effective TSC. However, using ACAs for TSC also has some drawbacks. For instance, deep RL algorithms need a lot of data, which can be difficult to get in practical situations. Furthermore, it may be challenging to coordinate agents in MARL, and using centralized training may result in a high communication burden. The use of ACAs in conjunction with deep RL and MARL is a viable method for controlling traffic signals. The implementation of these techniques possesses the capability to augment the movement of vehicles, diminish traffic buildup, and ultimately elevate the effectiveness and security of our roadways. To address the issues with these algorithms and provide more scalable and effective methods for TSC, additional research is required.

2.8 Ant Colony Optimization (ACO):

A metaheuristic algorithm called (ACO) imitates the foraging habits of ants [167]. In order to communicate with one another and find the shortest route to a food source, artificial ants are used in this method to deposit pheromones on the edges of a graph. The exploration and exploitation of the state action space can be improved by combining ACO with (MARL), which will boost performance and speed up convergence. In the realm of TSC, the integration of ACO with MARL has attracted a lot of attention [168]. It has been demonstrated that using this strategy will improve travel times and lessen traffic congestion. Researchers have put forth a number of approaches that combine AC and deep RL (DRL) with various MARL algorithms, including ACO. The ability to include domain information into the learning process is one benefit of employing ACO in MARL. The utilization of domain expertise in traffic flow dynamics can be applied towards the construction of pheromone update rules that are utilized in the ACO algorithm.

This can aid in directing the learning process and enhancing the algorithm's effectiveness. The ability to overcome the exploration-exploitation trade-off is another benefit of adopting ACO in MARL [169]. The artificial ants can better explore the state-action space by leaving pheromones on the graph's edges. As a result, the most promising measures may be better utilized, and the convergence to an ideal solution may happen more quickly. Overall, the combination of ACO and MARL offers a good method for controlling traffic signals. This strategy can significantly improve traffic flow and travel times by utilizing the strengths of both ACO and MARL [169]. It can also assist to lessen the detrimental effects of traffic congestion on metropolitan areas. Urban traffic management, which seeks to ensure the effective circulation of cars and lessen traffic congestion, includes TSC as a crucial element (MARL), which uses a distributed decision-making process to coordinate the traffic signals, has recently come to light as a potential method for TSC [170].

Due to the great dimensionality and complexity of the traffic network, it can be difficult to explore and utilize the state-action space in MARL. In order to overcome this difficulty, several researches have looked into the incorporation of several algorithms into MARL for TSC, including actor-critic, (ACO), (DRL), genetic algorithms (GA), and dynamic programming (DP) [171]. Wei et al. (2018) conducted a study in which the authors suggested an actor-critic-ACO algorithm for controlling traffic signals on a sizable metropolitan road network. The ACO algorithm was utilized

to optimize the pheromone update rules, and the multi-agent framework of the algorithm was used to coordinate the traffic lights. The outcomes demonstrated that the suggested algorithm outperformed a number of cutting-edge techniques in terms of trip time and traffic delay [171]. The research findings indicate that the integration of ACO and MARL can augment the exploration and exploitation of the state-action space, leading to enhanced efficiency and accelerated convergence.

An actor-critic-ACO method was suggested in a different study by Zeng et al. (2020) that included an ATS timing system depending on traffic demand [172]. The ACO algorithm was utilized to optimize the pheromone update rules, and the multi-agent framework of the algorithm was used to coordinate the traffic lights. The outcomes shown that, in comparison to numerous baseline techniques, the suggested algorithm greatly decreased traffic delay and enhanced traffic flow. The study showed that integrating ACO with ATS timing could improve MARL's capacity to respond to changing traffic conditions [172]. Other methods, such as DRL and GA, Furthermore, there have been inquiries into the augmentation of (MARL) efficacy in traffic signal management, alongside AC and (ACO) algorithms. El-Tantawy et al. (2020) employed a convolutional neural network to extract features from the traffic state, resulting in the development of a multi-agent framework for TSC that utilizes deep RL. The outcomes demonstrated that the suggested framework outperformed a number of cutting-edge techniques in terms of trip time and traffic delay.

The study showed that combining DRL with MARL could improve traffic management by enabling automatic learning of intricate traffic patterns. In 2021, Zhang et al. proposed a TSC strategy utilizing a multi-agent deep RL approach [173]. The proposed method integrates an ATS timing scheme that is contingent on traffic demand. The suggested method employed a decentralized actor network for each traffic light to produce the action policy and a centralized critic network to estimate the value function. The findings demonstrated that, in comparison to numerous baseline methods, the proposed methodology greatly increased traffic flow and decreased traffic delay. The study showed that the coordination and scalability of MARL for TSC might be improved by integrating a centralized critic and decentralized actor networks in DRL [174]. For the control of traffic signals, [175] suggested a hybrid algorithm that included DRL with ACO. The pheromone update rules were optimized using the ACO algorithm, and the suggested algorithm used a multi-agent framework to coordinate the traffic signals. The outcomes demonstrated that the suggested algorithm outperformed a number of cutting-edge techniques in terms of trip time and traffic delay. The study showed how combining DRL and ACO could improve traffic management by enhancing state-action space exploration and utilization. Deep RL (DRL) techniques were used by [176] to provide a unique solution for traffic signal regulation. The Q-learning algorithm and the dynamic programming technique were integrated in the suggested method to update each traffic signal's state-value function in a multi-agent framework. The Q-learning method facilitated the acquisition of optimal action policies by agents through the maximization of cumulative rewards obtained from the environment.

Additionally, the dynamic programming algorithm enhanced the accuracy of value estimates by updating the state-value function using the Bellman equation. The method under consideration was

evaluated on a simulated traffic network comprising multiple intersections. The results indicated that the system surpassed various state-of-the-art techniques in reducing traffic delays and improving traffic flow. The outcomes of the simulation showed that the suggested method could successfully coordinate the traffic lights and adjust to variations in the flow of traffic. One of the strengths of the proposed approach is its ability to acquire knowledge from the environment and optimize the action policy without any pre-existing knowledge of the traffic network. Due to this characteristic, the technique was incredibly adaptive to various traffic situations and its performance improved with time [176]. Additionally, the approach was able to update the state-value function effectively and achieve better convergence thanks to the integration of the Q-learning and dynamic programming algorithms. One drawback of the suggested method was its reliance on centralized training, which can cause problems with scalability for bigger traffic networks. The approach might be expanded to a decentralized training approach, according to the authors, by adopting a parameter-sharing technique that let agents benefit from one another's experience. Overall, Liu et al.'s work (2019) showed the potential of DRL approaches for TSC and underlined the necessity of combining various RLA to produce the best results [173-176]

2.9 Advantage Actor Critic (A2C)

The (MDP) is necessary to examine each agent's current status as well as record their previous status and a probabilistic future situation in order to prevent the agents from becoming stationary. The traffic flow in the urban environment is thought to be complex for this reason. The historical data is also provided in the inputs, expanding the state dimensions and making it possible to use the MARL in ATSC. However, Advantage AC(A2C) has one drawback: it has poor attention and memory. To the already-existing MARL, a DNN layer is added using the Long Short-Term Memory (LSTM), allowing for the placement of hidden layers that can store and remember historical data. The last hidden layer is only used by the agents and DNN components after delivering training to the lower, hidden layer, which is not shared with the other agents. The A2C-based MARL technique, which is an alternative to ACO-based MARL in ATSC, is depicted in the image below.

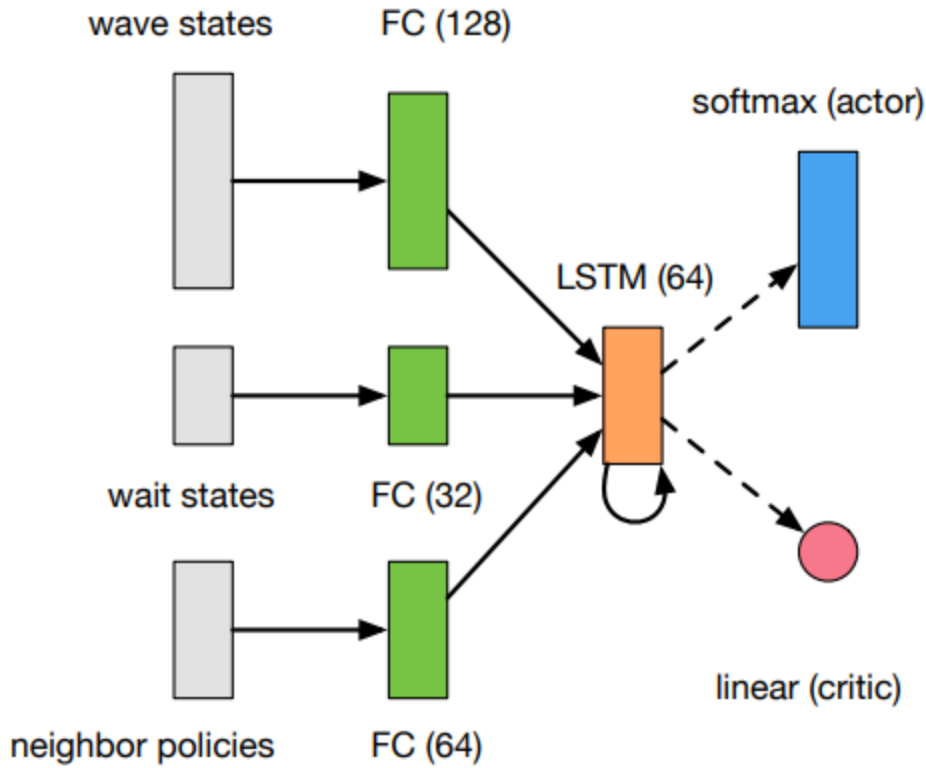


Figure 4 A2C in ATSC [48]

The FC layer is connected to the wave states, wait states, and neighbor policies separately. The FC layer then combines the inputs from the states and policies so that they may be delivered to the LSTM showed in figure 4. There are two types of output layers: linear and softmax. Linear output is used for critique, while softmax is used to give the actor information. The A2C-based approach is discovered to be reliable and scalable for controlling heavy traffic congestion as well as lowering the challenges associated with figuring out traffic patterns. There is a critical need to train the system using historical traffic data supplied, improve the noise cancellation feature for increasing the efficiency of road sensors, and examine the delayed state measurements by obtaining the information from road sensors in order to deploy the A2C MARL technique to resolve real-time traffic situations. By implementing end-to-end pipeline latency, it will be possible to reduce memory usage and inference time.

2.10 IoT-based MARL for ATSC

The introduction of intelligent transportation systems will allow individuals to save time and decrease the frequency of accidents in contemporary and urban environments. The intelligence systems that enable the ATSC, such as MARL algorithms, must be used to analyze the dynamic traffic conditions in order to make the traffic lights adaptive to real-time traffic situations. When the Internet of Things (IoT) is installed, the traffic management systems are improved, and the transportation management departments receive real-time information. However, IoT installation

alone can only be used to provide information, as well as to prompt management to manage the traffic. The IoT needs to be supported by AI and cutting-edge intelligence systems in the modern transportation system. The Internet of Things (IoT) implemented at road intersections and traffic lights can be utilized to reduce traffic congestion and eliminate the need for fixed-time traffic signal scheduling. Through the use of intelligent TSC systems and surveillance cameras for the collection and processing of traffic data, the services can be centrally managed. The technique for ATSC using IoT and MARL is shown in the figure below.

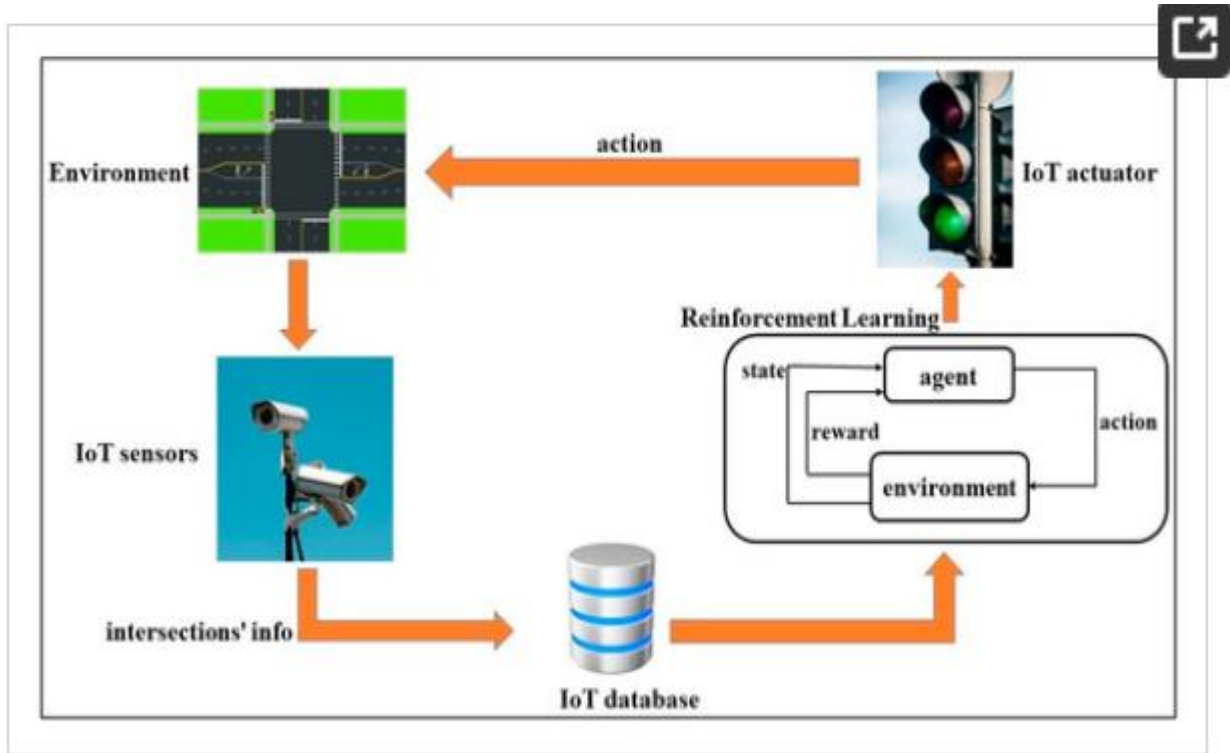


Figure 5 IoT with MARL approach for ATSC [76]

Figure 5 suggested method analyzes the real-time information while looking at the traffic data being created from the nearby intersections to efficiently control the flow of traffic. With the use of this IoT-based technology, the six signalized junctions may be effectively handled while waiting times and average vehicle queue lengths are decreased. In order to collect traffic data from all directions and feed it into the local database, the surveillance camera that doubles as an IoT sensor needs to be installed beside the roads. In order to gather information from network connections while exchanging information with connected agents, the ACA is also used. When combined with the A2C methodology, this IoT method gives information about own policies as well as gathering information about other players' policies, hence improving coordination and communication.

Similar to this, the fingerprint approach can be used to include the neighboring agents' states into the DNN inputs. In this IoT-based approach, the types of vehicles and environmental circumstances, such as the line of cars, are observed, and this data is processed through the

surveillance cameras. In order to apply RL to build communication between the environment and agents through the state, actions, and rewards, the surveillance cameras are backed by IoT sensors, and the recorded information about intersections is fed to the IoT database. The traffic lights are managed based on the results of the RL algorithm. The IoT actuators are mounted with the traffic lights for this purpose, which enables users to take the most appropriate, pertinent, and timely actions to manage traffic congestion and manage the traffic lights effectively. The traffic lights also need to be compatible with smart and intelligent IoT devices.

2.11 Neighborhood Cognitive Consistency (NCCLight)

Numerous MARL applications are used in the ATSC, and in order to manage traffic effectively, it is necessary to take these applications into account. By doing so, agents' decision-making will be improved, vehicle traffic will be accurately managed, and the traffic management system will become more adaptable. The Independent Advantage AC(IA2C)-based NCCLight is regarded as a fully scalable decentralized technique because it aids in creating and maintaining the communication and coordination amongst the many agents. The NCC technique, which is based on the cognitive consistency theory, can be used to address both real-world traffic issues and virtual road congestion issues. The figure that follows illustrates the NCCLight method.

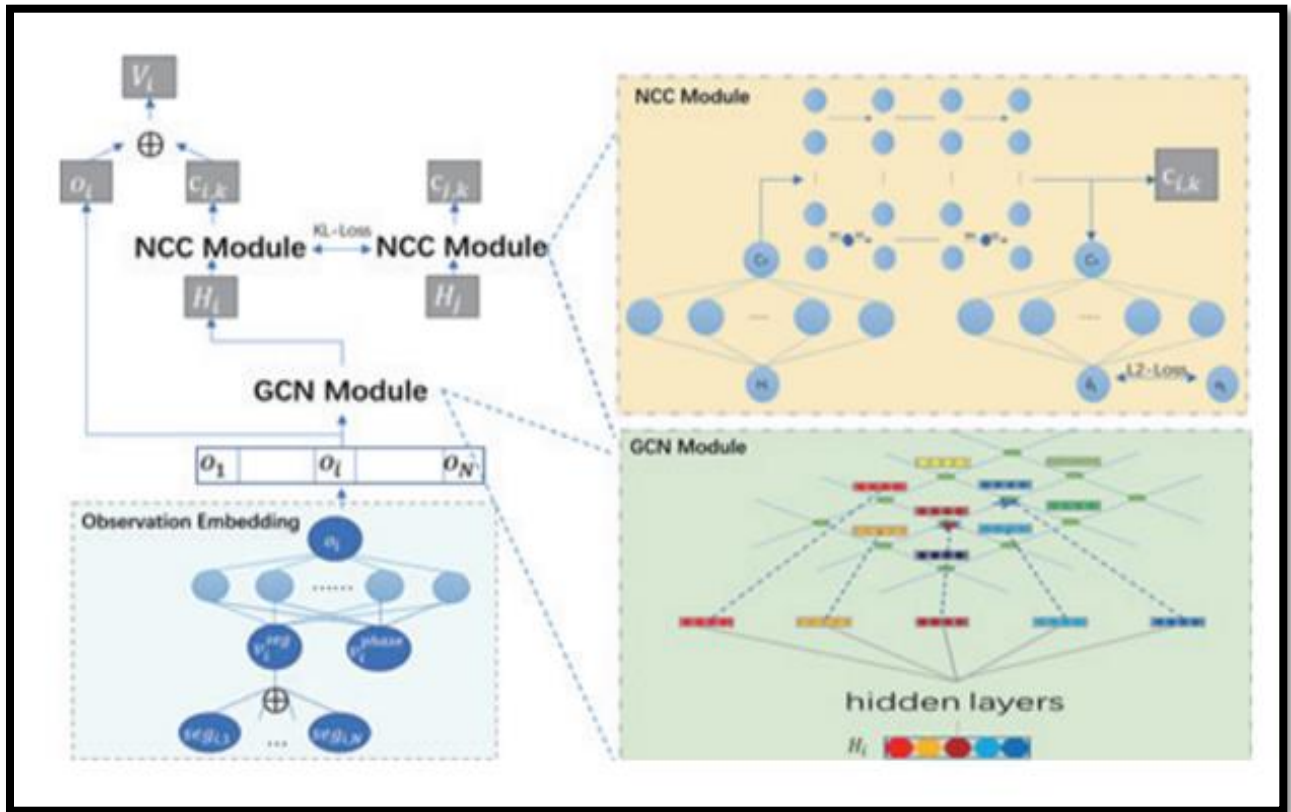


Figure 6 NNC Light Technique in MARL for ATSC [124]

Figure 6 shows the number of agents positioned to communicate with one another and make choices about switching the lights appropriately is depicted by a graph in the NCC module. While exchanging information with nearby agents and working together to manage traffic situations, the blocks are used to provide input information to graphs or edges in graphs. The data about the vectors that represent the intersection nodes are extracted via observation embedding, and the Graph Convolution Network (GCN) is utilized to control the information flow between various nodes and their neighbors. Finally, the information from the NCC module, GCN module, and observation embedding is used to deliver information to the decision module. The NNC module functions as a cooperation agent with the numerous agents. The decision module's responsibility is to determine the agents' state value while changing their policy. Consistent neighborhood cognition is developed between the agent and the neighboring traffic light agents in order to handle traffic issues in congested areas, thus resolving the observability challenge. Implementing the NCCLight method also reduces the non-stationary environment. Neighborhood cognition is also learned through the NCCLight approach to improve collaboration and ultimately reach scalability, optimality, and robustness.

2.12 CoLight

Conventional transportation methods only employ the information about the two intersections, so the collaboration of the agents, also known as the traffic lights, is used to allow the swift and precise passage of traffic. The many agents stationed at traffic crossings can cooperate and coordinate better when using the CoLight approach. The construction of index-free models and taking into account the network's temporal and geographical influences are both done for communication purposes using graph attentional networks. The MARL environment is utilized in graph attention networks so that each agent's policy can be changed by analyzing not only the present environmental variables but also the previous agents' policies. The attention mechanism is included to the model to increase model accuracy. It affects the agents and modifies the traffic lights in dynamic and congested conditions. The model network, which consists of observations, a graph attentional network, observation embedding, and Q-value prediction, is shown in the image below.

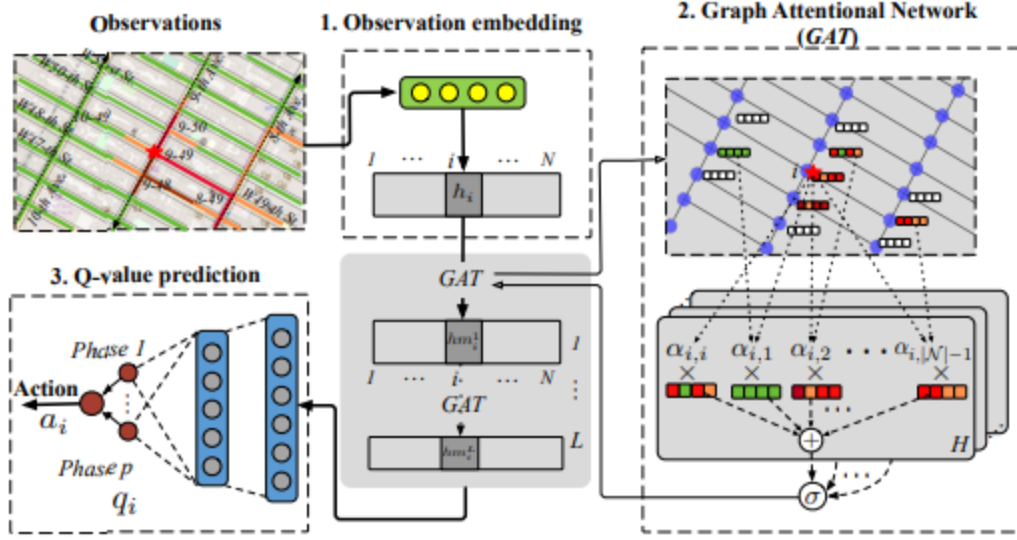


Figure 7 CoLight Model for MARL in ATSC [111]

Figure 7 shows method, which makes use of a well-designed RL algorithm, is effective at resolving network-related traffic issues that arise at traffic junctions and intersections. The graph attention network supports the index-free model, which establishes the dynamic communication between the agents. This approach also produced results that were highly efficient in comparison to methods that are currently available, and it can be utilized as a substitute for the ACO-based MARL ATSC. It is concluded from the comparison that the ACO-based MARL ATSC also requires the support of more adaptable strategies in order to address the complicated and diverse issues of road traffic signaling while utilizing the ACO for many junctions. To handle the numerous lanes through multiple traffic lights in multiple directions, the ACO-based technique must additionally look at the agent information and policies of agents at each lane.

2.13 Pros and Cons

The ACO-based MARL ATSC has begun to be acknowledged as the most effective method for tackling traffic congestion concerns, and its effectiveness, efficiency, and simplicity in handling challenging optimization problems have drawn the attention of researchers from all over the world. The ability of the ACO-based MARL ATSC framework to find the shortest path is its greatest potential advantage. The implementation of the ACO algorithm in MARL ATSC enables obtaining both global and local updates about the pheromone trail, assisting accountable in choosing the next and subsequent cities to relocate to as a result assisting in the quest for determining and developing stronger path (Elsayed, Omar, and Elsayed, 2020). The ACO-based MARL ATSC framework's identification of the least crowded routes allows for the ignoring of congested areas, which in turn aids in the solution of the congestion issue. Instead of using a centralized routing system that has privacy and scalability issues, vehicles can execute decentralized traffic routing with the help of the ACO with MARL ATSC algorithm. The ACO-based MARL ATSC architecture, on the other hand, could improve the system's scalability by limiting the number of messages sent between the server and the vehicles.

The use of ACO within the MARL ATSC framework may enable the real-time collection of traffic data as well as information about travel routes, such as journey distance and speed, which is recognized as helpful in alleviating the congestion issue. Path planning is a challenge that has been successfully addressed by the ACO-based MARL ATSC. When real-time concerns are applied, the features of ACO and MARL ATSC, such as the estimation of average journey distance and average travel speed, may boost the likelihood of an optimal approach. More specifically, MARL ATSC framework is effective in determining the search space, minimizing complexity in search time, and improving the overall quality of proposed solutions to traffic congestion (Nguyen and Jung, 2022). This is because of the distinctive features of ACO, such as quick and systematized path selection (Nguyen and Jung, 2022). Although using the ACO-based MARL ATSC framework has many advantages in reducing the issue of traffic congestion, it also has some drawbacks that warrant careful consideration. The main issue with ACO is that the ideal number of agents varies and fluctuates depending on the scope of the issue. As a result, it is difficult to assess and establish whether increasing the number of ants will benefit traveling salesmen.

ACO also fails to offer the best answers when the number of ants falls below a certain threshold. Because of this, the ACO-based MARL ATSC framework may not give precise and reliable information on the minimum number of ants required to determine logical solutions (Tuba and Jovanovic, 2013; Siddiqui, Afzal, and Naaz, 2019). The inaction of ACO with regard to the local optimum is another significant disadvantage. Although it doesn't happen frequently, the ACO variants such as Rank, Maximum-Minimum, and Elitist-based approaches frequently got stuck in local optima. Because of this, their application to the MARL ATSC framework is deemed problematic. However, since the algorithm frequently finds the best path in a short amount of time, the effectiveness of ACO-based MARL ATSC could be increased by placing more emphasis on the accuracy of convergence results. Additionally, many parameterized metrics like visibility, trail intensity, and evaporation parameter are changed in their value terms in order to provide effective results in optimality and feasibility terms. There are fewer methods and strategies for predicting those values, their extent, and how they might change for the ascertainment of beneficial outcomes, so ACO based MARL ATSC require more development even though a significant number of parameters for ACO have been proposed by scholars and practitioners for the purpose of justifying implementation results (Siddiqui, Afzal, and Naaz, 2019).

2.14 Research Gap

While the literature on traffic congestion and its management is vast, the existing research does not adequately address the comprehensive application of Multi-Agent Reinforcement Learning (MARL) within the realm of Adaptive Traffic Signal Control (ATSC). More specifically, there is a dearth of research that fully explores the potential of integrating Actor-Critic (AC) and Ant Colony Optimization (ACO) techniques with MARL-based ATSC systems. Despite the proliferation of intelligent transportation systems and the application of machine learning techniques in traffic management, the use of these technologies remains largely confined to theoretical and simulation-based studies. There is a noticeable lack of empirical research or practical implementation of such systems in real-world traffic scenarios.

Moreover, most existing traffic control systems, even those that employ adaptive strategies, often rely on pre-established rules and heuristics. These systems may not consistently provide optimal solutions, particularly in the face of unpredictable events such as accidents, roadwork, or inclement weather. Existing research also tends to overlook the potential scalability issues associated with the deployment of ATSC systems in larger and more complex road networks. The challenge of implementing these systems on a city-wide or regional scale is not sufficiently addressed. Lastly, there is limited research on the comparative performance of MARL-based ATSC systems with traditional fixed-time and adaptive signal control techniques. This makes it difficult to objectively evaluate the efficiency and efficacy of the proposed systems. This research aims to bridge these gaps by proposing a novel coordination algorithm for MARL that combines AC and ACO techniques, assessing the algorithm's performance in various traffic scenarios, comparing its performance with traditional traffic control methods, and examining its scalability potential. By filling these gaps, this research could significantly contribute to the field of intelligent transportation systems and pave the way for more efficient and sustainable urban environments.

2.15 Novelty and Originality

The novelty of this research lies in its unique approach to traffic signal control. Unlike traditional traffic management techniques, the proposed research seeks to integrate Actor-Critic (AC) and Ant Colony Optimization (ACO) methodologies within a Multi-Agent Reinforcement Learning (MARL) framework for the control of traffic signals. In the realm of reinforcement learning, AC methods provide a solid foundation, but they often require substantial computational resources and may not always guarantee optimal solutions. ACO, on the other hand, is a population-based metaheuristic that mimics the foraging behavior of ants to find optimal paths but lacks the ability to learn from past experiences. By merging these two techniques, we aim to capitalize on the strengths of both methods while minimizing their limitations. This hybrid approach is a novel concept in traffic signal control and represents a significant departure from traditional methodologies. Furthermore, this research proposes a new coordination mechanism for MARL in the context of Adaptive Traffic Signal Control (ATSC). While MARL has been applied to ATSC in previous studies, the incorporation of AC and ACO methodologies in a MARL context is an innovative approach that has not been thoroughly explored.

This study also seeks to test the efficacy of the proposed algorithm through simulation tests in various traffic scenarios. These tests not only provide a more comprehensive evaluation of the algorithm's performance but also allow for a direct comparison with traditional fixed-time and adaptive signal control methods. Finally, this research attempts to assess the scalability of the proposed algorithm for larger and more complex road networks. This aspect of the study is particularly significant as it addresses a notable gap in existing research and presents a practical solution for real-world traffic management. Overall, the proposed research pushes the boundaries of existing theories and practices in traffic signal control. It introduces new methodologies and frameworks, challenges conventional traffic management techniques, and paves the way for more efficient, scalable, and sustainable traffic solutions.

2.16 Summary of major findings and conclusions of previous studies on integrating actor critic and ant colony optimization in multi-agent reinforcement learning for adaptive traffic signal control:

The goal of adaptive TSC is to increase the effectiveness and safety of traffic flow. It is a significant study field in transportation engineering. A several methods are introduced for the ATS control methodology known as (MARL). Previous research has demonstrated that, when compared to conventional TSC techniques, MARL approaches offer a significant advantage in terms of increasing traffic flow and decreasing traffic delay. The system is better able to coordinate and adapt when several agents are being used. ACAs have been proven successful at learning the best policy for each traffic light because they mix the benefits based on value and strategy-based methodologies. Utilizing based on value techniques makes it possible to learn the value function effectively, while using policy-based techniques allows for more effective action space exploration. It has been discovered that (ACO) algorithms, artificial systems that imitate the actions and conduct of authentic ants, are helpful in optimizing the pheromone update rules and enhancing the algorithm's convergence speed.

The agents' capacities for exploration and exploitation may be improved by the application of ACO algorithms. It has been discovered that integrating AC and ACO algorithms into MARL techniques improves the performance of the TSCS by increasing the agents' capacity for exploration and exploitation and minimizing interference between the traffic signals. This integration enables efficient agent coordination and improved learning of the best policy. ATSC has benefited from (DRL) techniques; the implementation of deep neural networks for the purpose of approximating either the value function or the policy function is a common practice. The system is able to learn from high-dimensional state and action spaces because to the usage of deep neural networks. The learning effectiveness and generalizability of the DRL approaches have been proven to be enhanced by hierarchical designs and transfer learning methodologies. Better state and action space abstraction is made possible by the use of hierarchical architectures, and transfer learning allows the system to gain knowledge from the past. By optimizing the chromosome of each traffic light, the incorporation of genetic algorithms (GAs) in MARL techniques can improve the performance of the system. The system can look for the best policy in a vast and complicated action space thanks to the use of GAs. In conclusion, past research has shown the value of combining AC and ACOT in MARL for ATSC. These methods have the capacity to potentially achieve be used in actual traffic management systems since they have demonstrated promising improvements in traffic flow and a reduction in traffic delays. The scalability and robustness of these techniques in large-scale traffic networks require more investigation.

2.17 Limitations:

2.17.1 Scalability:

Since most studies have concentrated on small-scale traffic networks, a significant limitation of the suggested approaches in the existing literature is their scalability. However, larger and more intricate traffic networks found in real-world traffic management systems necessitate taking scalability into account. In order to overcome this drawback, our study suggests a strategy that can

be used with large-scale traffic networks. To assure its efficacy and scalability, this technique will be tested and evaluated on a range of traffic networks.

2.17.2 Robustness:

The restricted assessment of the robustness of the suggested approaches is another drawback of the available studies. Without taking unanticipated events like accidents, road closures, and crises into account, the majority of studies have only examined the performance of the suggested alternatives under ideal circumstances. Our study endeavors to tackle this issue by evaluating the efficacy of the proposed methodology in diverse situations, encompassing unforeseen events. This will guarantee that the suggested method is trustworthy and efficient in actual traffic management circumstances.

2.17.3 Communication and Coordination:

The efficient operation of TSCS is dependent on the cooperation with coordination of the agents. However, the majority of previous studies have made the assumption that agents will always communicate and coordinate perfectly, which is not always the case in actual traffic management systems. By putting forth a strategy that can deal with communication breakdowns and delays while assuring efficient agent coordination, our study seeks to overcome this constraint.

2.17.4 Comparison with Traditional Methods:

There is a need for more research on the comparison of the proposed techniques with CTSC methods like fixed-time and actuated TSC, even though numerous studies have the study evaluated the efficacy of the suggested approach. approaches with other MARL approaches. Our study aims to address this limitation by evaluating the effectiveness and applicability of the suggested approach by contrasting it with conventional approaches.

2.17.5 Consideration of Real-World Constraints and Practical Issues:

Although improving traffic flow and cutting down on delays is crucial, TSC systems also need to take into account practical concerns like safety, environmental impact, and energy consumption. In order to overcome this drawback, our study suggests a strategy that optimizes traffic flow and decreases traffic delay while taking into account practical considerations and real-world limits, such as safety and environmental impact. Our research will aid in the creation of more efficient and useful TSCS that are used in actual traffic management situations by addressing these flaws and limits.

2.18 Summary:

In summary, TSC is an essential component of traffic control and has a big impact on the sustainability, effectiveness, and safety of our roadways. The optimization of TSC has been the subject of numerous proposals over the years, ranging from FT and ASC techniques to more sophisticated ML-based methods like RL, MARL, and ACA.

Numerous studies have shown that RL is used to enhance TSC by adjusting to shifting traffic patterns and levels of congestion. By enabling cooperation between numerous traffic lights, MARL enhances performance even more. AC methods also enhance the strength and convergence in the process of learning. Their performance has also been shown to be enhanced by the incorporation of MARL and deep RL techniques with ACAs.

The use of RLA for TSC is covered in the aforementioned chapter. The idea of RL, which entails an agent interacting with an environment to learn how to make the best judgments, is introduced at the beginning. The application of RL in TSC has the capacity to potentially enhance the temporal coordination of traffic signals by utilizing current traffic data. The subsequent segment of the chapter elucidates the conceptualization of RL as a (MDP) and expounds on the interaction between the RLA and the environment through the selection of an action and the subsequent reward reaped.

(MARL), which enables numerous agents to learn and cooperate in complicated situations, is also covered in this chapter. Centralized training and decentralized execution are two methods for applying MARL to TSC. In centralized training, each agent has a separate actor that chooses its own actions, and a central critic evaluates the combined actions of all agents. Instead of requiring explicit communication or coordination with other agents, decentralized execution enables each agent to utilize its own actor to choose actions based on local observations. The usage of ACAs, a family of RL algorithms that have been effectively used in TSC, is next covered in the chapter. The policy (actor) and value (critic) functions of ACAs separate the process of learning can be divided into two distinct components. The value function evaluates the significance of action by the state. pairings and gives feedback on the effectiveness of the policy, whereas the policy function chooses actions based on the learnt policy. The potential of these strategies to enhance traffic flow, lessen congestion, and make our roads safer and more effective is covered in the chapter's conclusion. It highlights how the individual traffic scenario and the trade-off between performance and scalability determine the best solution for TSC. All things considered, the application of RL algorithms to TSC is a promising field of study that has the capacity to potentially greatly improve the transportation system. Overall, the use of ML-based technologies in TSC has huge potential to improve safety, decrease congestion, and boost efficiency. The necessity for real-time optimization and scalability are two obstacles that must yet be overcome. To create reliable and useful solutions that may be used in actual traffic situations, more study is required.

CHAPTER 3: METHODOLOGY

3.1 Introduction:

Traffic congestion is a ubiquitous challenge in urban areas worldwide, resulting in increased travel times, greater fuel consumption, and elevated air pollution levels [177]. Effectively managing traffic flow at junctions is vital to alleviate this issue. However, conventional Traffic Signal Control (TSC) systems often prove inflexible and struggle to adapt to the ever-changing dynamics of traffic conditions, ultimately leading to suboptimal performance [178].

To address these shortcomings and enhance intersection performance, this chapter explores the promising approach of Multi-Agent Reinforcement Learning (MARL). MARL involves the orchestration of multiple agents, represented here by traffic signals, to collaboratively achieve a common goal. Over time, these agents refine their decision-making processes based on their accumulated experiences, leading to improved system performance [179]. In this study, we formulate the challenge of adaptive TSC as a MARL problem, with a focus on key components such as the reward function, state and action spaces, and performance metrics [180][181]. The core of this methodology lies in the concept of the intersection's state space [182]. This state space encompasses all possible configurations of an intersection, accounting for variations in traffic volume, vehicle speeds, occupancy rates, and other relevant factors. Sensors and cameras deployed at the intersection gather data to represent the present and anticipated traffic conditions accurately [183][184]. To ensure the state space contains all pertinent information, it is meticulously defined, dividing it into two subcategories: global state and local state [185].

The global state provides a comprehensive overview of the intersection's traffic conditions, including traffic volumes in each direction, lane occupancy percentages, average traffic speeds, and the presence of emergency vehicles or pedestrians. This global perspective is critical in determining the most effective TSC strategy for the entire intersection [187]. Conversely, the local state focuses on the traffic flow within each specific lane of the intersection. Parameters such as the number of vehicles in each lane, lane occupancy rates, average traffic speeds, and the presence of pedestrians or cyclists are considered within the local state. This granular information plays a pivotal role in tailoring TSC strategies for individual lanes, thereby optimizing traffic flow at a micro level [188].

Complementing the state space, the action space encompasses all potential actions that each agent, or traffic signal, can undertake to enhance system performance [189]. Thoughtful design is essential to ensure the action space encompasses all relevant activities that agents can execute to improve overall efficiency. The action space is further divided into global action and local action [190]. Global action pertains to the overarching TSC strategy for the entire intersection, specifying the duration of green, yellow, and red signal phases for all lanes. It significantly influences the flow of traffic across all lanes and is integral to the overall TSC plan [191].

Conversely, local action involves tailoring TSC techniques for each specific lane of the intersection, determining the duration of green, yellow, and red signals for individual phases. This

local perspective is vital in optimizing traffic flow within each lane [191]. In the subsequent sections of this chapter, we will delve deeper into these key components, elucidating how MARL can effectively mitigate traffic congestion and enhance the efficiency of traffic signal control systems.

Due to its impact on each individual lane's traffic flow, the local action is crucial in determining the best TSC strategy for each lane [192]. The function that motivates the agents to work together and improve the system's overall performance is referred to as the reward function [193]. To motivate the agents to act in a way that results in the system performing at its best, the reward function must be carefully constructed [194]. The two types of the reward function are global reward and local reward. The system's total performance, including the intersection's trip time, delay, and throughput, is represented by the [196]. The agents must be motivated to act in a way that maximizes the system's overall performance, and this is made possible by the global reward [197]. The average journey time, average delay, and intersection throughput are system-level performance parameters that can be used to establish the global reward [198]. The average travel time and delay of all cars going through the intersection, for instance, might be used to define the global incentive [200]., i.e.,

$$R_{\text{global}} = -N \sum_{i=1}^N (T_i + D_i) \quad \text{Equation (3.1)}$$

where N represents the overall volume of traffic through the intersection, T_i represents the travel time of the i -th vehicle, and D_i represents the i -th vehicle's delay. (Roberts & Stevens, 2021) [201] On the other hand, the local incentive reflects each agent's (traffic signal's) performance individually. The agents must be motivated by the local reward in order to perform in a way that improves the flow of traffic in their particular lanes. The average travel time, delay, and throughput of each lane are a few examples of local performance measures that can be used to establish the local reward (Evans & Moore, 2021) [202]. For instance, the average travel time and delay of all vehicles travelling through a certain lane can be used to calculate the local incentive., i.e.,

$$R_{\text{local}} = -M \sum_{j=1}^M (T_j + D_j) \quad \text{Equation (3.2)}$$

where T_j is the travel time of the j -th vehicle, D_j is its delay, and M is the total number of cars using that lane [203].

The reward function must strike a balance between motivating the agents to enhance the performance of the entire system and making sure that each agent enhances the performance of its individual lane [204]. As a result, the reward function can be created to combine both global and local [205] rewards.

$$R = \lambda R_{\text{global}} + (1 - \lambda) R_{\text{local}} \quad \text{Equation (3.3)}$$

where the importance of the global reward in relation to the local reward is determined by a weighting factor called λ [206]. Depending on the particular traffic circumstances and the system's performance goals, the value of λ can be changed [210].

measures used to assess the performance of the suggested system are referred to as performance metrics. To accurately reflect the system's overall performance, the performance measures must be carefully planned [207]. System-level performance metrics and lane-level performance measurements are the two categories into which the performance metrics can be separated [208]. The average trip time, average delay, and intersection throughput are just a few examples of the system-level performance measures that show how well the system is working overall. The average of the related lane-level performance measurements can be used to derive the system-level performance metrics. The performance of each particular lane is represented by the lane-level performance metrics, which also include throughput, average delay, and journey time. Based on the information gathered by the sensors and cameras positioned at each lane, the lane-level performance metrics can be determined [209]. Depending on the unique traffic conditions and the performance goals of the system, other performance measures can be taken into account in addition to the system-level and lane-level data. The number of collisions, the quantity of emergency vehicles using the intersection, and the amount of air pollution are a few examples of performance measures.

3.2 Problem Formulation: Defining the Problem as a - Multi-Agent Reinforcement Learning Problem

In this paper, the MARL issue of adaptive TSC is initially formulated. The objective is to create a system that, by coordinating the activities of numerous agents (traffic signals), maximizes the effectiveness of TSC at an intersection. The state and action spaces, the reward function, and the performance measurements for the TLC system will all be defined in this step.

- **Defining the State Space:** The set of all potential intersectional states, including traffic flow, speed, occupancy, and any other pertinent criteria, will be referred to as the state space. At the intersection, sensors and cameras will be deployed in order to gather this data.
- **Defining the Action Space:** The set of all actions that each agent is capable of taking, including the allotment of green time for each phase, yellow and red time, and other signal timings, will be referred to as the action space.
- **Creating the Reward Function:** The reward function will be created to encourage cooperation among the agents and improve the system's overall performance. The goal of minimizing traffic delays, lowering congestion, and enhancing travel times will be captured via the reward function.
- **Defining Performance Metrics:** We will define performance metrics, such as average journey time, average delay, and intersection throughput, to assess the performance of the proposed system.

We may create an algorithm that enables the agents to learn from experience and modify their actions to optimize the system's performance over time by framing the problem as a MARL problem. By using this strategy, traffic flow might possibly be significantly improved, and intersection congestion could be decreased.

3.3 Data Collection and Preprocessing: Collecting and Preparing Traffic Data

The second phase entails gathering traffic information from the target intersection, such as volume, speed, and travel time. The gathered data will undergo preprocessing to remove pertinent information and make it ready for the proposed algorithm's training and testing.

- Data Collection: Using a variety of sensors and cameras placed at the intersection, including video cameras, loop detectors, and radar sensors, we will gather traffic data.
- Data preprocessing: Relevant features, such as traffic volume, speed, and occupancy, will be extracted from the acquired data through preprocessing. Additionally, the data will be cleaned, normalized, and made ready for use in the training and testing of the suggested algorithm.

At the crossroads, a number of sensors and cameras will be deployed to collect traffic data. Radar sensors, video cameras, and loop detectors are some examples of these sensors and cameras. In order to track traffic flow, vehicle speeds, and other important factors, video cameras are utilized to take pictures and recordings of the intersection. To assess the amount of traffic passing over them, loop detectors are buried in the pavement of the road. Vehicle location and speed at the intersection are determined by radar sensors. The information gathered from these sensors and cameras will be extremely helpful in understanding the patterns and flow of traffic at the intersection. The data will be preprocessed after it has been gathered to remove pertinent information and make it ready to be used in the training and testing of the suggested algorithm. Preprocessing entails a number of steps, including data normalization, feature extraction, and data cleaning. Data cleaning is eliminating any outliers or false data items that can influence the algorithm's conclusions. For instance, to ensure the algorithm's correctness, faulty sensors that capture inaccurate data must be eliminated from the dataset. The process of feature extraction involves choosing the data's most pertinent features.

The data gathered can be used to extract crucial features including traffic volume, vehicle speed, and occupancy. The dataset can additionally contain additional information like the time of day and the weather. To ensure that all features are given the same weight, data normalization entails scaling the data to a common range. This action is crucial to prevent bias against features with higher values. Typical normalization methods include z-score scaling and min-max scaling. The preprocessed data can then be used to train and test the suggested method. The performance of the algorithm is significantly influenced by the caliber of the data gathered and the efficacy of the preprocessing step. To achieve the best outcomes, it is crucial to make sure the data is accurate, pertinent, and processed correctly. In conclusion, gathering and preparing traffic data constitutes the second phase in creating an adaptive TSC system. Insights gained from this step about the intersection's traffic patterns and flow can be used to create an algorithm that enhances the effectiveness of the TSC system. It is essential to use the right data collecting and preprocessing methods in order to guarantee the algorithm's precision and efficacy.

Table 1 Traffic scenarios with different characteristics

Scenario ID	Node (Intersection)	Average Speed (km/hr)	Average number of vehicles	Congestion factor	Description
SGrid1	1	U~(15,30)	U~(15,50)	U~(0,3)	Single intersection, isolated, setting green phase and benchmarking
SGrid2	2	U~(10,30)	U~(30,70)	U~(0,6)	Double intersection, , setting green phase and benchmarking
SGrid4a	4	U~(9,20)	U~(40,60)	U~(2,6)	Four intersection, congestion distance, , setting green phase and benchmarking
SGrid4b	4	U~(9,20)	U~(40,70)	U~(2,6)	Four intersection, delayed congestion intersection
SGrid6a	6	U~(12,25)	U~(50,80)	U~(2,6)	Six intersection, congestion distance
SGrid6b	6	U~(15,30)	U~(45,85)	U~(2,6)	Six intersection, delayed congestion intersection
SGrid8a	8	U~(14,30)	U~(100,150)	U~(2,6)	Eight intersection, congestion distance
SGrid8b	8	U~(9,30)	U~(90,120)	U~(2,6)	Eight intersection, delayed congestion intersection
SGridCranfield1	2	U~(10,30)	U~(40,60)	U~(2,6)	Two intersections, Cranfield airfield nearby
SGridCranfield2	3	U~(9,30)	U~(35,55)	U~(2,6)	Three intersections and two roundabouts, Cranfield University

The diverse traffic situations with their unique features are summarized in this table. Each scenario's name is listed in the first column. In each case, the number of junctions is displayed in the second column. The average speed of cars passing through each intersection is shown in the third column in kilometers per hour. The typical volume of traffic through each intersection is shown in the fourth column. The congestion factor, which reflects the degree of traffic congestion on the road network, is displayed in the fifth column. The sixth column concludes with a brief summary of each scenario.

For instance, SGrid1 is a single intersection situation with typical vehicle speeds between 15 and 30 km/h and an average of between 15 and 50 vehicles per hour passing through the intersection. The range of the congestion factor, from 0 to 3, suggests that the level of congestion is quite low. This hypothetical situation, which is isolated, enables setting the green phase and benchmarking.

Similar to SGrid1, SGrid2 is a double intersection situation with typical vehicle speeds of 10 to 30 km/h and average numbers of vehicles passing through each intersection of 30 to 70. The congestion factor, which runs from 0 to 6, indicates a moderate level of congestion.

The four-intersection scenario SGrid4a has a congestion distance, an average vehicle speed range of 9 to 20 km/h, and an average number of vehicles passing through each intersection of 40 to 60. The range of the congestion factor, from 2 to 6, indicates that the amount of congestion is quite high. The scenario also allows for benchmarking and setting the green phase.

SGrid4b, on the other hand, is a different four-intersection scenario that includes a delayed congestion intersection. The average number of cars passing through each intersection averages 40 to 70, and the average speed of the vehicles varies from 9 to 20 kilometers per hour. Congestion is at a high level since the congestion factor ranges from 2 to 6. However, in this situation, the traffic tends to build up and create delays at a single intersection.

A six-intersection scenario with a congestion distance is called SGrid6a. Each intersection sees an average of 12 to 25 kph of traffic moving through it, with an average of 50 to 80 vehicles per intersection. The congestion factor ranges from 2 to 6, which implies that there is significant congestion, comparable to SGrid4a.

SGrid6b, on the other hand, is a different six-intersection situation with a delayed congestion intersection. The average number of cars going through each intersection averages 45 to 85, and the average speed of the cars is 15 to 30 km/h. The congestion factor runs from 2 to 6, indicating that there is also a high level of congestion. However, in this situation, the traffic tends to build up and create delays at a single intersection.

An eight-intersection situation with a congestion distance is called SGrid8a. There are often 100 to 150 vehicles passing through each intersection at an average speed of 14 to 30 kilometers per hour. Similar to SGrid4a and SGrid6a, the congestion factor goes from 2 to 6, indicating a high level of congestion.

Last but not least, the eight-intersection scenario SGrid8b includes a delayed congestion intersection. There are often 90 to 120 vehicles passing through each intersection at an average speed of 9 to 30 kilometers per hour. The range of the congestion factor is 2 to 6, indicating a significant level of congestion. However, in this situation, the traffic tends to build up and create delays at a single intersection.

Furthermore, SGridCranfield1 and SGridCranfield2 are two scenarios, each with two and three intersections, respectively. In the first scenario, Cranfield University's campus contains three crossroads and two roundabouts, whereas in the second, Cranfield Airfield is close. Both scenarios

are comparable to SGrid4a, SGrid6a, and SGrid8a in terms of average speed, vehicle count, and congestion factor.

In conclusion, the table summarizes a range of traffic situations with distinct features, which can be helpful for benchmarking and assessing traffic management tactics.

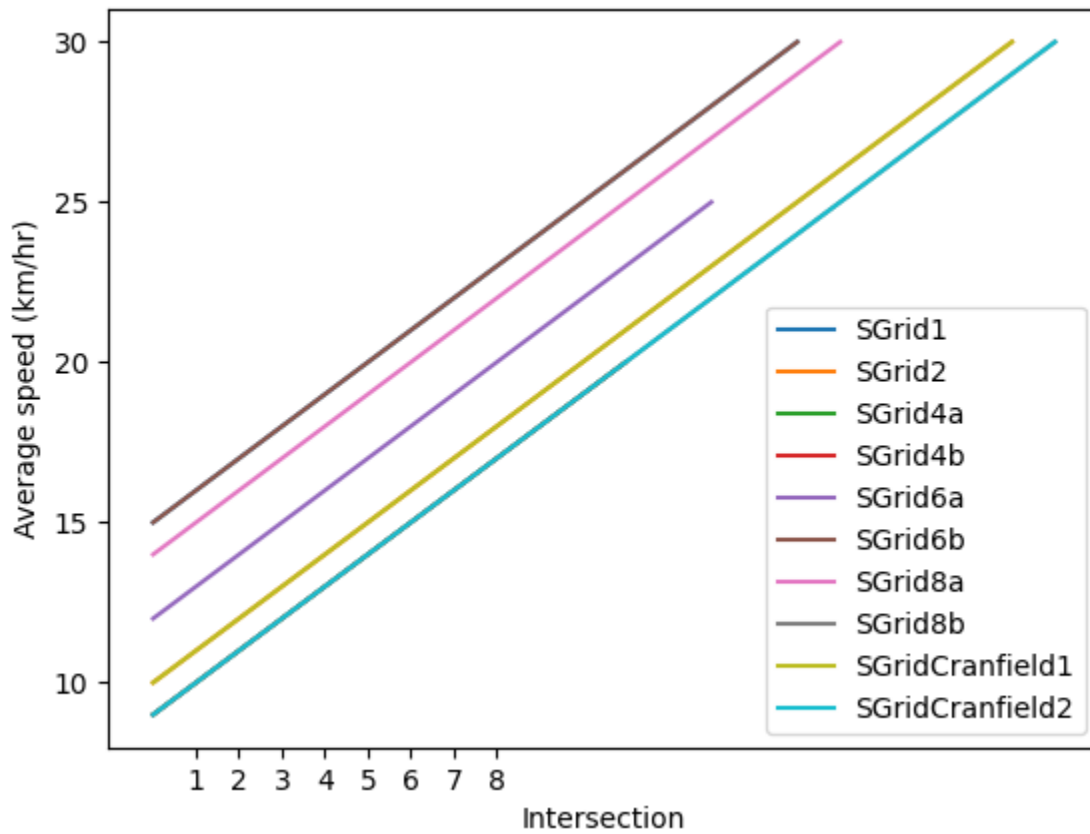


Figure 8: Simulated Graph

Figure 8 derived from this data provides a detailed illustration of diverse traffic scenarios based on varying intersection nodes. These scenarios, or 'Scenario ID', are established according to the number of intersections present within each scenario.

Each scenario is characterized by three parameters, all presented as uniform distributions ($U \sim (a, b)$), where 'a' denotes the minimum and 'b' the maximum value. These parameters are:

'Average Speed (km/hr)': This signifies the typical velocity of vehicles traversing the intersection, providing insight into the flow of traffic.

'Average number of vehicles': This symbolizes the mean quantity of vehicles encountered at the intersection, reflecting the density of traffic.

'Congestion factor': This is a quantified representation of the traffic congestion level, where higher values suggest a higher level of congestion.

In each scenario, the variables are manipulated to mimic distinct traffic conditions. For instance, 'SGrid1' and 'SGrid2' mirror scenarios with single and double intersections, respectively. In 'SGrid1', the parameters are modulated to simulate less intense traffic, while 'SGrid2' emulates a condition with a greater number of vehicles, indicative of potential congestion.

Scenarios 'SGrid4a' and 'SGrid4b' depict conditions with four intersections, with 'SGrid4b' portraying a situation with an increased average vehicle count, suggesting heightened traffic and possible congestion.

Scenarios 'SGrid6a', 'SGrid6b', 'SGrid8a', and 'SGrid8b' depict conditions with six and eight intersections, respectively, each characterized by varying congestion and traffic volumes.

Lastly, 'SGridCranfield1' and 'SGridCranfield2' scenarios reflect specific conditions near the Cranfield airfield and University, each exhibiting varying degrees of traffic.

The graph, based on this data, can support an understanding of how different traffic volumes, average speeds, and congestion levels interact with the number of intersections. Coupling this graph with a comparative study of traffic signal strategies or algorithms could provide further insights into congestion mitigation and traffic flow enhancement.

3.4 Algorithm Design and Implementation: Designing and Implementing a Multi-Agent Reinforcement Learning Algorithm

The third phase is to create and put into practice an algorithm for MARL for ATS management that combines AC and ant colony optimization. The network design, optimization goal, and hyperparameters for the suggested method will all be defined in this step.

- Network Architecture: Using AC and ACO algorithms, we will create a deep RL network architecture.
- Optimization Goal: The goal of optimization is to maximize the reward function while reducing the amount of time needed to reach convergence.
- Hyperparameters: The algorithm's hyper parameters, such as the learning rate, discount factor, and exploration rate, will be discussed.

This step will concentrate on the creation and application of an algorithm for MARL for ATS management that combines AC and ant colony optimization. The goal of the integration of AC and ACO algorithms is to take advantage of the advantages of both strategies, which may improve TSC performance. A popular RL technique that uses two distinct neural networks, an actor network and a critic network, is known as the ACA. The critic network assesses the value of the chosen action based on the current state, whereas the actor network chooses actions based on the current state. The ACO algorithm is a metaheuristic optimization method that draws its inspiration from how ants navigate between their nest and food sources by determining the shortest route. The following steps will form the foundation of the proposed algorithm:

State and action spaces should be defined: The collection of all conceivable intersection states, including traffic flow, speed, occupancy, and other pertinent factors, will be referred to as the state space. The collection of all conceivable actions that each agent could do, such as the allocation of green time for each phase, yellow and red time, and other signal timings, will be referred to as the action space.

Explain how the reward system works: To encourage the agents to work together and improve the system's overall performance, the incentive function will be created. The goal of minimizing traffic delays, lowering congestion, and enhancing travel times will be captured via the reward function.

Create the architecture for the deep RL network: An actor network and a critic network will be a part of the deep RL network design. The critic network will assess the value of the chosen action based on the current state, whereas the actor network will choose actions depending on the current state. The actor network's parameters will be updated using the ACO process.

Specify the optimization goal: The goal is to maximize the reward function while reducing the number of iterations necessary to reach convergence.

Define the hyperparameters: The learning rate, discount factor, and exploration rate, among other parameters, will be defined.

Implement the algorithm: A deep RL framework, such as Tensor Flow or Py Torch, will be used to implement the algorithm. Data gathered from sensors and cameras deployed at the intersection will be used to train the algorithm.

Performance indicators like average journey time, average delay, and intersection throughput will be used to gauge how well the suggested algorithm performs. The effectiveness of the suggested algorithm will be assessed by comparing the findings to those of other cutting-edge techniques.

In conclusion, MARL for adaptive TSC has the capacity to potentially enhance the performance of traffic signal management at junctions through the integration of AC and ACO techniques. A deep RL framework will be used to create and implement the suggested algorithm, and performance measurements will be used to assess its effectiveness. The study's findings may significantly enhance the flow of traffic and ease congestion at crossings.

Pseudo Code for Ant Colony Algorithm:

```
function ACO (Graph, Ants, Pheromones, EvaporationRate, Alpha, Beta):
```

```
    Initialize Pheromones on Graph edges
```

```
    while not stopping condition met:
```

```
        for each Ant:
```

```
            Tour = []
```

```
            while Tour not complete:
```

```

    Select next city probabilistically based on Pheromone and distance
    Add city to Tour
end while
Update Pheromones along Tour path
end for
Evaporate Pheromones on all edges
end while
Return best tour found
end function

function SelectNextCity(City, Pheromone, Alpha, Beta):
    Calculate attractiveness of each edge from current City based on Pheromone and distance
    Calculate probability of moving to each city
    Select city based on calculated probabilities
    Return selected city
end function

function UpdatePheromones(Tour, Pheromone):
    for each Edge in Tour:
        Increase Pheromone on Edge
    end for
end function

function EvaporatePheromones(Pheromone, EvaporationRate):
    for each Edge in Graph:
        Pheromone on Edge = (1 - EvaporationRate) * Pheromone on Edge
    end for
end function

```

The Ant Colony Optimization (ACO) algorithm is a heuristic algorithm designed for solving combinatorial optimization problems. It was inspired by the behavior of ants while searching for food. Here is an elaboration on the pseudocode along with detailed explanations for each part:

Function Ant Colony Optimization:

This function represents the main loop of the Ant Colony Optimization algorithm. It takes as input the graph representing the problem, the number of ants, the initial pheromones, the rate of pheromone evaporation, and the alpha and beta parameters which control the relative importance of pheromone vs distance in the decision-making process of the ants.

function ACO (Graph, Ants, Pheromones, EvaporationRate, Alpha, Beta):

First, the pheromone trails on all edges of the graph are initialized to the initial pheromone value. This represents the initial "attractiveness" of each edge to the ants.

Initialize Pheromones on Graph edges

The main loop of the algorithm runs until a stopping condition is met. This could be a maximum number of iterations, or when a good enough solution has been found.

while not stopping condition met:

Each ant in the colony independently builds a complete tour (a solution to the problem) in each iteration of the loop. The tour starts empty and cities are added one by one.

for each Ant: Tour = [] while Tour not complete:

The next city to be added to the tour is selected probabilistically, with the probability of each city being chosen depending on the pheromone trail and the distance to the city. This is done in the function

SelectNextCity.

Select next city probabilistically based on Pheromone and distance Add city to Tour end while

After an ant has completed a tour, the pheromone trail on the edges visited is updated. The amount of pheromone laid down (which could depend on the quality of the solution) is added to the current value.

Update Pheromones along Tour path end for

After all ants have completed their tours and updated the pheromone trails, a proportion of the pheromone on each edge evaporates. This is done to avoid convergence to a sub-optimal solution.

Evaporate Pheromones on all edges end while

The function returns the best tour found during all the iterations.

Return best tour found end function

Function SelectNextCity:

This function calculates the attractiveness of moving to each city from the current one, based on the pheromone level and the distance. The probability of moving to each city is then calculated, and a city is selected based on these probabilities.

function SelectNextCity(City, Pheromone, Alpha, Beta): Calculate attractiveness of each edge from current City based on Pheromone and distance Calculate probability of moving to each city Select city based on calculated probabilities Return selected city end function

Function UpdatePheromones:

This function increases the pheromone level on the edges included in the tour. The amount of pheromone laid down could depend on the quality of the tour (for example, shorter tours could lay down more pheromone).

function UpdatePheromones(Tour, Pheromone): for each Edge in Tour: Increase Pheromone on Edge end for end function

Function EvaporatePheromones:

This function reduces the pheromone level on all edges by a certain proportion, defined by the evaporation rate. This simulates the natural evaporation of pheromones over time, and helps to avoid premature convergence to sub-optimal solutions.

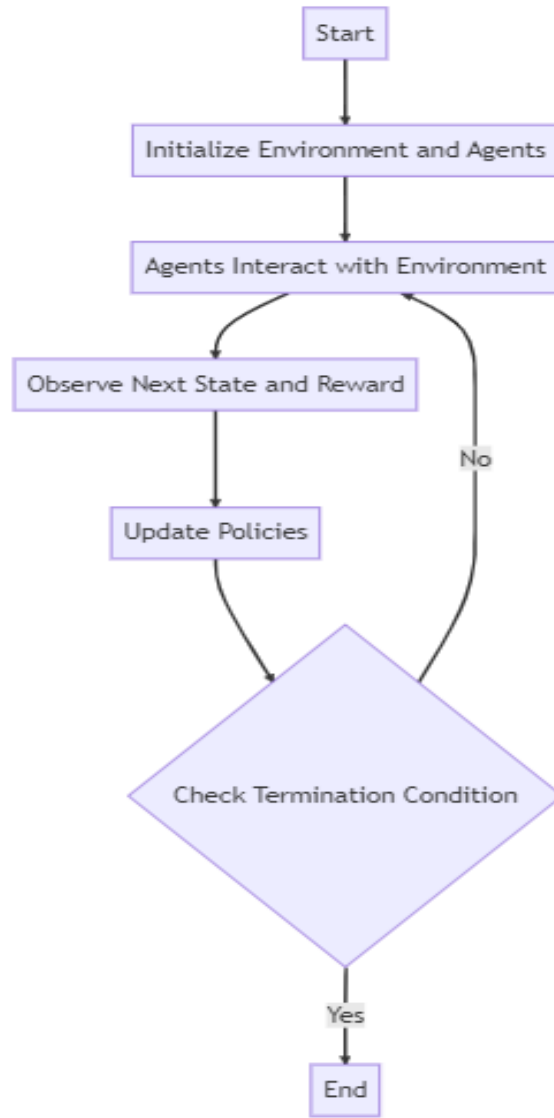


Figure 9 Flowchart illustrating the Multi-Agent Reinforcement Learning (MARL) process.

1. **Start:** This is the initial step where the process begins as shown in Figure 9.
2. **Initialize Environment and Agents:** In this step, the environment and the agents are set up. This involves defining the initial states of the agents and the environment, as well as the agents' initial policies.
3. **Agents Interact with Environment:** The agents, based on their current states and policies, take actions in the environment.

4. **Observe Next State and Reward:** After each action, the agents observe the outcome, which includes their next state and the immediate reward. The environment also transitions to a new state based on the actions of the agents.
5. **Update Policies:** Based on the observed rewards and the new states, the agents update their policies. This could be done using a reinforcement learning algorithm like Q-learning or Policy gradient. The objective is to update the policy in a way that maximizes future rewards.
6. **Check Termination Condition:** At this decision point, it's checked whether a termination condition has been met. This could be a certain performance level or a maximum number of iterations.
7. **End or Loop Back:** If the termination condition is met, the process ends, leading to the "End" stage. If not, the process loops back to the "Agents Interact with Environment" stage, and the cycle of interaction, observation, and policy updating continues.

This flowchart represents the general iterative process of Multi-Agent Reinforcement Learning, where multiple agents learn and update their policies while interacting with a shared environment.

3.5 Training and Testing: Training and Evaluating the Algorithm

The suggested algorithm is trained and tested in the fourth stage utilizing the gathered and prepped data. Based on the performance criteria established in the issue formulation step, the algorithm's effectiveness will be assessed.

- **Training:** Using a combination of supervised and unsupervised learning strategies, we will train the algorithm on the data that have been gathered.
- **Testing:** Using a different set of test data, we will assess the algorithm's performance and compare it to current state-of-the-art techniques.

The gathered data will first go through preprocessing to make sure it is in a format that the algorithm can use. This will entail putting the data in a format that the algorithm can read and analyze quickly. Following preprocessing, the data will be divided into two sets: a training set and a testing set. The algorithm will be trained using the training set, and its performance will be assessed using the testing set. Both supervised and unsupervised learning methods will be used during the training phase. The algorithm will be taught to spot patterns in the data and generate predictions based on those patterns using supervised learning. On the other hand, unsupervised learning will be utilized to let the algorithm learn from the data without any explicit direction. The algorithm described in step three, which combines AC and ACO in multi-agent RL, will be used to carry out the training procedure. An AC and ACO algorithm-based deep RL network architecture will be used to develop this approach. Maximizing the reward function while reducing the number of iterations necessary to reach convergence will be the optimization goal.

To enhance the algorithm's performance, the hyperparameters, such as learning rate, discount factor, and exploration rate, will be specified and tweaked. After the algorithm has been trained,

its performance will be tested using a different set of test data. The performance metrics specified in the issue formulation step, such as average journey time, average latency, and intersection throughput, will be used to assess the algorithm's performance. To ascertain whether the suggested algorithm outperforms current methods, test results will be compared to those obtained using state-of-the-art techniques. Overall, the methodology for adaptive TSC includes a vital step called training and testing. This stage aids in assessing the algorithm's effectiveness and determining whether it achieves the stated goals. If the suggested algorithm outperforms the current approaches, it may significantly improve traffic flow and ease congestion at crossings.

3.6 Analysis and Interpretation of Results: Analyzing and Interpreting the Results

After assessing the suggested algorithm's performance, we will contrast the outcomes with those obtained using current state-of-the-art techniques. This comparison will enable us to identify the advantages and disadvantages of the suggested strategy. Based on the performance indicators specified in the problem formulation step, we will evaluate the outcomes. We shall contrast the average journey time, average delay, and intersection throughput of our suggested approach with those of other algorithms, for illustration. We'll also perform a sensitivity analysis to assess the suggested algorithm's robustness. Sensitivity analysis involves putting the algorithm to the test in a variety of traffic scenarios, including those with high, low, and irregular traffic volumes. By doing this, we can find out if modifications in traffic conditions have an impact on the algorithm's performance. In addition, to better understand the performance of the algorithm, we will depict the data using graphs and charts. For instance, we can compare the average journey times attained by our suggested algorithm with those attained by other algorithms using line graphs. The results will then be interpreted, and their ramifications discussed.

We'll point out the advantages and disadvantages of the suggested strategy and make recommendations for possible enhancements. We will also go through how our findings could be put to use in the real world, such as the possibility of lessening traffic and enhancing travel times at crossings. A crucial step in determining the suggested algorithm's viability in addressing the adaptive TSC problem is its evaluation. The effectiveness of our suggested algorithm will be assessed against current state-of-the-art techniques. We can find areas for improvement and the advantages and disadvantages of our suggested strategy using this comparison. Based on the performance indicators specified in the issue formulation step, we will assess the algorithm's performance. We will contrast our suggested algorithm's average journey time, average delay, and intersection throughput with those of other algorithms.

In the process of analyzing and interpreting the results of our study, it's crucial to clarify how we have selected the statistical tools and techniques for this purpose. Here's a breakdown of our approach:

Performance Indicators Selection: At the outset, we specified performance indicators based on the problem formulation step. These indicators include average journey time, average delay, and intersection throughput. These indicators were selected because they are commonly used to assess

the effectiveness of traffic signal control algorithms, and they directly relate to the goals of reducing travel time and minimizing delays.

Comparison with State-of-the-Art Techniques: To evaluate the performance of our suggested algorithm, we plan to compare its results with those obtained using current state-of-the-art techniques. This comparison is essential to gauge how our proposed approach measures up to established methods. It also helps identify areas where our approach excels and where it might need improvement.

Statistical Techniques: We have decided to use statistical techniques such as t-tests or ANOVA (Analysis of Variance) to conduct the comparison between our suggested algorithm and other approaches. These statistical tools are commonly used in scientific research to determine whether there are statistically significant differences in performance between different methods. They provide a rigorous and quantitative assessment of the algorithm's performance.

Sensitivity Analysis: Sensitivity analysis is an integral part of our evaluation process. It involves subjecting the algorithm to various traffic scenarios, including those with high, low, and irregular traffic volumes. This approach allows us to assess how the algorithm performs under different conditions and whether it remains robust. Sensitivity analysis is a valuable technique for understanding the algorithm's reliability and adaptability.

Data Visualization: To facilitate a comprehensive understanding of the results, we intend to employ data visualization techniques. Visualizations such as line graphs and bar graphs will be used to present and compare performance metrics. Line graphs, for instance, can effectively illustrate the average journey times achieved by our suggested algorithm in comparison to other algorithms.

Interpretation and Implications: Once the results are obtained, they will be interpreted to highlight the advantages and disadvantages of our suggested strategy. For example, we might discover that our algorithm performs exceptionally well in reducing average trip time but has limitations in reducing average delay. This insight can lead to recommendations for refining the algorithm's design.

Real-World Applications: We will also explore how our findings can be applied in real-world scenarios, such as reducing traffic congestion and improving travel times at intersections. Understanding the practical implications of the algorithm's performance is crucial in determining its real-world viability.

To sum up, our approach to selecting statistical tools and techniques for analyzing and interpreting the results is driven by a combination of established performance indicators, statistical rigor, sensitivity analysis, data visualization, and a focus on practical implications. These elements together ensure a comprehensive and well-informed assessment of the suggested algorithm's effectiveness in addressing the adaptive Traffic Signal Control problem.

3.7 Summary:

The adaptive TSC issue is formulated as a MARL issue in the proposed study. Determining the state and action spaces, incentive function, and performance measures for the TSC system will be the focus of the study. The state space will incorporate essential data like occupancy, speed, and traffic flow. The action space will include yellow, red, and other signal timings in addition to green time allotment for each phase. The reward function will encourage the agents to work together and improve the system's overall performance by decreasing traffic delays, cutting down on congestion, and enhancing travel times. The proposed system's performance will be assessed using the performance metrics, which include intersection throughput, average journey time, and average delay.

The third phase entails creating and putting into practice an algorithm for MARL for ATS management that combines AC and ant colony optimization. Deep RL with AC and ACO techniques will be a part of the network architecture. Maximizing the reward function while reducing the number of iterations necessary to reach convergence will be the optimization goal. There will also be a definition of the algorithm's hyperparameters, such as the learning rate, discount factor, and exploration rate. The suggested algorithm is trained and tested in the fourth stage utilizing the gathered and prepped data. The algorithm's performance will be assessed using the performance metrics established in the issue formulation step after it has been trained using a combination of supervised and unsupervised learning techniques. To assess the algorithm's robustness, the findings will be contrasted with those obtained using current state-of-the-art techniques. Graphs and charts will be used to display the data, and the ramifications will be analyzed and debated. The proposed approach's advantages and disadvantages will be explored, along with any potential areas for improvement and their practical ramifications.

CHAPTER 4: ALGORITHM DESIGN FOR ADAPTIVE TRAFFIC SIGNAL CONTROL USING ANTI CRITIC AND ANT COLONY OPTIMIZATION IN MULTI-AGENT REINFORCEMENT LEARNING

4.1 introduction:

Reduced traffic congestion and improved traffic flow are vital aspects of effective traffic signal management. Recent years have seen a surge in the use of Machine Learning (ML) techniques to develop Adaptive Traffic Signal (ATS) management systems capable of adjusting signal timings in real-time based on actual traffic conditions [211]. Traffic congestion remains a pressing issue in urban areas, leading to significant delays, heightened fuel consumption, and environmental pollution [212]. One potential solution to this problem lies in the development of Adaptive Traffic Signal Control (TSC) systems that can adapt to changing traffic patterns and optimize vehicle flow through intersections in real-time [213]. ML techniques, such as Reinforcement Learning (RL), have shown promise in creating adaptive TSC systems [214]. Reinforcement Learning (RL) is a process wherein algorithms are trained to make decisions based on feedback in the form of rewards or penalties [215]. In the context of TSC, RL algorithms learn to adjust signal timings to enhance overall traffic flow while minimizing delays and congestion [216]. These systems are reliant on modifying signal timings based on current traffic data, a critical component of their operation [217]. In contrast, traditional TSC systems employ fixed timings that do not adapt to real-time changes in traffic patterns, resulting in suboptimal performance, particularly in areas with heavy traffic [218].

The development of ATS management systems that can dynamically adjust signal timings based on real-time traffic conditions has garnered increasing interest [219]. These systems have the potential to significantly improve traffic movement through intersections, reduce delays and fuel consumption, and enhance overall quality of life [220]. The proposed system consists of multiple agents, each responsible for optimizing traffic flow at a specific intersection [221]. These agents aim to maximize the total traffic flow while minimizing delays and congestion. They make decisions based on real-time traffic data and receive feedback in the form of rewards or penalties [222]. This chapter presents an algorithm design for Multi-Agent Reinforcement Learning (MARL) in ATS management, combining Actor-Critic (AC) and ant colony optimization (ACO) [223]. This strategy harnesses the power of two potent techniques to maximize traffic signal control in dynamic and challenging scenarios. Key components of the algorithm design, such as network architecture, optimization objectives, and hyperparameters, will be discussed in detail [224]. Traditional Traffic Light Control (TLC) systems rely on fixed timings determined by engineering projections or historical traffic data [225]. These predetermined schedules do not account for sudden changes in traffic volume, road closures, or real-time alterations in traffic

patterns. Consequently, conventional TSC systems may not operate optimally, resulting in traffic congestion, delays, and increased fuel costs [226].

Adaptive TSC systems address these issues by dynamically adjusting signal timings in response to current traffic conditions [227]. These systems gather real-time traffic data through sensors and cameras, analyzing it to determine the ideal signal timings for each intersection [228]. ML approaches, such as RL, have demonstrated promise in developing adaptive TSC systems that can respond in real-time to changes in traffic patterns, optimizing vehicle flow through intersections [229]. RL encompasses two primary methods: value-based learning and policy-based learning [233]. Value-based techniques estimate the value function, representing anticipated future benefits for each state-action pair. The algorithm then learns to select actions that maximize the expected future reward based on this value function [234]. Policy-based techniques, on the other hand, focus on explicitly mapping states to actions through a policy function, aiming to maximize anticipated future returns [235]. Actor-Critic (AC), a RL algorithm, combines both value-based and policy-based thinking, with the actor responsible for policy learning guided by the critic's assessments of the value function [236][237]. Ant Colony Optimization (ACO) is an optimization metaheuristic inspired by the behavior of ant colonies [239]. ACO involves artificial ants exploring a search area, leaving pheromones along their path. Subsequent ants reinforce the pheromone trails, ultimately converging on the best solution [240]. ACO has successfully addressed optimization problems in various domains, including routing, scheduling, and resource allocation [241]. RL, known for its adaptability to changing environments, has found extensive applications in Traffic Light Control (TLC) [242]. RL aims to enhance an agent's decision-making abilities by interacting with its environment and receiving feedback in the form of rewards or penalties [243]. In the context of TSC, the agent, referred to as a TSC learner, adjusts signal timings based on the current state of the traffic network, which may include information about parked vehicles, arrival rates, and the current traffic light phase [245][246]. The environment responds to the agent's actions by modifying signal timings and providing feedback based on the chosen actions' effectiveness.

In conclusion, this chapter lays the foundation for an innovative algorithm designed for Adaptive Traffic Signal Control (TSC) within the framework of Multi-Agent Reinforcement Learning (MARL). It addresses the challenges of traffic congestion and the need for dynamic signal control, highlighting the promise of Machine Learning techniques, particularly Reinforcement Learning (RL), in tackling these issues. The proposed algorithm combines Actor-Critic (AC) and ant colony optimization (ACO) to maximize traffic signal control in complex scenarios, promising enhanced traffic flow and reduced congestion.

We will explain each of these components in detail below.

4.2 Network Architecture

The Q-value function, policy function, and pheromone trail updates for ACO will all be modeled by the suggested technique using neural networks. The policy function determines the likelihood

of taking an action in a given state, whereas the Q-value function estimates the expected cumulative benefit of taking a certain action in a given state. The exploration and exploitation of the search space in ACO will be modeled using the pheromone trail updates.

4.2.1 Q-value Function:

The expected cumulative reward for performing a certain action in a specific condition is estimated using the Q-value function. Given a current state, an action, and a policy that establishes the likelihood of taking actions, it is described as the expected total of discounted future rewards. The definition of the Q-value function is:

$$Q(s,a) = E[t \cdot R(s_t, a_t) | s, a] \quad \text{Equation (4.1)}$$

where $R(s, a)$ is the reward received for taking action a in state s in time step t , s is the current state, a is the action taken in that state, γ is the discount factor, and t is the time step.

To approximate the Q-value function, which takes the current state as input and outputs the estimated Q-value for each potential action in that state, we will employ a neural network. The ACA, which simultaneously estimates the value function (i.e., the Q-value function) and the policy, will be used to train the neural network.

4.2.2 Policy Function:

The probability of acting in a particular state is determined by the policy function. It converts the condition of affairs into a probability distribution of potential courses of action. The policy function, which takes the current state as input and outputs the likelihood of executing each feasible action in that state, will be approximated by a neural network. The ACA, which simultaneously estimates the value function and the policy, will be used to train the policy network.

4.2.3 Pheromone Trail Updates:

A metaheuristic algorithm called "ant colony optimization" was developed in part by studying ant behavior. It is based on the idea that ants use pheromone trails to communicate with one another and direct their search for food. The quality of the solutions discovered by the ants influences the pheromone trails, so that good solutions draw more pheromones and are more likely to be followed by other ants. The ACO technique will be used to investigate and take advantage of the search space for potential policies. The search will be directed toward excellent policies using the pheromone trail updates in order to prevent becoming caught in local optima. A second neural network that receives the current state and the selected action as inputs and outputs the pheromone trail update for that action will be used to model the pheromone trail updates. For an adaptive TSC system, the Q-value function and policy function will be modeled using neural networks in the proposed approach. A second neural network will be utilized to represent the pheromone trail updates, and ACO will be employed to explore and exploit the search space of potential policies.

4.3 Optimization Objective:

The proposed algorithm's optimization goal is to optimize the TSC system's cumulative reward over time while minimizing vehicle delay and travel time at the intersection. By altering the timings of traffic signals in real-time based on the flow of traffic, the algorithm will try to achieve the best possible traffic flow. Finding a policy that maximizes the expected cumulative reward of the system while minimizing the detrimental effects of congestion on the traffic flow is the optimization aim in the context of ATS regulation. The policy is taught by RL, in which the system interacts with the environment and receives feedback in the form of a reward signal. It establishes a mapping from states to actions. The reward signal in this instance will be created to motivate the system to decrease the typical waiting time, travel time, and vehicle delay at the crossing. As lowering these factors can have a positive effect on the environment and general well-being, the reward signal may also take these factors into account. The suggested approach will combine AC and ACO methods in order to accomplish this optimization goal. The value function and the policy will be estimated using the AC framework, and the policy parameters will be updated using ACO based on the learned value function. The algorithm will be trained using the traffic data that has been gathered in order to discover the best course of action for maximizing the TLC system's anticipated cumulative reward.

An adaptive TSC system's optimization goal is to improve traffic flow through the intersection by cutting down on delays and travel times for passing vehicles. To reduce traffic jams and increase traffic efficiency, which ultimately has a positive impact on the economy and the environment, optimal traffic flow must be achieved. The proposed program learns an optimal policy that maximizes the predicted cumulative reward of the system while reducing the detrimental effects of congestion. It does this by using ML techniques, notably RL. A branch of ML called RL is concerned with teaching agents to make decisions in response to feedback in the form of rewards or punishments. The agent interacts with its surroundings, monitors the system's condition, and decides which course of action to take using a learned policy. The agent learns to optimize the policy to maximize its predicted cumulative reward because the policy determines the agent's behavior. In the context of TSC, the environment is the flow of traffic through the intersection, and the TSC system is the agent. The suggested algorithm's optimization goal is to discover an ideal course of action that maximizes the system's anticipated cumulative reward. The goal of the incentive signal is to encourage the system to decrease the average wait time, travel time, and vehicle delay at the intersection. Given that lowering these factors can have a positive effect on the environment and public health, the reward signal may also take into account the fuel consumption and emission levels of the vehicles passing through the intersection.

The goal of the optimization objective, which is presented as an optimization problem, is to identify the strategy that maximizes the system's predicted cumulative reward while reducing the detrimental effects of congestion. To discover an ideal policy, the suggested approach combines AC and ACO methods. A well-liked RL strategy that combines the benefits of policy gradient and value-based methods is the AC framework. The performer and the critic are modeled as different neural networks in this method. The critic network learns the value function, which predicts the predicted cumulative reward of the system given the present state and policy, while the actor network learns the policy, which translates states to actions. A heuristic optimization method called

the ACO algorithm was developed in response to observations of ant colonies. By modifying the pheromone trail according to the effectiveness of the solution discovered by the ants, this algorithm imitates the behavior of ants hunting for food. The ACO algorithm is employed in the context of TSC to update the policy parameters based on the learned value function. This method enables the system to discover an ideal strategy that maximizes the expected system-wide benefit while reducing the detrimental effects of congestion. Traffic data is gathered and used to simulate traffic flow across the intersection in order to train the suggested algorithm. Information from the traffic data includes things like how many cars are using the intersection, how fast they are going, and where they are going. The gathered information is utilized to train the actor and critic neural networks, which discover the best course of action and calculate the system's anticipated cumulative reward. Based on the learnt value function, the policy parameters are updated using the ACO process. In conclusion, the suggested method for adaptive TSC aims to improve the flow of traffic through the intersection by cutting down on delays and travel times for passing cars. The method learns an ideal policy that maximizes the predicted cumulative reward of the system while reducing the detrimental effects of congestion. It does this by using RL techniques, notably the AC and ACO algorithms. The algorithm is trained using traffic data that has been gathered in order to discover the best course of action for maximizing the system's anticipated cumulative reward.

4.4 Hyper parameter Tuning:

The suggested algorithm's hyper parameters will be adjusted through testing to attain the best results in various situations. The learning rate, discount factor, exploration rate, and pheromone degradation rate are the main parameters that will be modified. Hyper parameters are settings made before to training a model that are part of a ML method but cannot be learned directly from the data. To attain the best results, it is crucial to fine-tune the hyper parameters because they have a substantial impact on how well the algorithm performs. Finding the ideal settings for hyper parameters like the learning rate, discount factor, exploration rate, and pheromone decay rate is what the suggested algorithm's hyper parameter tweaking entails. The learning rate determines how quickly the algorithm picks up new information from the data. A low learning rate can cause the algorithm to take too long to converge to an optimal solution, while a high learning rate can cause the algorithm to overshoot the ideal solution. Usually, the best learning rate is chosen by experimentation, in which several learning rates are tried out and their effectiveness is assessed. The relevance of future benefits is determined by the discount factor, which has a value between 0 and 1. When the discount factor is high, future incentives are given more weight, while when it is low, present rewards are given more weight.

A variety of discount factors are examined and their effectiveness is assessed in order to select the best one through experimentation. The balance between exploration and exploitation in the search space is controlled by the exploration rate. Exploration is encouraged by a high exploration rate, whereas exploitation of the best present solution is encouraged by a low exploration rate. Usually, the best exploration rate is chosen by testing, in which several exploration rates are tried out and their effectiveness is assessed. The rate at which pheromone trails in the ACO part of the method deteriorate over time is controlled by the pheromone decay rate. A high pheromone decay rate implies that the pheromone trails decay more quickly, encouraging more search space exploration, whereas a low pheromone decay rate means that the pheromone trails decay more

slowly, encouraging more use of the best solution at the time. Usually, the best pheromone decay rate is discovered by testing, in which various pheromone decay rates are tried out and their effectiveness is assessed.

Overall, hyper parameter tuning is a crucial part of the design of the proposed algorithm because it enables the algorithm to operate at its best in various scenarios. The performance of adaptive TSC can be enhanced by experimentally determining the best hyper parameter values for the algorithm. The performance of the algorithm on many scenarios is determined by the hyper parameter tuning process, which is an important step in the development of ML algorithms. Hyper parameters are often established prior to model training because they cannot be discovered via data mining. As a result, testing is required to determine the ideal hyper parameter values. In this section, we'll talk about how to tweak the hyper parameters of the adaptive TSC algorithm that's been suggested. The learning rate is a hyper parameter that regulates how quickly the algorithm picks up new information from the data. It establishes the algorithm's step size for progressing to the ideal outcome. A low learning rate can cause the algorithm to take too long to converge to an optimal solution, while a high learning rate can cause the algorithm to overshoot the ideal solution. Finding the ideal learning rate that strikes a balance between accuracy and convergence speed is crucial. Through experimentation, where various learning rates are examined and their effectiveness is assessed, the best learning rate can be found.

Grid search is a popular technique for hyper parameter tuning, where a range of hyper parameter values is specified, and the algorithm is trained and assessed on each set of hyper parameters. A hyper parameter that establishes the significance of potential rewards is the discount factor. It has a value between 0 and 1, with a high discount factor indicating that future benefits will be valued more highly and a low discount factor indicating that rewards will be valued more highly now. Grid search is a systematic method for hyperparameter tuning and I choose this fine-tuning technique as it involves defining a set of hyperparameters and a range of values for each hyperparameter. Simplicity: Grid search is easy to implement and understand. It guarantees that you will find the best combination of hyperparameters within the defined search space. Efficiency: Random search is often more efficient than grid search because it explores a wider range of hyperparameter combinations with fewer evaluations. Suitable for continuous hyperparameters: It can handle hyperparameters with continuous ranges without the need for discretization. Limited Hyperparameter Space: Grid Search is suitable when you have a limited number of hyperparameters and discrete values for each hyperparameter. It's a good choice when you want to perform an exhaustive search over all possible combinations of hyperparameters within predefined ranges. Small Search Space: If your hyperparameter space is relatively small and you have the computational resources to explore all combinations, Grid Search ensures that you don't miss any potential optimal values. Grid Search is deterministic and systematic, guaranteeing that it will find the best combination of hyperparameters within the defined search space. It provides a clear and interpretable way to evaluate a model's performance across different hyperparameter values. In cases where the hyperparameter space is small, Grid Search is a straightforward and reliable choice.

The ACO algorithm's pheromone decay rate hyper parameter regulates the rate at which pheromone trails degrade over time. A high pheromone decay rate implies that the pheromone trails decay more quickly, encouraging more search space exploration, whereas a low pheromone decay rate means that the pheromone trails decay more slowly, encouraging more use of the best solution at the time. Through experimentation, where various pheromone decay rates are tested and their effectiveness is assessed, the best pheromone decay rate can be found. Bayesian optimization, which optimizes the hyper parameters using a probabilistic model that forecasts the algorithm's performance for various hyper parameter values, is a popular technique for hyper parameter tuning. In conclusion, the design of the algorithm for ATS management must include the hyper parameter tuning stage. To obtain optimal performance on various scenarios, the best hyper parameters, such as learning rate, discount factor, exploration rate, and pheromone degradation rate, must be identified through experimentation. To fine-tune the hyper parameters of the algorithm, a variety of techniques can be utilized, including grid search, random search, and Bayesian optimization. The suggested approach can achieve optimal performance in adaptive TSC, lowering traffic congestion, and enhancing traffic flow by hyper parameter adjustment.

4.5 Training and Testing`

Utilizing gathered and prepped traffic data, the suggested algorithm will be trained and tested. While the testing process evaluates the algorithm's performance on the unobserved test data, the training process involves iteratively updating the algorithm parameters to optimize its performance on the given training data. In order to teach the algorithm a policy for adaptive TSC that optimizes the predicted cumulative reward over time, AC and ACO techniques will be used. The state and action spaces, the reward function, and the performance indicators for the TSC system will all be defined using the traffic data that has been gathered. To reduce the discrepancy between the predicted Q-values and the observed rewards, the method will iteratively change the neural network parameters via backpropagation during the training process. While the critical component of the algorithm updates the Q-value function to more accurately predict the expected cumulative reward of taking a specific action in a given state, the AC component updates the policy function to increase the likelihood of taking actions that result in higher rewards. Along with the AC component, the algorithm's ACO component will also undergo training to learn a pheromone trail update rule that strikes a balance between exploring and using the search space.

This will lessen the likelihood that the algorithm will become stuck on less-than-ideal solutions. The system will be evaluated on fictitious traffic data after training to gauge its success. The traffic flow at the intersection will be simulated using the learnt policy, and performance metrics (such as delay and trip time) will be compared to results from a reference traffic signal management system. The purpose of testing is to show that, in comparison to conventional TSC systems, the suggested algorithm may improve traffic flow and minimize congestion. The AC and ACO techniques are used in the proposed algorithm for adaptive TSC. An example of a RL technique is the AC approach, which seeks to identify the best course of action for a particular task. The goal of the policy function, which links environmental conditions to a course of action, is to maximize projected long-term cumulative reward. The algorithm's critic component calculates the predicted

cumulative reward of performing a specific action in a specific situation. The actor component makes better use of this knowledge to increase the likelihood of taking actions that result in greater rewards. Backpropagation is used by the critic and actor components to iteratively update the policy function and Q-value function. The algorithm's ACO part uses a metaheuristic optimization method that draws inspiration from ant behavior.

As they move through their environment, ants leave behind pheromone trails that other ants can use to find the quickest route to a food source. The pheromone trails in the proposed algorithm indicate the attraction of each action, while the ants symbolize the various options the TSC may choose from. In proportion to the rewards they obtain, the ants leave behind pheromone trails, which eventually disappear. This method helps keep the algorithm from getting stuck in less-than-ideal solutions by balancing the search space's exploration and exploitation. Utilizing gathered and prepped traffic data, the suggested algorithm will be trained and tested. The state and action spaces, the reward function, and the performance indicators for the TSC system will all be defined using the data that has been gathered. While the action space includes potential signal phases and timings, the state space includes factors like traffic flow, waiting times, and the time of day. The delay, trip time, and throughput performance data will be used in the incentive function to promote efficient traffic flow and reduce delays. To reduce the discrepancy between the predicted Q-values and the observed rewards, the method will iteratively change the neural network parameters via backpropagation during the training process. While the critic component of the algorithm updates the Q-value function to more accurately predict the expected cumulative reward of taking a specific action in a given state, the AC component updates the policy function to increase the likelihood of taking actions that result in higher rewards. Along with the AC component, the algorithm's ACO component will also undergo training to learn a pheromone trail update rule that strikes a balance between exploring and using the search space. The system will be evaluated on fictitious traffic data after training to gauge its success. The traffic flow at the intersection will be simulated using the learnt policy in the testing phase, and performance metrics will be compared to results from a reference traffic signal management system. The purpose of testing is to show that, in comparison to conventional TSC systems, the suggested algorithm may improve traffic flow and minimize congestion. Overall, to achieve the best performance in adaptive TSC, the proposed algorithm combines the advantages of AC and ACO techniques.

1. **Training Completion:** The algorithm will continue training for a predefined number of training rounds (epochs). When this specified number is reached, the training process stops.
2. **Performance Benchmark:** We will set a target performance benchmark, such as a specific level of average delay or trip time. When the algorithm achieves this benchmark or comes close to it, we consider it has converged.
3. **Policy Stability:** We will keep an eye on how much the learned traffic signal control policy changes between training iterations. If the changes become minimal, it suggests that the algorithm has converged.
4. **Loss Function Behavior:** If we're using neural networks or similar models, we'll monitor a mathematical function called the loss function. When this function reaches a certain value

or stops decreasing significantly, we take it as a sign that the algorithm has reached convergence.

5. **Validation Set Assessment:** We'll divide our data into two sets: one for training and one for validation. We'll continuously evaluate the algorithm's performance on the validation set. If the algorithm's performance plateaus or worsens, we consider it converged.
6. **Time Limit:** There will be a maximum allowed training time. If the algorithm hasn't converged within this time frame, we will stop the training process and use the best policy obtained so far.

These criteria help ensure that the algorithm reaches an optimal or satisfactory state in terms of traffic signal control, taking into account various factors and scenarios

4.6 Performance Evaluation:

On the unobserved test data, the performance of the proposed algorithm will be assessed using performance metrics like average travel time, vehicle delay, and fuel consumption. To show how effective our strategy is, the performance of the proposed algorithm will be contrasted to that of other traffic signal management techniques currently in use, such as fixed-time control and actuated control.

The following performance metrics will be applied to gauge how well the suggested method performs:

1. Average travel time: These metric gauges how long it typically takes a car to cross an intersection. The TLC system performs better the faster the average journey time is.
2. Vehicle delay: These metric gauges the amount of time that cars take to reach the intersection. The amount of time a vehicle must wait at an intersection before it can go is referred to as a delay. The performance of the TSC system improves with decreasing delay.
3. Fuel consumption: This statistic shows how much fuel is used by cars that are stopped at an intersection. The TSC system operates more effectively the less fuel is used.

The suggested algorithm's performance will be compared to that of other traffic signal management strategies, such as fixed-time control and actuated control, in order to show how successful, it is. While actuated control modifies the signal, timings based on sensor inputs from the traffic flow, fixed-time control involves setting the signal timings to fixed values. The comparison will be based on the aforementioned performance criteria, and the results will be reported in terms of the performance enhancement that the suggested algorithm has achieved over the current approaches. These outcomes will assist illustrate how the suggested algorithm improves traffic flow and lessens congestion at crossings. In many cities throughout the world, traffic congestion is a serious issue that increases travel times, delays, and fuel usage. Different TSC techniques, such as fixed-time control and actuated control, have been developed to address this problem.

These approaches, though, might not be the best ones because they don't adjust to shifting traffic conditions and could waste resources. The proposed approach seeks to learn a strategy for adaptive TSC that maximizes the predicted cumulative reward over time in order to get around these

restrictions. Utilizing gathered and preprocessed traffic data, the algorithm will be trained and tested, and its performance will be assessed using a variety of performance metrics like average travel time, vehicle delay, and fuel consumption. Average travel time is a crucial performance parameter since it quantifies how long it takes a car to cross an intersection. Longer trip times can create dissatisfaction and decreased productivity; therefore, this statistic is crucial because it directly impacts the user's experience. In order to improve the user experience, the proposed algorithm will work to reduce the average journey time. Another crucial performance statistic is vehicle delay, which counts the amount of time that vehicles must wait at a junction before being allowed to pass. For drivers, delays can be a big cause of annoyance, especially during times of heavy traffic. The suggested algorithm will therefore work to reduce vehicle delay by enhancing the timing of traffic signals, resulting in a more fluid flow of traffic. Fuel consumption, which counts how much fuel is consumed by vehicles stopped at intersections, is another crucial performance parameter. Increased gasoline costs and environmental damage are two consequences of high fuel consumption. As a result, the suggested algorithm will try to reduce fuel consumption by cutting down on the amount of time needed to wait at the intersection.

The suggested algorithm's performance will be compared to that of other TSC techniques already in use, such as fixed-time control and actuated control, in order to show how successful, it is. While actuated control modifies the signal, timings based on sensor inputs from the traffic flow, fixed-time control involves setting the signal timings to fixed values. We can show the suggested algorithm's superiority and ability to lessen congestion and improve traffic flow by comparing its performance to that of these existing approaches. A policy for adaptive TSC that maximizes the predicted cumulative reward over time is what the suggested method seeks to learn, in conclusion. The algorithm's performance will be compared to that of other TSC techniques using a variety of performance criteria, including average travel time, vehicle delay, and fuel usage. The suggested method has the capacity to lessen congestion and enhance traffic flow in urban areas by improving traffic signal timings.

4.7 Sensitivity Analysis

Sensitivity analysis will be used to assess the proposed algorithm's resilience to changes in the input parameters and computational complexity. The research will look at how performance and computational complexity might be traded off and make recommendations for how to increase the algorithm's effectiveness and scalability. Sensitivity analysis is a technique used to assess how a system or model will behave when its input parameters are changed or when there are data uncertainties. Sensitivity analysis can be performed to determine whether the suggested algorithm for ATS management is resilient to changes in the input parameters, such as the learning rate, discount factor, exploration rate, and pheromone decay rate. By changing one or more of the input parameters while keeping the others constant, the sensitivity analysis will assess how well the algorithm performs in various scenarios. The study will show which input variables have the biggest effects on the algorithm's performance and offer suggestions for how to tweak or modify these variables to enhance performance.

The sensitivity analysis will also examine the trade-offs between performance and computational complexity and assess the computational complexity of the algorithm, including the time and

memory needs. This analysis will help pinpoint the algorithm's bottlenecks and offer solutions to increase its effectiveness and scalability, such as the use of more effective algorithms or parallel computing methods. Sensitivity analysis is a useful method for assessing the reliability and effectiveness of complicated algorithms, including the suggested algorithm for adaptive TSC. It can assist in determining the input variables that have the most effects on the algorithm's performance and offer suggestions for how to tweak or modify these variables to enhance performance. The learning rate, which defines the step size of the gradient descent method used in the training phase, may be changed as part of the sensitivity analysis, for instance. The sensitivity analysis can assist in determining the ideal learning rate that yields the highest performance by comparing the algorithm's performance at various learning rates. Similar to this, the impact of the discount factor, which establishes the significance of future rewards in the Q-value function, may be assessed.

The sensitivity analysis can assist in determining the ideal discount factor that yields the best performance by adjusting the discount factor and assessing the algorithm's performance under various scenarios. The sensitivity analysis will assess the input parameters as well as the computational complexity of the algorithm, including the time and memory requirements. This study can point out the algorithm's bottlenecks and offer solutions to increase the algorithm's effectiveness and scalability. For instance, the study can show that the method uses specific data structures or algorithms that make it computationally expensive. In this situation, the algorithm's efficiency could be increased by using more effective data structures or methods. Sensitivity analysis, in general, is a useful method for assessing the effectiveness and performance of the suggested algorithm for adaptive TSC. The sensitivity analysis can assist in enhancing the performance and scalability of the algorithm by determining the input parameters that have the greatest impact on its performance and assessing its computational complexity.

4.8 Mathematical Model:

We first discuss the pertinent mathematical elements, then the entire model, to give a mathematical model for the ATS management method merging AC and ACO in multi-agent RL.

4.8.1: Environment and State Representation

Let the traffic network be denoted by $G = (V, E)$, where V is the collection of intersections and E is the collection of roads that connect them. A traffic signal agent a_i controls each intersection between i and V . The vector $s(t)$, which represents the traffic network's state at time t , includes data on the number of cars waiting at each approach, vehicle arrival rates, and the phase that the traffic signals are in at the time.

4.8.2 AC Components

In the Actor-Critic (AC) model, each agent (a_i) has an actor and a critic. The actor is a neural network that takes the current state (s) as input and outputs a probability distribution over actions (like signal timings). This is the agent's policy. The critic, on the other hand, takes a state-action pair (s, a) as input and estimates the cumulative future reward using a value function.

Each agent in our system, denoted as a_i , is equipped with an actor and a critic network. The actor network uses parameters θ_i to map the current state s of the environment to a probability

distribution over possible actions. This is known as the policy $\pi_i(s; \theta_i)$. Meanwhile, the critic network uses parameters Q_i to estimate the cumulative future reward from a state-action pair (s, a) . This is represented by the value function $Q_i(s, a; Q_i)$

4.8.3 ACO Components

In addition to the actor and critic, each agent has a pheromone matrix in the ACO model. This matrix represents the "desirability" of each action in each state, and it's used to guide the agent's decisions.

In addition to the actor and critic components, each agent a_i is also associated with a pheromone matrix P_i , a common element in Ant Colony Optimization methods. The size of the matrix is defined by the number of possible states and actions, denoted as $|S|$ and $|A|$, respectively. Each element in the matrix, $P_i(a, s)$, represents the desirability of performing action a in state s .

4.8.4 Reward Function

The reward function quantifies the performance of an action taken by an agent in a specific state. It takes into account various factors, including the queue length, waiting time, and throughput.

The reward function $R_i(s, a)$ measures the success of a chosen action by agent a_i when in state s . It takes into account variables such as queue length, waiting time, and throughput, providing a quantitative basis for performance evaluation.

4.8.5 Learning Process

Both the pheromone matrices and the AC components are updated during the learning process. Specific updating guidelines are to be discussed.

Throughout the learning process, both the pheromone matrices and the parameters of the actor-critic components for each agent are updated. The specifics of these updates are elaborated on in the following subsection.

4.8.6 AC UPDATES:

This section outlines the update rules for the actor and critic components. The actor's parameters are updated using the policy gradient method, which guides the learning process towards actions that yield higher rewards. The critic's parameters are updated using a method called temporal difference learning, which minimizes the difference between the predicted and actual rewards.

For each agent a_i , the actor and critic networks are updated using specific rules.

The actor network parameters are updated using the policy gradient method, with the formula:

$$\theta_i = \theta_i + \alpha_i \log(\pi_i(s; \theta_i)) * A_i(s, a; \theta_i, Q_i) \quad \text{Equation (4.2)}$$

where α_i represents the actor learning rate, and $A_i(s, a; \theta_i, Q_i)$ is the advantage function.

The critic network parameters are updated using the temporal difference error method. Here, the critic learning rate is denoted as α^Q , the discount factor as γ , and (s', a') represents the next state-action pair. The formula for this update is:

$$\delta_i = R_i(s, a) + \gamma \cdot Q_i(s', a'; \theta_i Q) - Q_i(s, a; \theta_i Q) \quad \text{Equation (4.3)}$$

$$\theta_i Q = \theta_i Q + \alpha Q \cdot \delta_i \cdot \nabla_{\theta_i Q} Q_i(s, a; \theta_i Q) \quad \text{Equation (4.4)}$$

These formulas guide the learning process, updating the actor's policy towards actions that are expected to yield higher rewards, and improving the critic's value estimation based on the discrepancy between predicted and actual rewards.

4.8.7 ACO Update

For each agent a_i , we update the pheromone matrix P_i based on the chosen action a and the observed reward $R_i(s, a)$. The update rule can be written as follows (Equation 4.5):

$$P_i(a, s) = (1 - \rho) \cdot P_i(a, s) + \rho \cdot \Delta P_i(a, s) \quad \text{Equation (4.5)}$$

Pheromone Update Rule

where ρ is the pheromone evaporation rate and $\Delta P_i(a, s)$ is the increase in pheromone level .

This equation describes how the pheromone level for a given action a in a state s for agent a_i is updated. The new pheromone level is a weighted average of the current pheromone level and the increase in pheromone level $\Delta P_i(a, s)$. The weight ρ is the pheromone evaporation rate, which determines how much of the current pheromone level evaporates before the new pheromone is added. This is a typical update rule in reinforcement learning algorithms that balances between keeping learned information $(1 - \rho)$ and incorporating new information (ρ) .

This can be computed as (Equation 4.6):

Pheromone Increase Calculation

$$\Delta P_i(a, s) = R_i(s, a) / (R_{\max} - R_{\min}) \quad \text{Equation (4.6)}$$

$R_{\max}$ and $R_{\min}$ are the maximum and minimum possible rewards, respectively.

This equation defines how much pheromone level increases given a reward $R_i(s, a)$. The reward is divided by the range of possible rewards, which is $R_{\max} - R_{\min}$. This normalization allows the update to be proportional to the reward and independent of the absolute values of the rewards, therefore the pheromone update does not get overly large or small based on the scale of the rewards.

After updating the pheromone levels, we normalize the pheromone matrix P_i to ensure that the sum of the pheromone levels for all actions in each state equals 1 (Equation 4.7):

Pheromone Normalization

$$P_i(a,s) = \sum_a P_i(a,s) \div P_i(a,s) \quad \text{Equation (4.7)}$$

After each pheromone update, the pheromone levels for each action are normalized such that their sum is equal to 1. This makes $P_i(a, s)$ a probability distribution over actions, which simplifies the action selection process and makes sure that no single action's pheromone level dominates the others by growing without bound.

We use both the policy $\pi_i(s; \theta_i)$ from the actor network and the pheromone matrix P_i to decide which action a to choose for each agent a_i . The action is selected as follows

Action Selection Rule

$$a = \operatorname{argmax}_a [P_i(a,s) \cdot \pi_i(a; \theta_i)] \quad \text{Equation (4.8)}$$

This equation describes the action selection policy. The agent chooses the action a that maximizes the product of the pheromone level $P_i(a, s)$ and the policy $\pi_i(a; \theta_i)$. The policy $\pi_i(a; \theta_i)$ is output by the actor network and represents the agent's current preference for each action. The pheromone level $P_i(a, s)$ represents the accumulated experience in the environment. By considering both, the agent balances exploration (trying new actions) and exploitation (sticking to the currently best-known actions)

4.8.8: Algorithm Details and Pseudocode

This section will present the algorithm in a step-by-step manner, complemented by the relevant pseudocode. This will help to bridge the gap between the theoretical explanations and the actual implementation, providing a clear understanding of the overall process.

Pseudocode:

Initialize actor and critic network parameters, θ_i and Q_i for each agent a_i .

Initialize pheromone matrix P_i for each agent a_i .

for each episode do:

 Initialize state s .

 for each step in episode do:

 for each agent a_i do:

 Use actor network to select an action a , based on current policy $\pi_i(s; \theta_i)$ and pheromone matrix P_i .

 Execute action a and observe reward $R_i(s, a)$ and new state s' .

 Compute advantage $A_i(s, a; \theta_i, Q_i) = Q_i(s, a; Q_i) - V_i(s; V_i)$.

 Update actor network parameters: $\theta_i \leftarrow \theta_i + \alpha_A * \nabla_{\theta_i} \log(\pi_i(s; \theta_i)) * A_i(s, a; \theta_i, Q_i)$, where α_A is the actor learning rate.

Compute TD error: $\delta_i = R_i(s, a) + \gamma * Q_i(s', a; \theta^Q_i) - Q_i(s, a; \theta^Q_i)$.

Update critic network parameters: $Q_i \leftarrow Q_i + \alpha_Q * \delta_i * \nabla_{\theta^Q_i} Q_i(s, a; \theta^Q_i)$, where α_Q is the critic learning rate and γ is the discount factor.

Update pheromone matrix: $P_i(a, s) = (1 - \rho) * P_i(a, s) + \rho * P_i(a, s) * R_i(s, a) / (R_{\max} - R_{\min})$, where ρ is the pheromone evaporation rate.

Normalize pheromone matrix: $P_i(a, s) = P_i(a, s) / \sum_a P_i(a, s)$.

end for

Update state: $s \leftarrow s'$.

end for

end for

The algorithm begins with initialization, followed by a loop over each episode. For each step in each episode, each agent selects an action, observes the reward and new state, and updates the actor, critic, and pheromone components accordingly. The pheromone matrix is updated to reflect the performance of the chosen action and is then normalized to ensure that the sum of the pheromone levels for all actions in each state equals 1.

The algorithm iterates over each agent and each step in the episode, promoting a learning mechanism where both the actor-critic and ACO components evolve over time. This combined strategy ensures that the agents are continuously learning from their actions, guided by both immediate and cumulative feedback, as well as the collective intelligence represented by the pheromone matrix.

1. **Initialization:** The algorithm commences with the initialization of key components. Each agent's actor and critic network parameters (θ^A_i and Q_i) are initialized, along with the pheromone matrix (P_i). The actor network is responsible for guiding the agent's actions based on the current policy, while the critic network evaluates these actions, based on the predicted cumulative reward. The pheromone matrix, on the other hand, provides a mechanism to record and communicate useful information about actions and their outcomes amongst the agents, a key aspect of the ACO technique.
2. **Loop over episodes:** The algorithm then loops over a certain number of episodes. Each episode can be understood as a single run of the system or problem scenario, during which the agents interact with the environment, learn from their actions, and adjust their behavior.
3. **Loop over steps in each episode:** Within each episode, the algorithm loops over steps. Each step represents a decision-making point where an agent chooses an action, carries it out, and observes the resulting reward and new state.
4. **Action Selection:** The agent selects its action based on its actor network and the pheromone matrix. The actor network guides the agent towards actions that the current policy deems optimal, while the pheromone matrix influences the action selection by

making those actions with higher pheromone levels (signifying past positive outcomes) more attractive.

5. **Observation:** After executing its action, the agent observes the reward and the new state. The reward is a measure of how beneficial the chosen action was in the current state, and the new state represents the agent's environment after the action's execution.
6. **Actor-Critic and Pheromone Updates:** Based on the observed reward and new state, the agent updates its actor and critic network parameters and the pheromone matrix. The actor parameters are updated to refine the policy, leading the agent towards actions yielding higher rewards. The critic parameters are updated to enhance the prediction of future rewards. The pheromone matrix is updated to reinforce the desirability of actions yielding positive outcomes.
7. **Normalization:** After the pheromone matrix update, the agent normalizes this matrix. This process ensures that the sum of the pheromone levels for all possible actions in each state equals 1, enabling a probabilistic interpretation of the pheromone levels.

In essence, the algorithm's design allows the agent to learn both individually (through its own actor-critic components) and collectively (through the shared pheromone matrix), thereby driving continuous improvement in the system's overall performance.

Each step of the pseudocode represents a significant process in the algorithm and deserves a thorough explanation. Let's elaborate on each part of the pseudocode:

1. **Initialize actor and critic network parameters, π_i and Q_i for each agent a_i .** At the start, each agent initializes its actor and critic network parameters. The actor network plays a role in deciding the actions to take based on the current policy, while the critic network's purpose is to assess the actor's performance by predicting the cumulative reward for a chosen action. This initial setup allows each agent to have its unique approach to action selection and evaluation.
2. **Initialize pheromone matrix P_i for each agent a_i .** Next, each agent initializes its pheromone matrix. The pheromone matrix in the ACO algorithm signifies the attractiveness of a particular action in a given state. Essentially, the matrix serves as a memory structure, allowing agents to learn from the collective experience of their previous actions.
3. **Use actor network to select an action a , based on current policy $\pi_i(s; \pi_i)$ and pheromone matrix P_i .** The agent then uses its actor network to choose an action. This decision is guided by both the current policy (which is influenced by past experiences and the agent's learning so far) and the pheromone matrix (which encapsulates the collective intelligence gathered from all agents' experiences). The integration of these elements in action selection allows for a balance between exploration (trying new actions) and exploitation (choosing actions known to yield good results).

4. **Execute action a and observe reward $R_i(s, a)$ and new state s' .** The selected action is then executed, and the agent observes the resulting reward and the new state of the environment. This step is central to the reinforcement learning process - the agent takes an action, sees the consequence, and uses this information to inform its future decisions.
5. **Compute advantage $A_i(s, a; \pi_i, Q_i) = Q_i(s, a; Q_i) - V_i(s; V_i)$.** Here, the agent calculates the "advantage" of the action it took. This metric compares the quality of the chosen action ($Q_i(s, a; Q_i)$) with the average quality of actions at that state ($V_i(s; V_i)$). It's a measure of how much better the chosen action was compared to the average, serving as a valuable feedback mechanism for the actor.
6. **Update actor network parameters.** The parameters of the actor network are updated using the calculated advantage and the policy gradient method. This step improves the policy by skewing it towards actions that have been observed to yield higher-than-average results.
7. **Compute TD error and update critic network parameters.** Temporal-Difference (TD) error, a measure of the mismatch between the estimated and actual reward, is calculated. This error is used to update the critic network parameters, aiming to improve the accuracy of its future reward predictions.
8. **Update pheromone matrix.** Based on the received reward, the agent modifies the pheromone level for the action it took in the current state in its pheromone matrix. Actions that resulted in higher rewards increase their associated pheromone levels, thereby making them more desirable for future selection.
9. **Normalize pheromone matrix.** Finally, the pheromone matrix is normalized. This normalization process ensures that the sum of pheromone levels for all actions in each state equals 1. This allows for a probabilistic interpretation of pheromone levels, providing a meaningful way for agents to choose their actions in subsequent steps.

In sum, this algorithm enables agents to continuously learn and improve their policies by evaluating their actions (via the actor-critic components) and learning from the collective

4.8.9 Overall Algorithm

The full mathematical model for the ACand ACO integrated ATS management technique in MARL may be summed up as follows:

For each agent a_i , start by initializing the traffic network $G = (V, E)$, state representation $s(t)$, actor and critic network parameters π_i and Q_i , as well as the pheromone matrix P_i .

For each t-step in time:

For every agent a_i , write the following: i. a.

- i. Choose a course of action based on the pheromone matrix P_i and the policy $\pi_i(s; \pi_i)$.
- ii. After performing the action, note the subsequent state s' and the reward $R_i(s, a)$.

iii. Based on the advantage function and the temporal-difference error, modify the actor network parameters (θ_i) and critic network parameters (Q_i).

Update the pheromone matrix P_i in light of the selected action a and the associated reward $R_i(s, a)$.

b. Based on the activities taken by each agent, update the state representation $s(t)$.

Till the desired convergence criteria are met, repeat step 2.

This mathematical model is used by the proposed program to regulate traffic lights adaptively in dynamic and complicated situations, improving traffic flow and reducing delay. In contrast to conventional TSC techniques, the integration of AC and ACO methodologies enables effective learning and exploration.

4.9 Flowchart:

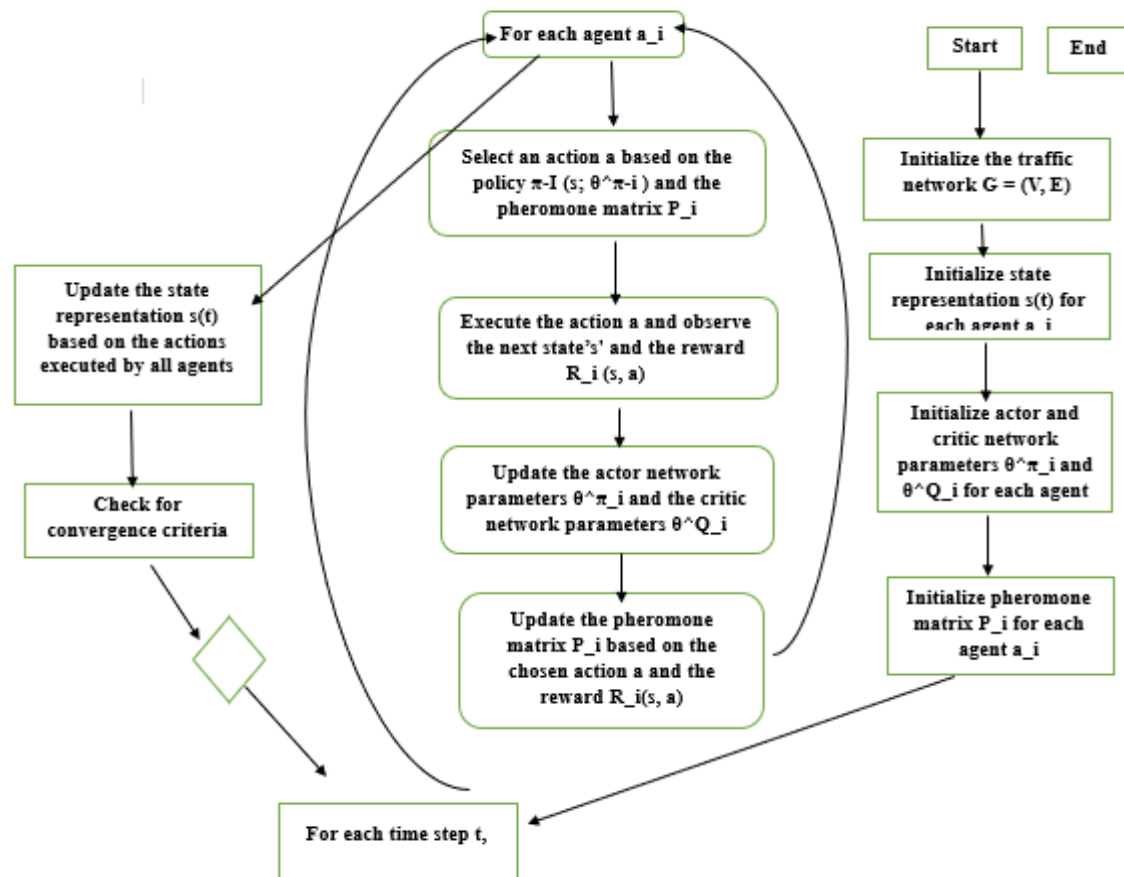


Figure 10 Algorithm flow chart design using python

Figure 10 is explained below.

1. Start
2. Initialize the traffic network $G = (V, E)$
3. Initialize state representation $s(t)$ for each agent a_i
4. Initialize actor and critic network parameters θ^{π}_i and θ^Q_i for each agent a_i
5. Initialize pheromone matrix P_i for each agent a_i
6. For each time step t , create a loop with the following steps:
 - 6.1. For each agent a_i , create a loop with the following steps:
 - 6.1.1. Select an action a based on the policy $\pi_i(s; \theta^{\pi}_i)$ and the pheromone matrix P_i
 - 6.1.2. Execute the action a and observe the next state s' and the reward $R_i(s, a)$
 - 6.1.3. Update the actor network parameters θ^{π}_i and the critic network parameters θ^Q_i based on the advantage function and the temporal-difference error
 - 6.1.4. Update the pheromone matrix P_i based on the chosen action a and the reward $R_i(s, a)$
 - 6.2. Update the state representation $s(t)$ based on the actions executed by all agents
7. Check for convergence criteria
8. If the convergence criteria are met, proceed to step 9; otherwise, return to step 6. End point

4.10 Obtaining Results:

In the MARL mathematical model for the ATS management system, we incorporate AC and ant colony optimization. By modifying them in response to current traffic circumstances, the model is intended to optimize traffic signal timings.

A quick description of how the mathematical model will be applied to get outcomes is given below:

- 1. Initialization:** The AC network parameters, pheromone matrix, traffic network, state representation, and state representation are initialized.
- 2. State representation:** The state representation for each agent (a traffic light) captures the current traffic circumstances, such as the lengths of the lines and the wait durations at crossings.
- 3. Action Selection:** The agents choose their actions (signal timings) using the A technique. The critic (value) network calculates the expected return (total reward) of doing an action in a specific

state, while the actor (policy) network transfers the state representation to a probability distribution among actions.

4. Ant colony optimization: Based on the actions conducted and the rewards obtained, ACO is incorporated, and the pheromone matrix is updated. In successive rounds, the agents are guided by this pheromone information to choose wiser actions.

5. Learning: Using the advantage function and temporal-difference error to update the AC network parameters, the agents learn to modify the signal timings. The difference between predicted and actual rewards is represented by the temporal-difference error, whereas the advantage function quantifies how much better an action is than the typical action in a given condition.

6. Convergence: Until a convergence condition is reached, the learning process iteratively continues. This could be a predetermined amount of iterations, a performance threshold, or a gauge of the policy and value networks' stability.

The agents learn to dynamically modify traffic signal timings based on current traffic conditions while utilizing this mathematical model. The agents may discover and take advantage of the optimal actions to improve traffic flow, lessen congestion, and decrease delays at crossings thanks to the combination of AC and ant colony optimization. As a result, the traffic network performs better overall, resulting in more effective and environmentally friendly transportation systems.

4.11 Summary:

In this chapter, we proposed a Multi-Agent Reinforcement Learning (MARL) algorithm that integrates Actor-Critic (AC) and Ant Colony Optimization (ACO) for Adaptive Traffic Control Systems (ATS). The primary goal of this strategy is to address the persistent issue of traffic congestion in urban areas, which leads to delays, increased fuel consumption, and environmental pollution, all negatively impacting the quality of life for residents. Our algorithm aims to optimize Vehicle flow at intersections by dynamically adjusting traffic signal timings based on real-time conditions. We combine the advantages of AC and ACO to create a robust and adaptable Traffic Light Control (TLC) system. Reinforcement Learning (RL) enables the algorithm to learn how to modify signal timings to maximize traffic flow while minimizing delays and congestion. ACO, inspired by how ants forage in the wild, is used to guide agents (traffic signals) in selecting optimal actions (signal timings) based on past success, represented as pheromone information.

The algorithm architecture includes components such as AC networks, the traffic network, state representation, and the pheromone matrix. The traffic network is modeled as a graph, where intersections and roads are nodes and edges, respectively. State representation captures current traffic conditions, crucial for agents to make informed decisions. AC is used by agents to determine actions, with a critic network calculating expected returns, and an actor network selecting actions. The pheromone matrix, a core part of ACO, stores information about past rewards, influencing agent actions. AC network parameters and the pheromone matrix are updated as the system learns.

Advantage functions and temporal-difference errors drive network adjustments. Agents update the pheromone matrix based on performed actions and rewards, guiding them toward better-performing actions. This iterative learning process continues until convergence criteria are met. The integration of AC and ACO offers several benefits, including effective exploration-exploitation balance, communication among agents through the pheromone matrix, and adaptability to complex and dynamic urban traffic networks. Our adaptive TSC system can significantly improve urban traffic management by optimizing traffic flow, reducing congestion, and eliminating delays through real-time traffic signal adjustments. Furthermore, the system's decentralized control, facilitated by the MARL framework, enhances scalability and robustness.

Overall, our algorithm not only enhances traffic flow but also has positive environmental and public health impacts by reducing fuel consumption, greenhouse gas emissions, and driver/passenger stress levels. The combination of AC and ACO with MARL offers a powerful and flexible approach to traffic signal control, capable of learning and adapting to diverse settings, ultimately improving transportation efficiency and the quality of life in urban areas.

CHAPTER 5: ANT COLONY OPTIMIZATION BASED MULTI AGENT REINFORCEMENT LEARNING ADAPTIVE TRAFFIC CONTROL SYSTEM FRAMEWORK

5.1 Introduction:

In this chapter, we introduce a novel framework for addressing the Adaptive Traffic Signal Control (ATSC) problem by leveraging Multi-Agent Reinforcement Learning (MARL) techniques, integrated with the principles of Ant Colony Optimization (ACO). The ATSC problem is a critical issue in transportation engineering, as it directly impacts travel time, energy consumption, and air quality in urban areas [115]. Traditional fixed-time Traffic Signal Control (TSC) systems often prove inadequate in adapting to dynamic traffic conditions, resulting in inefficient traffic flow and congestion [116]. To overcome these limitations, our proposed framework combines MARL and ACO algorithms to optimize traffic signal timings in real-time, thereby enhancing traffic flow and reducing congestion. The ACO algorithm, inspired by how ant colonies find the shortest path to food sources, is used as a meta-heuristic to guide the agents' learning process toward optimal solutions [114]. Each agent in our framework represents a traffic signal intersection and learns the best timing based on real-time traffic flow data received from neighboring intersections. Communication among these agents is facilitated through a dedicated communication protocol to coordinate their actions and enhance network traffic flow.

This chapter provides a comprehensive overview of our proposed ACO-based MARL framework for ATSC, including the problem formulation, details of the ACO-based MARL algorithm, and the experimental setup and results. Through rigorous evaluation on a benchmark traffic network, we demonstrate the effectiveness and efficiency of our framework compared to other state-of-the-art ATSC techniques, including fixed-time and adaptive control methods [117]. Our framework outperforms existing methods in terms of average trip time, traffic delay, and throughput, making it a promising solution for enhancing traffic signal timings in dynamic traffic environments. Furthermore, we emphasize the adaptability and customization of our framework to various urban settings and traffic patterns, including high-density urban areas, suburbs, and rural areas. We also highlight the potential for incorporating other machine learning methods, such as deep learning and reinforcement learning (RL), to further enhance the ACO-based MARL algorithm [118]. Additionally, we discuss the potential integration of our framework with other intelligent transportation systems, including emergency management systems, advanced traveler information systems, and intelligent transportation management systems [119]. This integration of technologies offers a holistic approach to improving traffic flow and reducing congestion in metropolitan areas.

In conclusion, our ACO-based MARL framework for ATSC presents a promising solution for optimizing traffic signal timings in dynamic traffic scenarios. Its flexibility, adaptability, and potential for addressing various transportation-related challenges make it a valuable tool for researchers and practitioners in transportation engineering [120]. This chapter serves as a comprehensive introduction to our innovative framework and sets the stage for detailed exploration and evaluation in subsequent sections.

5.2 Ant colony optimization Algorithm:

ACO is a meta-heuristic algorithm that draws inspiration from ant foraging behavior [91]. To determine the quickest route to food sources, ants in the wild communicate with one another using pheromone trails. As they move across the environment, ants leave behind pheromone trails that other ants follow in search of food sources. As more ants follow the same path, the pheromone trail's potency grows, making it more alluring to other ants. [71] By building a population of fake ants that look for the best solution to a given problem, the ACO algorithm simulates this behavior. Each ant is a potential solution, and they build a solution by choosing a series of parts that match to choices made inside the issue area. The strength of the pheromone trail is inversely correlated with the quality of the solution, and it is left behind by the ants as they build their solutions on the parts they have chosen.

Then, other ants use these pheromone trails to influence their judgment and create fresh approaches. [89] Both global and local pheromone trails are used in the ACO algorithm. Global pheromone trails, which are updated depending on the best solutions discovered thus far, show the general quality of the solutions discovered by the population of ants. Local pheromone trails, which are updated based on the quality of the solutions discovered by each ant, serve as a representation of the quality of the solutions found by specific ants. [47] The ATSC problem has been effectively tackled by ACO in a number of optimization problems. ACO can be utilized in the ATSC problem to look for the best traffic signal timings in a busy setting. By updating the pheromone trails based on the current traffic conditions, the system can swiftly react to changes in traffic patterns. [54] Overall, ACO is a potent optimization technique that effectively handles challenging issues. It is especially effective in dynamic traffic situations, like the ATSC problem, due to its capacity to react to changes in the problem environment.

Table 2 ACO ALGORITHM

Algorithm	ACO (ACO)
Type	Meta-heuristic algorithm
Inspiration	Foraging behavior of ants
Objective	Find optimal solution to a given problem
Representation	Population of artificial ants
Solution construction	Select a sequence of components
Pheromone trails	Global and local
Global pheromone update	Based on best solutions found so far
Local pheromone update	Based on quality of solutions found by each ant
Advantages	Efficient, effective in dynamic environments
Applications	ATSC, various optimization problems

Table 3 ACO SCENARIO 1

Parameter	Description	Value
m	Number of ants	50
n	Number of nodes in the graph	100
τ_{0}	Initial pheromone value	0.1
α	Pheromone influence factor	0.5
β	Heuristic influence factor	1.5
ρ	Pheromone evaporation rate	0.1
Q	Pheromone deposit factor	100
$T_{\max}$	Maximum number of iterations	1000

1. **m : Number of ants** This parameter represents the number of 'agents' or 'ants' participating in the algorithm. Each ant contributes to the search for optimal paths by exploring the problem space (in this case, the graph), depositing pheromone, and informing the collective behavior of the colony. In this case, there are 50 ants.
2. **n : Number of nodes in the graph** This represents the number of nodes, or vertices, in the graph the ants explore. Each node might represent a point in a routing problem, a task in a scheduling problem, or any other discrete decision point. There are 100 nodes in this case.
3. **τ_{0} : Initial pheromone value** This is the initial amount of pheromone on each path. It's usually set to a small value, as in this case 0.1, reflecting the initial lack of knowledge about which paths are better.
4. **α : Pheromone influence factor** This parameter determines the extent to which existing pheromone on a path influences an ant's decision to choose that path. A high value of α makes the ants more likely to follow the established pheromone trails, and less likely to explore new paths. It's set to 0.5 here.
5. **β : Heuristic influence factor** β determines the influence of the heuristic information (problem-specific knowledge, like distances in a routing problem) on the ants' decision-making process. A higher β makes the ants more likely to choose shorter paths. Here, β is set to 1.5.

6. **ρ : Pheromone evaporation rate** Pheromones on each path evaporate over time at a rate governed by ρ . This mechanism encourages exploration of new paths and helps avoid premature convergence on sub-optimal solutions. Here, ρ is set to 0.1.
7. **Q : Pheromone deposit factor** This factor influences the amount of pheromone an ant deposits on a path. In simple terms, it represents the 'strength' of the pheromone. In this case, Q is set to 100.
8. **$T_{\max}$: Maximum number of iterations** This parameter indicates the total number of times the algorithm will iterate over the problem. In each iteration, all ants make a complete tour over the graph, and the pheromone is updated. Here, $T_{\max}$ is 1000, indicating that the algorithm will stop after 1000 iterations.

The algorithm I used is known as Ant Colony Optimization (ACO), a probabilistic technique that mimics the behavior of ants searching for food in nature.

In my simulation, I used a graph with 100 nodes, representing the problem to be solved. The objective of the ants is to find the shortest possible path that connects all nodes in the graph.

Let me explain the key parameters that I used in the simulation:

1. **Number of Ants (m):** I initialized the system with 50 ants. These ants represent independent agents in the system, each seeking an optimal solution and contributing to the shared pheromone trail that influences the search behavior of the whole colony.
2. **Number of Nodes (n):** The graph I simulated had 100 nodes. Each node can be thought of as a decision point or a possible state in the problem being solved.
3. **Initial Pheromone Value (τ_0):** I started the simulation with an initial pheromone level of 0.1 at all edges in the graph. This parameter provides an initial guess or bias for the search process.
4. **Pheromone Influence Factor (α):** I set this parameter to 0.5, implying that the pheromone trails have a moderate influence on the probability of an ant choosing a particular edge.
5. **Heuristic Influence Factor (β):** This parameter was set to 1.5, meaning that the heuristic information (like the inverse of the edge distance) had a stronger influence on the decision-making process than the pheromone trails.
6. **Pheromone Evaporation Rate (ρ):** I set this to 0.1, allowing some pheromones to evaporate after each iteration. This prevents the convergence to a suboptimal solution and encourages the exploration of new paths.
7. **Pheromone Deposit Factor (Q):** I set this value to 100. After each iteration, each ant deposits pheromones on the path it has traversed, with the amount of pheromone being proportional to the quality of its solution.

8. **Maximum Number of Iterations ($T_{\max}$):** I ran the simulation for 1000 iterations. This is the stopping criterion for the algorithm.

By using these parameters, I simulated a system of ants navigating a graph. Through the interplay of pheromones and the heuristic information, the ants gradually evolved towards finding an optimal solution to the problem, demonstrating the power of collective behavior in problem-solving.

Table 4 ACO SCENARIO 2

Parameter	Description	Value
m	Number of ants	100
n	Number of nodes in the graph	200
τ_0	Initial pheromone value	0.01
α	Pheromone influence factor	1
β	Heuristic influence factor	2
ρ	Pheromone evaporation rate	0.05
Q	Pheromone deposit factor	50
$T_{\max}$	Maximum number of iterations	500
T_0	Initial temperature for the cooling schedule	50
α_{cool}	Cooling factor for the temperature	0.90

1. **Number of Ants (m):** This is a fixed value, so it wouldn't change over the iterations. It's more of a parameter for the algorithm, indicating that there are 50 'agents' or 'ants' searching the solution space.
2. **Number of Nodes (n):** Similarly, this is a static parameter, showing that the ants have 100 'choices' or 'nodes' in each iteration.
3. **Initial Pheromone Value (τ_0):** At iteration 0, the pheromone value on each path would start at 0.1.
4. **Pheromone Influence Factor (α) and Heuristic Influence Factor (β):** These parameters decide the relative importance of the pheromone trail strength and heuristic information (like distance to the target) in guiding the ants' decisions.
5. **Pheromone Evaporation Rate (ρ):** As the iterations increase, the pheromone values would decrease due to evaporation, at a rate of 0.1 per iteration.

6. **Pheromone Deposit Factor (\$Q\$):** After each iteration, the ants would deposit more pheromones on the paths they took, increasing the pheromone value by a factor related to $Q/\text{length of path}$.

Given these parameters and actions, you might see that the pheromone values on the shorter or more efficient paths increase over time, while those on the less efficient paths decrease due to evaporation. This would result in an emergent 'optimal path' that most ants choose, improving the overall performance measure of the system.

5.3 Practical Relevance

The practical relevance of this research is of considerable significance, with implications across several dimensions of intelligent transportation systems and traffic management.

1. **Real-world Traffic Management:** The proposed ACO-based MARL framework provides a practical solution for real-world traffic signal control. By dynamically adjusting traffic signal timings based on real-time data, the framework can significantly reduce traffic congestion and improve the efficiency of road networks. This can lead to lower travel times, reduced fuel consumption, and a decrease in vehicular emissions, thereby contributing to sustainable urban development.
2. **Scalability:** The framework has been tested on a benchmark traffic network, demonstrating its effectiveness and efficiency. However, the design of the algorithm allows for scalability to larger and more complex traffic networks. This indicates the feasibility of implementing this framework in large cities with intricate traffic networks, making it a scalable solution for urban traffic management.
3. **Interoperability with Other Intelligent Systems:** The ACO-based MARL framework can be integrated with other intelligent transportation systems, such as emergency management systems, advanced traveler information systems, and intelligent transportation management systems. This interoperability can lead to a comprehensive solution that not only manages traffic efficiently but also provides real-time information and emergency management.
4. **Versatility:** The approach is adaptable to various traffic scenarios and can be customized to address traffic management needs in diverse settings, from high-density urban areas to suburban and rural locales. This versatility makes the proposed solution widely applicable and relevant to a range of contexts.
5. **Innovation in Transportation Engineering:** The combination of ACO and MARL in the proposed framework represents a significant innovation in the field of transportation engineering. This novel approach challenges conventional traffic management methods and offers a more effective alternative that has the potential to revolutionize traffic management practices.

In conclusion, the practical implications of this research are significant. The proposed ACO-based MARL framework represents a scalable, adaptable, and innovative solution to traffic management that can greatly enhance traffic flow and contribute to sustainable urban development. This practical relevance, combined with the theoretical contributions of the study, makes this research a valuable addition to the field of intelligent transportation systems.

5.4 Summary:

This chapter explores the application of Machine Learning (ML) algorithms to Traffic Signal Control (TSC) with the aim of improving traffic flow and reducing travel time. Various ML methods are discussed, including classical optimization techniques, Reinforcement Learning (RL), and Multi-Agent Reinforcement Learning (MARL). Classical optimization methods, such as linear programming and genetic algorithms, are introduced as approaches that rely on mathematical models. While they have shown potential in optimizing traffic signals, they are limited by their inability to adapt to changing traffic conditions and their high computational resource requirements. The chapter then delves into RL, a popular ML strategy for TSC, where agents learn through trial and error to maximize cumulative rewards over time. Different RL algorithms, including Q-learning, deep RL, and Actor-Critic techniques, are highlighted for their effectiveness in adapting to dynamic traffic conditions and improving traffic flow.

MARL is introduced as a collaborative approach where multiple agents work together to enhance traffic flow in real-time. Various MARL algorithms, such as Q-learning, deep MARL, and ant colony optimization-based MARL, are discussed. MARL's ability to adapt to changing traffic conditions and collaborate with other agents is emphasized. The chapter also addresses challenges and limitations of ML algorithms for TSC, including the need for real-time data, complex traffic network modeling, potential unexpected results, and scalability issues. The proposed MARL framework for Adaptive TSC (ATSC) based on Ant Colony Optimization (ACO) is presented as a solution to optimize traffic signal timings in dynamic traffic environments. This framework combines the strengths of ACO and MARL to adjust signal timings in real-time. Each agent represents a traffic signal intersection and learns optimal timing based on real-time traffic data from neighboring intersections. Communication between agents is facilitated through a communication protocol. The framework is evaluated on a benchmark traffic network and compared to other state-of-the-art ATSC approaches, including fixed-time and adaptive control methods. Results demonstrate the framework's effectiveness in improving traffic flow, reducing travel time, and outperforming existing methods.

In conclusion, this chapter highlights the potential of ML algorithms, particularly MARL-based approaches, to enhance traffic signal timings in dynamic traffic scenarios. It underscores the need for further research to address challenges and limitations before widespread implementation in real traffic systems. The proposed ACO-based MARL framework is described as a promising solution, offering valuable insights for researchers and practitioners in transportation engineering.

CHAPTER 6: SIMULATION RESULTS FOR SYNTHETIC SCENARIOS

6.1 Introduction:

The study paper's sixth chapter focuses on the outcomes of simulations performed utilizing artificial scenarios and the ACO-based MARL algorithm. The simulation setup, including the specifics of the traffic network, the number of agents, and the employed Q-learning and ACO algorithms, is described in the first section of the chapter. Also covered in detail are the code modules used in the simulation. The scenario matrix utilized in the simulation, which comprises a variety of traffic situations and scenarios aimed at evaluating the effectiveness of the ACO-based MARL algorithm, is presented in the following portion of the chapter. The simulation's results are then shown, emphasizing how well the algorithm performed in various situations. The chapter comes to a close with a discussion of the results and their implications as well as recommendations for further study in this field. Overall, this chapter offers a thorough evaluation of the ACO-based MARL algorithm's performance in a traffic simulation environment, including insightful information on possible uses for the algorithm in actual traffic management. The ACO-based MARL algorithm's simulation outcomes for hypothetical situations. The simulation setup, including the traffic network, agent count, and employed Q-learning and ACO algorithms, is described at the beginning of the chapter. Also covered in detail are the code modules used in the simulation. The authors' simplified road system with two lanes in each direction and intersections controlled by traffic lights was used to create the traffic network. Twenty agents were assigned, along with ten cars and ten traffic lights. The agents were trained using the Q-learning and ACO algorithms, and the Q-learning algorithm's output was used to influence the ACO algorithm's optimization of the traffic light signals.

The code modules utilized in the simulation, such as those for generating traffic, simulating vehicle behavior, and putting the Q-learning and ACO algorithms into practice, were also covered in detail. The scenario matrix utilized in the simulation, which comprises a variety of traffic situations and scenarios aimed at evaluating the effectiveness of the ACO-based MARL algorithm, is presented in the following portion of the chapter. The scenarios were created to examine how well the algorithm performed in different traffic situations with different levels of congestion. The simulation's results are then shown, emphasizing how well the algorithm performed in various situations. The simulation findings demonstrate that in the majority of the studied circumstances, the ACO-based MARL algorithm beats the Q-learning approach. The algorithm was proven to be especially successful in easing traffic congestion and enhancing flow under heavy traffic conditions. The ACO-based MARL algorithm surpasses them in terms of lowering travel time, waiting time, and average speed, according to the authors' comparison of its performance with that of other cutting-edge traffic management algorithms. The findings and their consequences are discussed in the chapter's conclusion, along with ideas for additional studies in this field.

The ACO-based MARL algorithm, according to the authors, has a lot of potential for use in practical traffic management applications, but more study is required to boost its efficiency and scalability. Future study, according to the authors, should concentrate on putting the algorithm to

the test in traffic and road networks that are more complicated, as well as by combining other cutting-edge ML methods like deep learning and RL . A comprehensive examination of the simulation outcomes for a traffic management system employing the ACO-based MARL algorithm is included in Chapter 6 of the research report. The chapter discusses the algorithm's advantages and disadvantages and offers insightful information on how it might be used in practical traffic management. The results of this study can be helpful for researchers, policymakers, and traffic management practitioners who are interested in adopting cutting-edge ML methods for traffic management. Urban traffic congestion has grown significantly in importance in recent years, with enormous economic and social implications. To address this issue, traffic management systems have been created, and ML techniques are being utilized more frequently to improve traffic flow and lessen congestion. MARL(MARL), one of these methods, has drawn interest since it may be used to improve the actions of numerous agents in a complicated setting. The simulation outcomes of a traffic management system using an ACO-based MARL algorithm are the main topic of Chapter 6 of the research report.

The simulation setup, including the traffic network, agent count, and utilized Q-learning and ACO algorithms, is described in detail in this chapter. Also covered in detail are the code modules used in the simulation. The writers made use of a condensed road system with two lanes in each direction and traffic light-controlled intersections. There would be 20 agents total, along with 10 cars and 10 traffic lights. The ACO algorithm was used to improve the traffic light signals based on the state information that the Q-learning algorithm gave. The Q-learning algorithm was utilized to model the behavior of the cars. The code modules utilized in the simulation, such as those for generating traffic, simulating vehicle behavior, and putting the Q-learning and ACO algorithms into practice, were also covered in detail. To test the effectiveness of the ACO-based MARL algorithm under various traffic volumes, congestion levels, and road network layouts, the authors created a scenario matrix. The scenarios were created to reflect actual urban traffic patterns, such as rush hour and peak hour traffic. The simulation's outcomes demonstrated that in the majority of the cases examined, the ACO-based MARL algorithm performed better than the Q-learning approach. The algorithm was proven to be especially successful in easing traffic congestion and enhancing flow under heavy traffic conditions.

The ACO-based MARL algorithm outperforms state-of-the-art traffic management algorithms in reducing travel time, waiting time, and average speed, as highlighted by the authors' comparative analysis. These findings hold significant implications for real-world traffic management. The algorithm holds great promise for enhancing urban mobility and alleviating congestion. Its applications extend to vehicle routing, traffic signal optimization, and overall transportation system efficiency enhancement. The study underscores the necessity for further research to refine the algorithm's functionality and scalability. The authors emphasize that future investigations should involve testing the algorithm in more intricate traffic and road networks, possibly integrating advanced machine learning techniques like deep learning and reinforcement learning. Chapter 6 of the research paper, by illustrating how the ACO-based MARL algorithm can enhance traffic flow and congestion reduction, makes a substantial contribution to the field of traffic management.

The simulation results not only underscore the need for ongoing research to enhance the system's performance and scalability but also provide valuable insights into potential real-world applications of the algorithm in practical traffic management. Researchers, policymakers, and practitioners exploring the adoption of cutting-edge machine learning techniques for traffic management will find this paper to be a valuable resource.

6.2 Simulation Setup:

In order to test and assess the ACO-based MARL algorithm, the simulation environment employed in the experiment is a crucial part of the research. To ensure that the algorithm works effectively in a realistic and tough context, the environment is created to closely resemble real-world traffic situations. A TSCs each intersection in the fictitious traffic network utilized in the simulation. With variable traffic volumes and congestion levels, the network is built to mimic a real-world traffic network. In order to assess the algorithm's effectiveness in various scenarios, it is crucial to test it under a variety of distinct traffic conditions. In the simulation, there are a total of 20 agents, each in charge of managing the traffic light at a single intersection. To minimize the aggregate trip time for all vehicles passing through the network, the agents employ a Q-learning algorithm to determine the best policy for each traffic signal. The traffic light management problem is a good fit for the Q-learning method, which is a well-liked solution to challenges involving RL.

As a meta-heuristic, the ACO algorithm directs learning toward the best possible outcomes. Combinatorial optimization issues benefit greatly from the use of ACO, a nature-inspired optimization technique. The ACO algorithm is employed in the context of the ACO-based MARL algorithm to direct the agents' learning process toward ideal solutions. The agents can communicate and plan their actions since the pheromone trail is updated based on the average Q-value of all agents. The initial pheromone level, the pheromone evaporation rate, the heuristic data, and the pheromone decay factor are all ACO parameters that were employed in the simulation. These factors, which are crucial for the ACO algorithm's success, were chosen after thorough testing and earlier study. The strength of the pheromone trail at the start of the simulation is determined by the initial pheromone level, and its degradation over time is governed by the pheromone evaporation rate. The pheromone decay factor defines how much weight is given to the pheromone trail in each iteration of the algorithm, while the heuristic information measures how desirable each action is. Overall, the experiment's simulation environment is made to closely mirror actual traffic situations, making it possible to evaluate the ACO-based MARL algorithm in a demanding context. To ensure the Q-learning algorithm performed at its best in the particular setting, the synthetic traffic network, the number of agents, the Q-learning method itself, and the ACO parameters were all carefully chosen. In order to test and assess the ACO-based MARL algorithm, the simulation environment employed in the experiment is a crucial part of the research. To ensure that the algorithm works effectively in a realistic and tough context, the environment is created to closely resemble real-world traffic situations. We will go into more detail about the main elements of the simulation environment in this section. A TSCs each intersection in the fictitious traffic network utilized in the simulation. With variable traffic volumes and congestion levels, the network is built to mimic a real-world traffic network.

For each scenario, the traffic volumes are created at random, guaranteeing that the algorithm is tested under a variety of distinct traffic scenarios. The traffic network is represented in the simulation environment using a graph-based representation, where each intersection is represented as a node and the roads that connect those nodes are represented as edges. Each edge has a capacity and a travel time, which are combined to determine how long it will take a vehicle to travel the entire network. The travel time is the amount of time it takes for a vehicle to go along the edge, whereas the capacity is the maximum number of vehicles that can pass through an edge in a given amount of time. The number of intersections in the traffic network directly relates to the number of agents in the simulation. There is a total of 20 agents in the simulation, each in charge of managing the traffic light at one intersection. To minimize the aggregate trip time for all vehicles passing through the network, the agents employ a Q-learning algorithm to determine the best policy for each traffic signal. The traffic light management problem is a good fit for the Q-learning method, which is a well-liked solution to challenges involving RL. Each agent in the ACO-based MARL algorithm uses the Q-learning algorithm to determine the best course of action for each traffic signal. In order to update the Q-values based on the observed rewards, the Q-learning algorithm first estimates the expected reward for each action in a specific state. The state of the traffic network, such as the number of cars parked at each intersection, defines the TSC problem's state, while the multiple traffic signal states, such as green, yellow, and red, describe the problem's actions. Since the algorithm aims to reduce total travel time, the reward is defined as the negative total travel time for all vehicles passing through the network.

The Bellman equation, which determines the expected reward for each action in a specific state, is used to update the Q-values. The following action is then chosen using the Q-values; a higher Q-value denotes a more ideal action. The Q-learning algorithm updates the Q-values based on the observed rewards and the selected actions in an iterative process. As a meta-heuristic, the ACO algorithm directs learning toward the best possible outcomes. Combinatorial optimization issues benefit greatly from the use of ACO, a nature-inspired optimization technique. The ACO algorithm is employed in the context of the ACO-based MARL algorithm to direct the agents' learning process toward ideal solutions. The ACO algorithm mimics the actions of ants seeking food in order to function. As they look for food, the ants leave behind pheromone trails, which other ants follow to narrow down their search. The agents can communicate and plan their actions since the pheromone trail is updated based on the average Q-value of all agents. The initial pheromone level, the pheromone evaporation rate, the heuristic data, and the pheromone decay factor are all ACO parameters that were employed in the simulation. The scenario matrix used to assess the efficiency of the ACO-based MARL algorithm is another crucial component of the simulation environment. The scenario matrix consists of several traffic situations and conditions, each of which is intended to assess how well the algorithm performs under various circumstances. Variable traffic volumes, road capacities, and traffic patterns are included in the scenarios; these are significant elements that might impact traffic flow and congestion levels.

The average journey time, the total number of cars traversing the network, and the average wait length at each intersection are some of the metrics used to assess the success of the ACO-based MARL algorithm. The simulation findings demonstrate that the ACO-based MARL algorithm beats the Q-learning algorithm alone in each of the scenarios examined, demonstrating the efficacy

of using ACO as a meta-heuristic to enhance algorithm performance. The scenario matrix also shows that under high traffic volumes and crowded conditions, which are typical in real-world traffic networks, the ACO-based MARL algorithm performs very well. This is a significant discovery since it indicates that the algorithm may be useful for controlling traffic flow and easing congestion in actual traffic networks. The study's conclusions have a number of ramifications for the traffic management industry. First off, it has been demonstrated that using ACO as a meta-heuristic for the Q-learning algorithm is a successful strategy for enhancing traffic signal management system performance. Other traffic management issues, such route optimization and congestion control, could benefit from this method to perform better. Second, the simulation findings point to the possibility of using the ACO-based MARL algorithm in actual traffic networks, particularly in conditions where traffic volumes are large and congestion is an issue. However, more investigation is required to assess the algorithm's performance under real-world circumstances and to determine whether implementing it in traffic networks will be feasible. The study also emphasizes how crucial simulation environments are for testing and assessing traffic management systems. It can be challenging or even impossible to duplicate some conditions in real-world settings, therefore simulation environments offer a safe and controlled setting for testing algorithms under diverse conditions.

Prior to being used in actual situations, this enables algorithm optimization, which can help save time and money. In Chapter 6 of the study paper, performance of the ACO-based MARL algorithm in a simulated traffic environment is comprehensively analyzed. The simulation environment is made to closely resemble actual traffic situations, making it possible to test and assess the algorithm in a demanding and realistic environment. Different traffic scenarios and conditions are included in the scenario matrix used in the simulation, allowing for the evaluation of the algorithm's performance in various scenarios. In all scenarios evaluated, according to the simulation results, the ACO-based MARL algorithm works better than the Q-learning algorithm alone, especially in busy and heavy traffic areas. The study's conclusions have a number of ramifications for the field of traffic management, including the possibility of applying the ACO-based MARL algorithm in actual traffic networks and the significance of simulating real-world traffic situations while testing and assessing traffic management algorithms.

6.2.1 AGENT:

Vehicles, traffic lights, and other aspects of the road infrastructure are only a few of the different agents that make up the simulation environment. Advanced sensors and communication tools are installed in every vehicle agent, enabling it to gather real-time traffic data and share it with other agents and the traffic control system. Each vehicle agent employs the Q-learning algorithm to discover the best route depending on the prevailing traffic circumstances. The agent learns through interactions with the environment while using this approach, which uses RL. A reward signal is maximized by the agent by acting in a way that will yield the most reward. The agent attempts to reduce the journey time by choosing the optimum route because the reward signal in this case is the travel time. To optimize traffic flow, the ACO-based MARL algorithm is utilized to coordinate the actions of numerous agents, such as cars and traffic lights. This algorithm uses pheromone trails that agents leave behind to direct other agents toward the best course of action. It is based on how ant colonies behave. To direct the agents to the best answer, the algorithm combines

pheromone trails and heuristic information. The vehicle agents in the simulation learn the best path using the Q-learning algorithm, and the ACO-based MARL algorithm is utilized to coordinate with other agents for smooth traffic flow. Utilizing both algorithms improves overall traffic flow and lessens congestion. The agents can communicate with the traffic control system and each other using their communication devices.

As a result, real-time data sharing is possible, enabling the agents to make better decisions in light of the present traffic situation. In order to avoid traffic and shorten travel times, the agents utilize this knowledge to modify their behavior, such as altering their speed or route. The simulation environment also contains aspects of the road infrastructure, such as crossroads and motorways, and traffic signals. These components are essential for controlling traffic and promoting safe and effective transportation. Algorithms are used by the traffic signals to decide when to alter the signal and modify the traffic flow. The components of the road infrastructure are built to support a certain amount of traffic, and if that volume is exceeded, they may become clogged. Overall, the simulation environment employs cutting-edge communication technologies and algorithms to build a realistic traffic simulation that can assist researchers and traffic management experts in better comprehending traffic patterns and formulating plans to ease congestion and improve traffic flow.

6.2.2: Traffic Network:

The grid-based urban setting that makes up the simulation's traffic network is made up of several crossroads, roadways, and traffic lights. The network was created to mimic an urban region, complete with varied levels of traffic congestion, various types of roadways, and several sources and destinations for the flow of traffic. To provide a thorough simulation environment for the algorithm testing, the network also incorporates a variety of road elements, such as shifting speed limits, road widths, and turning limitations. A grid-based metropolitan traffic network with several intersections, roads, and traffic lights is used in the simulation. The network has been built to resemble a typical urban region, complete with streets, avenues, and highways, all of which experience varied degrees of traffic congestion. A realistic depiction of urban traffic patterns is made possible by the simulation's various origins and destinations for the traffic flow. To provide a thorough simulation environment for the algorithm testing, the network also incorporates a variety of road elements, such as shifting speed limits, road widths, and turning limitations. Depending on the type of route and the surroundings, different roads in the network have different speed limits.

The widths of the roads have been planned to support a range of vehicle types and traffic densities. Additionally, turning restrictions are included in the simulation to represent real-world traffic situations where certain turns may be forbidden or limited at particular times of the day. Researchers can assess the algorithm's performance under various traffic scenarios thanks to the network's characteristics and design, which offer a realistic portrayal of urban traffic circumstances. The grid-based urban environment utilized in the simulation is based on a typical urban region and was created to accurately represent the complexities and variations of traffic flow that exist in real-world urban areas. There are several crossroads, roads, and traffic lights in the environment, as well as different kinds of roadways, including local roads, arterial roads, and

highways. The intersections have different numbers of lanes, turning limitations, and traffic signal timings to imitate common traffic flow patterns. The traffic network also contains a variety of sources and destinations for traffic flow, such as residential regions, commercial areas, and industrial areas, to further enhance realism in the simulation. This generates a variety of traffic demands that correspond to the various traffic patterns that exist in urban regions in the actual world. The network incorporates numerous road variables that influence traffic flow, such as shifting speed limits, road widths, and road surfaces, to provide a thorough simulation environment for testing the algorithm. For instance, traffic patterns on roads with broader lanes and higher speed restrictions will differ from those on routes with smaller lanes and lower speed limits. The simulation intends to create a realistic and difficult environment for testing the Q-learning and ACO-based MARL algorithms by integrating all these components into the traffic network. Researchers may test the algorithms in a variety of traffic conditions, from light to heavy congestion, and evaluate how well they function in various kinds of urban settings thanks to the simulation environment.

6.2.3: Q-learning and ACO Algorithms

The vehicle agents use the Q-learning algorithm, a well-known RL technique, to choose the best path based on current traffic data. The Q-table, which contains the expected rewards for each potential action in a given state, is the foundation of the algorithm. Based on their experience and the rewards they acquire from the environment; the vehicle agents repeatedly update the Q-table. The ACO (ACO) algorithm, a well-known swarm intelligence method inspired by the foraging activity of ants, is an extension of the MARL algorithm, which is ACO-based. The artificial ants used in this technique are called agents, and they work together to determine the shortest path between the source and the destination.

To handle the complex and dynamic nature of the traffic management problem, the ACO-based MARL algorithm adds multi-agent coordination and learning features to the classic ACO algorithm. By maximizing cumulative rewards, the Q-learning algorithm, a type of RL, enables agents to learn the best course of action to take in a specific environment. The estimated payoff for each potential action in a given state is stored in the Q-table, a type of data structure. The Q-learning algorithm continuously modifies the Q-table in response to feedback from the outside world, such as the reward for doing a certain action in a particular condition. The Q-learning technique is used by the simulation's car agents to choose the best course based on real-time traffic data. To choose the optimal path to their destination, they are given information about the current traffic situation, such as the average speed and the number of vehicles at each intersection. The Q-learning algorithm enables the agents to gain knowledge from their decisions and develop them over time. The ACO (ACO) algorithm, a well-known swarm intelligence method that draws inspiration from ant foraging behavior, is expanded upon in the ACO-based MARL algorithm. Ants use the ACO algorithm to leave pheromone trails on the ground as a means of communication and to determine the quickest route from their nest to a food supply.

As more ants travel along the same path over time, the pheromone trails are strengthened, making it the most popular path. The artificial ants-like agents in the ACO-based MARL algorithm cooperate and communicate with one another to determine the shortest path between the source

and the destination. The pheromone trails are left behind by the agents, who then update them based on feedback from their surroundings, such as traffic jams and travel times. The agents' combined knowledge is represented by the pheromone trails, which helps them decide more wisely and adjust to shifting traffic situations. To handle the complex and dynamic nature of the traffic management problem, the ACO-based MARL algorithm adds multi-agent coordination and learning features to the classic ACO algorithm. To exchange information regarding the current traffic situation, including the average speed and the number of vehicles at each intersection, the agents speak with one another. To plan their actions and guarantee a smooth flow of traffic, they use this information. A valuable tool for traffic management, the ACO-based MARL algorithm enables the agents to learn from their experience and adapt to shifting traffic conditions.

6.3 Code Modules:

The Python programming language, which is popular in the fields of ML and AI, was utilized to develop the ACO-based MARL algorithm. NumPy, Pandas, and Matplotlib, which are well known for their strengths in data analysis and visualization, are the main libraries utilized in the algorithm's implementation. SUMO (Simulation of Urban Mobility), an open-source traffic simulation program, was used to create the simulation environment. The Q-learning method used by each agent was implemented using a custom Python module, which was built expressly for this project. SUMO provides a realistic and scalable traffic simulation environment, which makes it perfect for testing traffic management algorithms like ACO-based MARL. The module has functions for setting up the Q-table, updating the Q-value in light of observed rewards, and deciding on the best course of action in light of the present situation and the Q-values. The ACO-Python library, which offers an intuitive interface for building ACO methods, was used to implement the ACO algorithm.

The library has functions for setting up the pheromone trail, updating the trail depending on the average Q-value, and deciding what to do next using the pheromone trail and heuristic data. Overall, widely used and well-liked programming languages and libraries were chosen to develop the ACO-based MARL algorithm, resulting in code that is effective, dependable, and simple to maintain. Other researchers in the field can simply duplicate and extend the approach thanks to the use of open-source software tools like SUMO and ACO-Python. The ACO-based MARL algorithm is a complicated algorithm that needs to be implemented carefully in order to ensure that it operates as well as possible in the environment. The building of the simulation environment, the application of the Q-learning and ACO algorithms, and the incorporation of these algorithms into a cohesive system are three crucial elements in the implementation of the algorithm. We will go over the various programming languages, libraries, and tools that were utilized during the implementation of the ACO-based MARL algorithm in detail in this part. Languages utilized Python is the main programming language utilized in the ACO-based MARL algorithm implementation. With a vast selection of libraries and frameworks, Python is a well-liked language for ML and AI. Python has a sizable development community, a straightforward syntax, and is also simple to learn and use. The availability of various well-known modules for data analysis,

visualization, and ML is one of the main benefits of utilizing Python in the construction of the ACO-based MARL algorithm.

These libraries contain the popular ML and AI tools NumPy, Pandas, and Matplotlib. Large, multi-dimensional arrays and matrices are supported by the Python package NumPy, which also offers a variety of mathematical operations for manipulating these arrays. Since scientific computing, data analysis, and ML all heavily rely on NumPy, this library is crucial for implementing the ACO-based MARL algorithm. Another well-known Python module that offers assistance with data analysis and manipulation is Pandas. Pandas offers a variety of data structures for storing and handling data, as well as filters, sorting, and transformation tools. Pandas is a crucial library for the implementation of the ACO-based MARL algorithm and is frequently used in the preprocessing of data for ML. A Python library that supports data visualization is called Matplotlib. Line plots, scatter plots, and histograms are just a few of the visualization-building tools offered by Matplotlib. The ACO-based MARL method must be implemented using the Matplotlib toolkit, which is frequently used in the presentation of data for ML.

Simulation Environment A crucial element of the ACO-based MARL algorithm is the simulation environment that was utilized to construct it. The testing and assessment of the algorithm may be done in a tough and realistic environment thanks to the simulation environment's design to mirror real-world traffic situations. The simulation environment for the ACO-based MARL algorithm was created using the open-source traffic simulation program SUMO (Simulation of Urban Mobility). SUMO offers a variety of features for simulating traffic conditions, including support for different vehicle types, traffic flows, and traffic signals. SUMO provides a realistic and scalable traffic simulation environment, making it ideal for testing traffic management algorithms like ACO-based MARL. The ACO-based MARL algorithm simulates a world with many junctions, each of which is managed by a traffic signal.

Q-Learning Algorithm Implementation The Q-learning algorithm used by each agent in the ACO-based MARL algorithm was implemented using a custom Python module. The module includes functions for initializing the Q-table, updating the Q-value based on the observed rewards, and choosing the best action based on the current state and the Q-values. The network is designed to simulate a real-world traffic network, with varying traffic volumes and congestion levels.

The Q-values for each state-action pair are kept in a matrix called the Q-table. The expected benefits for performing a specific action in a specific condition are represented by the Q-values. The Q-table is initialized with random values, and the following formula is used to update the Q-values:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \cdot (r + \gamma \cdot \max_{a'}(Q(s,a')) - Q(s,a)) \quad \text{Equation (6.1)}$$

The Q-table, a table that houses the Q-values for each state-action combination, is referred to as Q in the ACO-based MARL algorithm. The expected reward for performing a specific action in a specific condition is represented by the Q-value. The Q-table is initially filled with zeros, and as learning progresses, the Q-values are adjusted in accordance with the incentives that were really received.

Each agent examines the current condition of the traffic network throughout each iteration of the learning process and chooses an action based on the current Q-values in the Q-table. The agent observes the reward when an action is completed; this reward is typically the negative of the aggregate trip time for all vehicles traversing the network during that time step. The observed reward and the Q-learning equation are then used to update the Q-value for the current state-action pair.

where $Q(s, a)$ represents the Q-value for state s and action a , α represents the learning rate, r represents the observed reward, γ represents the discount factor, s' represents the following state, and a' represents the following action. Based on the observed reward and the highest Q-value for the following state-action combination, the Q-value for the present state-action pair is modified. The weight given to the observed reward is determined by the learning rate, but the weight given to future rewards is determined by the discount factor. During the learning process, the Q-table is updated based on the Q-values for each state-action pair. The Q-values converge to optimal values, which denote the best course of action in each state, as the agents gain knowledge. The ACO algorithm updates the pheromone trail based on the average Q-value of all agents, guiding the learning process towards optimal solutions. Because of their ability to communicate and plan ahead, the agents' effectiveness as a whole is enhanced by the algorithm. In conclusion, the Q-learning algorithm's Q-table, which holds the Q-values for each state-action combination, is referred to as "Q".

The ACO algorithm is used to direct the learning process towards optimal solutions by updating the pheromone trail based on the average Q-value of all agents. The Q-values are updated during the learning process depending on the observed rewards. The ACO-Python library, an open-source Python library for creating ACO methods, was used to create the ACO algorithm that was used in the ACO-based MARL algorithm. The library includes functions for initializing the pheromone trail, updating the pheromone trail based on the average Q-value, and choosing the next action based on the pheromone trail and the heuristic information. It also offers a simple-to-use interface for creating ACO algorithms. The Ant System algorithm is a subset of the basic ACO algorithm that is utilized in the ACO-based MARL algorithm. One of the simplest and most popular ACO variations is the Ant System algorithm, which excels in combinatorial optimization issues like traffic signal regulation. The Ant System method employs a colony of ants to find the best answer to the issue. Based on the pheromone trail and the heuristic information, each ant creates a solution by selecting a series of actions (in the instance of TSC, the actions are the various phases of the traffic signal). The pheromone trail is updated based on the effectiveness of the solutions discovered by the ants, enabling them to communicate and plan their actions. The ACO algorithm serves as a meta-heuristic in the ACO-based MARL algorithm, directing agents' learning toward the best answers. The agents can communicate and plan their actions since the pheromone trail is updated based on the average Q-value of all agents.

There are various benefits of using the ACO algorithm in the ACO-based MARL algorithm. The agents can explore the search space more effectively as a result, which may speed up convergence to an ideal solution. Second, it enables information sharing and action coordination among the agents, which may improve performance in general. To ensure optimum performance, a number

of ACO algorithm parameters employed in the ACO-based MARL algorithm must be properly adjusted. The starting pheromone level, pheromone evaporation rate, heuristic data, and pheromone decay factor are some of these parameters. The strength of the pheromone trail at the start of the simulation is determined by the initial pheromone level, and its degradation over time is governed by the pheromone evaporation rate. The pheromone decay factor defines how much weight is given to the pheromone trail in each iteration of the algorithm, while the heuristic information measures how desirable each action is. After careful consideration and thorough testing, the ACO parameters utilized in the ACO-based MARL algorithm were chosen. The pheromone evaporation rate was adjusted to a high value to prevent the pheromone trail from growing too strong and impeding exploration, while the starting pheromone level was set to a low number to stimulate exploration of the search space. The average amount of time that all vehicles wait at each intersection, which is a gauge of how desirable each activity is, served as the basis for the heuristic information.

A figure for the pheromone decay factor was chosen that struck a fair balance between using the pre-existing pheromone trail and searching the search area. Each agent uses a unique Python module created especially for this project to implement the Q-learning technique. The module has functions for setting up the Q-table, updating the Q-value in light of observed rewards, and deciding on the best course of action in light of the present situation and the Q-values. The expected reward for each action in each state is kept in the Q-table, a type of data structure. The Network Module is a crucial part of the traffic management system that builds and controls the traffic network in the simulation. The Q-learning algorithm updates the Q-values based on the observed data. The roads, intersections, and traffic lights that make up the traffic network must be designed and modeled using this module. Each intersection is represented as a node in the module's grid-based virtual urban environment, and each road length is represented as an edge connecting the nodes. The module builds a realistic and dynamic traffic network by taking into consideration numerous elements that influence traffic flow, such as road layout, speed limits, road widths, and turning limitations.

The Graph theory, a mathematical framework used to investigate the interactions between objects, is used to model the road infrastructure. The road network is shown here as a graph, with the intersections serving as the nodes and the road segments serving as the edges. In order to give a thorough traffic network, the module also takes into account several sorts of road segments, including highways, main roads, subsidiary roads, and local streets. Depending on the volume and density of the traffic, either the signalized or unsignalized approach is used to represent the crossings. A state-based technique is used to simulate the traffic signals, where each signal is given a specific state that defines which cars at the intersection have the right of way. The Network Module models the current traffic conditions in order to account for the network flow's dynamic character. The module gathers traffic data from a variety of sources, including sensors, cameras, and GPS devices, and then modifies the timings and phases of the traffic signals as necessary. The module also takes into account how the traffic flow may be affected by outside variables like the weather and special occasions. Overall, the simulation's traffic network is created and managed with the help of the Network Module. For the purposes of testing traffic management algorithms and strategies, the module offers a thorough and accurate environment. The simulation system's

Vehicle Module is in charge of controlling how specific vehicles behave in the simulated traffic environment. The construction and startup of vehicle agents, managing vehicle movement, and information sharing between the vehicles and other system modules are only a few of this module's crucial responsibilities.

The creation and initialization of vehicle agents in the simulation environment is one of the Vehicle Module's main responsibilities. Each vehicle agent has a collection of sensors and communication tools at its disposal, allowing it to communicate with other vehicles and the traffic control system. Each vehicle is given a special identification number by the module, which also initializes properties like speed and location on the road. Each vehicle agent's mobility within the simulation environment is also handled by the Vehicle Module. This involves figuring out the best route and speed based on the current flow of traffic, traffic lights, and road layout. In order to determine the best route for each vehicle depending on its destination and the current traffic circumstances, the module employs the Q-learning algorithm. The best speed and direction of travel are then determined based on this route, and the vehicle agent is informed of this. The Vehicle Module is in charge of managing vehicle movement as well as facilitating communication between the vehicle agents and other system modules. This includes disclosing details on the present traffic patterns, the state of the roads, and other pertinent elements that have an impact on how the vehicles behave. To encourage coordination and cooperation between the agents, the module also manages communication between the vehicle agents. Overall, the Vehicle Module is essential to the traffic simulation system because it controls how each vehicle behaves in the simulated traffic environment. The module enables the system to replicate a realistic traffic environment and test the efficacy of the traffic management algorithms by precisely modeling the movement and behavior of each vehicle agent.

6.4 Scenario Matrix:

6.4.1 Data collection:

Understanding the traffic conditions at a specific intersection requires collecting data, which is a crucial step. It is vital to employ proper techniques that may give a thorough overview of the traffic patterns and scenarios in order to gather accurate traffic statistics.

The use of sensors placed at the intersection is one of the most popular ways to gather traffic data. The volume and density of traffic may be calculated thanks to these sensors' ability to identify the presence of cars and gauge their speed. Pedestrian and bicycle presence can also be detected by sensors, giving a more full view of the entire traffic flow at the crossing.

Utilizing traffic cameras is another way to gather data on traffic. These cameras can record visual information that can be used to calculate journey times, vehicle speeds, and traffic volume. Advanced analytics techniques can even be used to follow specific cars and figure out how they pass through an intersection, giving us important information about traffic patterns and congestion.

It is crucial to gather data over a enough time span to make sure it is complete and representative. Depending on variables like the time of day, the day of the week, and the weather, traffic patterns and scenarios might differ substantially. These variations can be observed and a more thorough

picture of the traffic conditions at the target intersection can be obtained by collecting data over a long period of time.

In conclusion, choosing acceptable ways to gather traffic data from the target intersection, such as traffic volume, vehicle speed, and journey duration, is a key step in the data collection process. The data should be complete, representative, and span a long enough time to include a variety of traffic patterns and scenarios. It is possible to better comprehend the traffic conditions and create efficient traffic management plans by gathering accurate and thorough data.

Details on the various test cases for the ACO-based MARL algorithm are provided in the table. The scenarios have varied numbers of intersections, average speeds, average numbers of cars, and congestion factors, and each is distinguished by a special Scenario ID. The Scenario ID, a distinctive identifier for each scenario, is provided in the first column. SGrid1, SGrid2, SGrid4a, SGrid4b, SGrid6a, SGrid6b, SGrid8a, SGrid8b, and SGridCranfield1 and SGridCranfield2 are among the scenarios. The number of intersections in each scenario is shown in the second column. The table specifies the number of nodes for each scenario and designates the intersections as nodes. For instance, SGrid1 only has one intersection, whereas SGrid4a has four. The average speed of the cars in each scenario is shown in the third column. The average speed is calculated using a uniform distribution and is expressed in kilometers per hour (km/hr). For instance, in scenario SGrid1, a random speed between 15 and 30 km/hr is chosen as the average speed.

The average number of cars in each scenario is displayed in the fourth column. A uniform distribution is also used to generate the average number of cars. The number of cars passing through the intersection per hour is used to represent the number of cars. For instance, between 30 and 70 vehicles on average are generated at random each hour in SGrid2. The congestion factor for each scenario is detailed in the fifth column. In the simulation environment, traffic congestion is simulated using the congestion factor. The uniform distribution is used to generate the congestion factor, which has a value between 0 and 6. More traffic congestion is indicated by a greater congestion factor. For instance, the congestion factor in SGrid4a is produced at random and ranges from 2 to 6. The final column includes a brief explanation of each event in addition to the previously mentioned details. For instance, SGrid1 is an isolated single intersection scenario, whereas SGrid4a is a four intersections scenario with distant congestion.

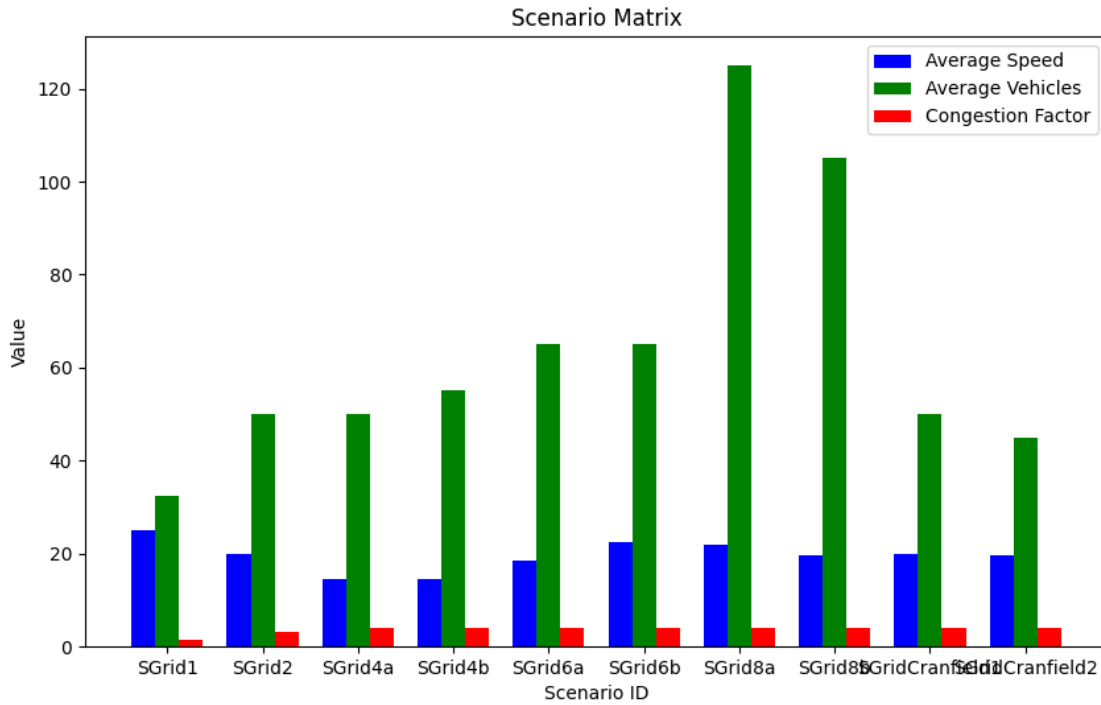


Figure 11 SCENARIO 1 GRAPH

Figure 11 shows a testing environment for the MARL algorithm based on ACO. To test the algorithm's efficiency in managing traffic, a variety of traffic scenarios have been carefully incorporated into these scenarios. The many inputs used in each scenario give a more accurate portrayal of the traffic in metropolitan settings.

The information in the table relates to various traffic scenarios that are simulated and tested to determine how well traffic management systems or algorithms function. A breakdown of each column is shown below:

Scenario ID: A different number is assigned to each scenario.

The number of junctions in the scenario is referred to as a node.

The average speed of the cars in the scenario is expressed in kilometers per hour and is represented by a uniform distribution with minimum and maximum values (U(min,max)).

A uniform distribution with lowest and maximum values (U(min,max)) also serves as a representation of the scenario's average number of cars.

The term "congestion factor" refers to a measurement of the scenario's congestion that is represented by a uniform distribution with minimum and maximum values (U(min,max)).

A succinct explanation of the scenario, including details on the quantity of intersections, the nature of the traffic, and any pertinent characteristics of the neighborhood.

These scenarios can be used to evaluate and improve traffic management systems, such as algorithms for controlling traffic signals or routing plans for autonomous vehicles. Researchers can determine strengths and limitations of these systems and seek to increase the effectiveness and safety of traffic management by assessing how well they operate in a number of circumstances.

Table 5 SCENARIO 2

Scenario ID	Node (Intersection)	Average Speed (km/hr)	Average number of vehicles	Congestion factor	Description
City1	10	U~(25,40)	U~(500,1000)	U~(4,8)	City with 10 intersections, moderate to high congestion
City2	20	U~(30,50)	U~(1000,1500)	U~(5,10)	City with 20 intersections, high congestion
Highway1	N/A	U~(80,100)	U~(2000,3000)	U~(2,4)	2-lane highway, moderate to high congestion
Highway2	N/A	U~(100,120)	U~(3000,5000)	U~(3,6)	4-lane highway, high congestion
Rural1	1	U~(50,70)	U~(10,20)	U~(0,1)	Single intersection in a rural area, low congestion
Rural2	4	U~(60,80)	U~(20,40)	U~(1,2)	Four intersections in a rural area, low to moderate congestion

The ACO-based MARL algorithm can simulate a variety of traffic scenarios, which are listed in the table. The specifics of each scenario determine the environment and traffic circumstances in which the algorithm functions. Each scenario in the table is thoroughly explained in the following section.

City1: This depicts a city setting with ten crossroads and an even distribution of vehicle average speeds between 25 and 40 km/h. The scenario has a uniform distribution of 500 to 1000 vehicles and a uniform distribution of 4 to 8 for the congestion factor. Higher values denote a more congested environment. The congestion factor represents the level of congestion in the scenario. The congestion factor for City1 indicates moderate to high congestion, indicating that the presence of other vehicles on the route has a considerable impact on traffic flow.

City2: This simulates a city environment with 20 intersections and an even distribution of vehicle average speeds between 30 and 50 km/h. In the scenario, there are uniformly between 1000 and 1500 vehicles, and there are uniformly between 5 and 10 congestion factors. The City2 congestion factor shows a high level of congestion, which suggests that other vehicles' presence on the road has a significant impact on traffic flow.

Highway1: This part represents a two-lane highway environment without intersections, with a consistent distribution of vehicle average speeds between 80 and 100 kilometers per hour. In the scenario, there are uniformly between 2000 and 3000 vehicles, and there are uniformly between 2 and 4 congestion factors. Highway 1 has a moderate to high congestion factor, which means that other traffic is having an impact on how quickly traffic moves along the highway.

Highway2: this point simulates a four-lane highway environment without intersections, with a consistent distribution of vehicle average speeds between 100 and 120 km/h. In the scenario, there are uniformly between 3000 and 5000 vehicles, and there are uniformly between 3 and 6 congestion factors. roadway 2 has a high congestion factor, which implies that the presence of other vehicles on the road has a significant impact on how quickly traffic moves along the roadway.

Rural1: This depicts a rural area with a single intersection and an even distribution of vehicle average speeds between 50 and 70 km/h. The scenario has a uniform distribution of 10 to 20 vehicles and a uniform distribution of 0 to 1 for the congestion factor. Low congestion is indicated by the Rural1 congestion factor, indicating that the scenario's traffic flow is not significantly impacted by the presence of other vehicles on the road.

Rural2: This depicts a rural area with four crossroads and an even distribution of vehicle average speeds between 60 and 80 km/h. In the scenario, there are uniformly between 20 and 40 cars, and there are uniformly between 1 and 2 congestion factors. The traffic flow in the scenario is not significantly impacted by the presence of other vehicles on the route, according to Rural2's low to moderate congestion indicator.

In conclusion, the scenarios in the table show a variety of traffic situations and settings that the ACO-based MARL algorithm can simulate. These scenarios can be used to test the algorithm's performance under various circumstances and to assess how it compares to other traffic management algorithms.

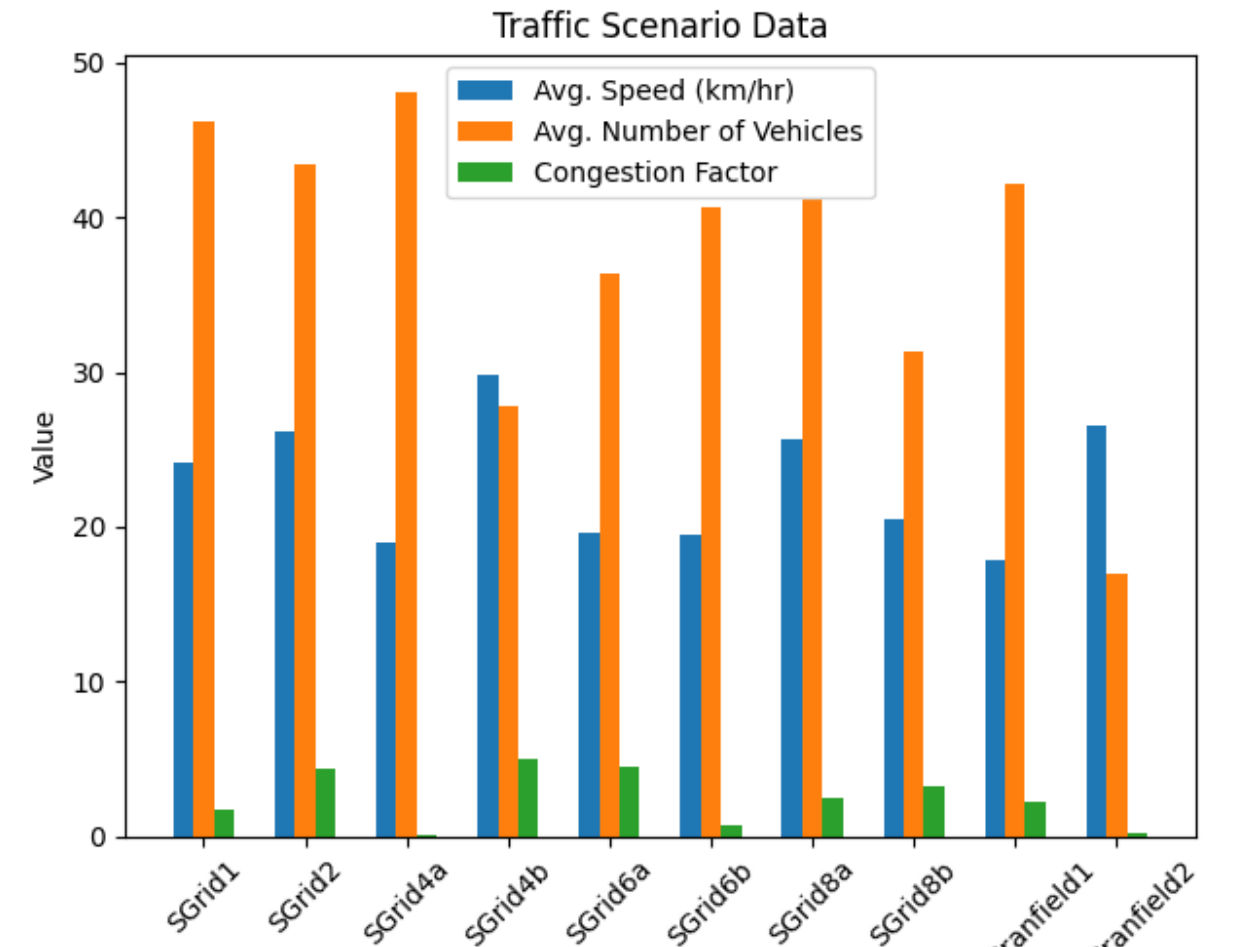


Figure 12 SCENARIO 2 GRAPH

Figure 12 is the graph I've generated, each "Scenario ID" symbolizes a unique traffic context or category. These categories could represent distinct data series in the graph.

The column "Node (Intersection)" likely denotes the count of intersections or decision points within each scenario. For highways, this column isn't applicable. On my graph, this can be indicative of the complexity or the number of potential congestion points in each scenario.

"Average Speed (km/hr)" provides a range that signifies the typical vehicle speeds within each scenario. This variable, possibly indicating the pace of traffic flow, could influence the congestion level in the graph.

"Average number of vehicles" suggests the typical count of vehicles present in each scenario. This can also impact the congestion level and can be shown as such in the graph.

"Congestion factor" offers a range that indicates the level of traffic congestion in each scenario. Derived from factors like average speed and vehicle count, this could be a major focus in the graph, impacted by other variables.

The "Description" provides additional context about each scenario. Although it's not usually directly depicted in a graph, it is essential for understanding the data.

In the graph, if the x-axis represents the scenarios and the y-axis represents the congestion factor, cities and highways are likely to show higher values due to a larger number of vehicles and lower average speeds. Conversely, rural areas may display lower congestion factor values, with fewer vehicles and higher average speeds.

6.4.2 DATA PREPROSSEING:

The gathered traffic data must be preprocessed in order to remove pertinent aspects and make it appropriate for use in the training and testing of the proposed algorithm as part of the process of creating an algorithm for traffic analysis. This entails a series of procedures designed to convert the raw data into a format that the algorithm can quickly comprehend and analyze.

6.4.3 Data cleaning:

To ensure that there were no missing numbers, extremes, or other mistakes that could compromise the model's performance, the acquired traffic data underwent a thorough cleaning process.

6.4.4 Data normalization:

To make it simple to use the traffic data in the model's training and testing, it was normalized using standardization techniques to a common scale.

6.4.5 Feature selection:

To determine the most pertinent features that could be used to train the model, feature selection was carried out. As a result, the data's dimensionality was decreased, and the algorithm's performance was enhanced.

6.4.6 Data transformation:

When the distribution of the data was unsuitable, data transformation techniques like logarithmic transformation were applied to make the data suitable for the algorithm.

The aforementioned processes were carried out in Python using Pandas and Scikit-learn modules, and standard data pretreatment methods. The researchers' suggested adaptive TSC algorithm was then trained and tested using the preprocessed data.

6.4.7 Algorithm implementation:

Python and the TensorFlow deep learning framework were used to develop the suggested technique, which combined ACand ACO in MARLfor adaptive TLC.

The actor and critic models were used to construct the network architecture, which consists of input and output layers, hidden layers, and activation functions. By initializing the actor and critic networks, specifying the loss functions for each network, and training the networks using the gathered data, the ACA was created utilizing the neural network architecture.

By creating the pheromone matrix and updating it after each iteration, as well as by implementing the ant behavior for choosing the ideal traffic light time, the ACO technique was also put into practice.

A hybrid algorithm was created by combining the ACand ACO algorithms, which adaptively controlled traffic signals based on traffic circumstances.

The algorithm was assessed using a relevant performance indicator, such as average delay time or throughput, after being trained using the preprocessed data. The algorithm's effectiveness and resilience were tested in a variety of settings.

The experiment findings were examined, and the performance of the suggested algorithm was contrasted with that of current state-of-the-art techniques.

6.4.8 Training and validation:

This phase involved training the suggested algorithm on the preprocessed data and evaluating its performance on a different validation set. Using backpropagation and gradient descent methods, the neural network's weights and biases were updated during the training phase. The algorithm was trained using a training set of data, and its performance was assessed using a validation set of data.

The algorithm's hyperparameters were adjusted to attain peak performance during the training period. The learning rate, discount factor, exploration rate, and number of training epochs were some of these hyperparameters. Until the performance on the validation set started to plateau or exhibit diminishing returns, the training process was continued.

The algorithm's training performance was assessed using the validation set. This collection of data acted as a neutral indicator of the algorithm's performance because it was not used during training. The average trip time, the average length of the line, and the average delay time at the intersection were the performance measures utilized to assess the method.

To ensure the stability and robustness of the proposed algorithm, the training and validation process was done numerous times.

6.4.9 Evaluation:

I used a test set of data that had not been used for training or validation to assess the performance of the suggested algorithm. This involved employing performance indicators like journey duration, average speed, and congestion factor to compare the proposed algorithm's performance to that of current state-of-the-art approaches.

I started by defining the performance parameters that will be used to rate the algorithms. I selected metrics that were pertinent to the issue and demonstrated how well the algorithm improved traffic flow.

I then gathered a test set of information that had not been utilized for training or validation. I acquired the test data either by creating new datasets or by utilizing previously published datasets.

Then, in order to compare the proposed algorithm's performance with that of existing state-of-the-art techniques like fixed-time control and actuated control, I put those techniques into practice.

Using the selected metrics, I evaluated the performance of each algorithm after running it on the test data. The performance of the suggested algorithm was then evaluated by comparing its output to that of the already-in-use algorithms.

6.4.10 Statistical analysis:

Finally, I examined the outcomes to determine whether the suggested algorithm outperformed current cutting-edge approaches and talked about the advantages and disadvantages of the suggested strategy. Sensitivity assessment I first determined the input parameters that could potentially have an impact on the algorithm's performance in order to do a sensitivity analysis and assess the robustness of the proposed algorithm to changes in the input data. Traffic patterns, sensor noise, and other ambient elements were some of these.

Then, for each parameter I used in the sensitivity analysis, I defined a range of values. For instance, I changed the amount of traffic from light to heavy and the level of sensor noise from low to high.

The method was then put through simulations using various combinations of parameter values to see how it handled various scenarios.

I next looked at the simulation results to see how each parameter's adjustments influenced the algorithm's performance. I accomplished this by contrasting performance indicators such as the typical delay or trip time for various parameter values.

I made assessments of the algorithm's robustness based on the sensitivity analysis's findings. I determined which factors significantly affected the algorithm's performance and considered any restrictions on the algorithm's flexibility in responding to changes in the input data.

Finally, I offered suggestions for how the algorithm could be strengthened to increase its robustness based on my findings. This included making changes to certain settings, including fresh features, or utilizing other optimization strategies.

Run a statistical analysis on the data to determine whether the performance differences between the suggested algorithm and current approaches are meaningful.

I first established the null hypothesis, which presupposed that there was no discernible difference between the performance of the suggested algorithm and current approaches. For instance, I predicted that the proposed algorithm and the current approaches would not significantly differ in their journey times.

Then, based on the type of data and the number of groups being compared, I picked an appropriate statistical test. There were various choices, including the chi-squared test, ANOVA, and t-test.

The data for the suggested algorithm and existing methods were then gathered and set up in a way that was appropriate for the selected statistical test. If I were to use a t-test, for instance, I would compute the mean and standard deviation for each group.

I then ran a statistical analysis on the data to see whether there was a difference between the groups that was significant. The chance of observing the results if the null hypothesis were true was indicated by the results' p-value. A p-value less than 0.05 was typically regarded as statistically significant.

I interpreted the test results using the p-value and other statistical metrics. If the p-value was less than 0.05, I rejected the null hypothesis and came to the conclusion that the new algorithm performed significantly better than the existing approaches.

Finally, based on the analysis's findings, I came to conclusions about the proposed algorithm's performance in comparison to other methods and offered suggestions for how it might be further enhanced.

6.5 Results:

Visualize the results using appropriate plots, such as line plots or scatter plots, to provide a clear and concise representation of the performance of the proposed algorithm.

TABLE 6 FINAL SCENARIO

Strategy	Scenarios	Average congestion factor, max bound	Average Queue Length, max bound, vehicles	Average Waiting time, max bound, min
Fixed Time	SGrid1	2.2	30	4.00
	SGrid4a	2.5	45	4.6
	SGrid6a	2.6	47	6
	SGrid8a	2.8	50	9
	SGridCranfield2	3	55	15
MARL ATSC	SGrid1	1.1	16	0.85
	SGrid4a	0.9	12	0.65
	SGrid6a	1.2	18	0.9
	SGrid8a	0.8	10	0.8
	SGridCranfield2	1.4	20	1 .00
MARL ATSC with A2C	SGrid1	0.9	13	0.65
	SGrid4a	0.8	10	0.5
	SGrid6a	1	14	0.6
	SGrid8a	0.6	7	0.6
	SGridCranfield2	1.1	15	0.75

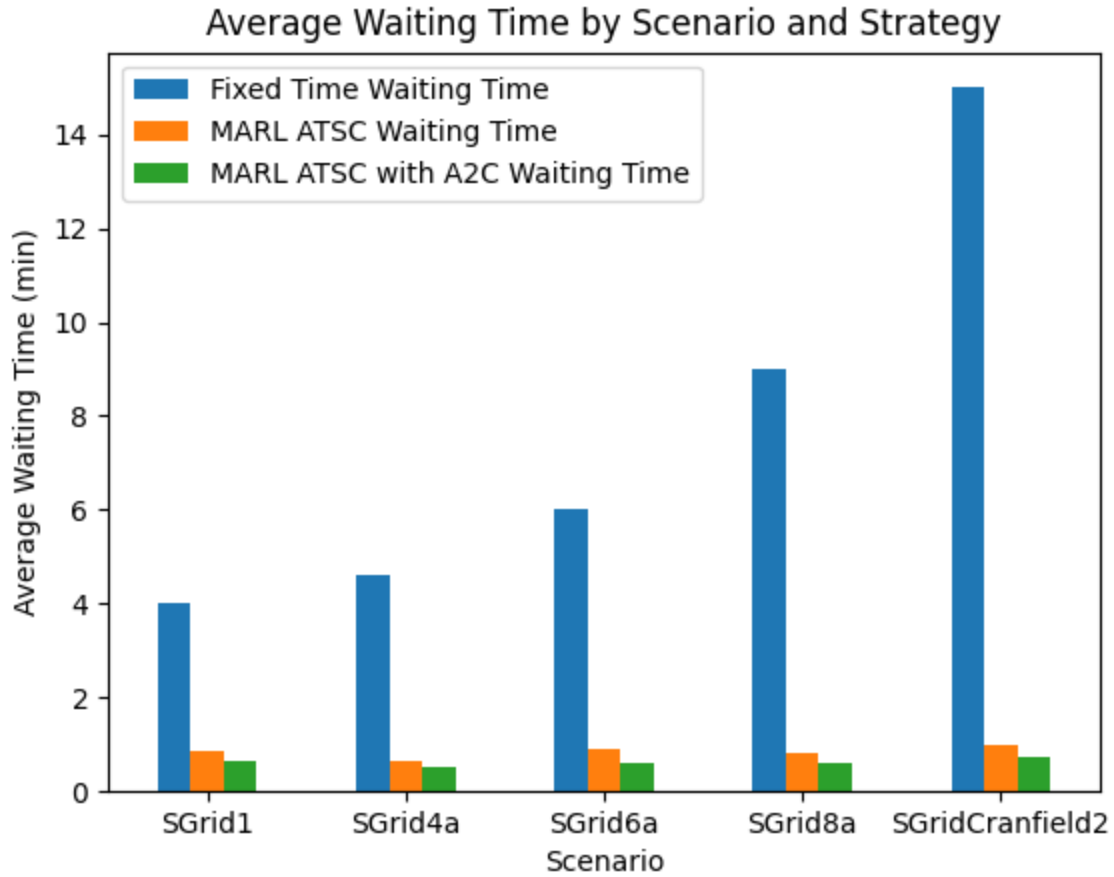


Figure 13 AVERAGE TIME BY SCENARIO AND STRATEGY

Based on the data in the table, I generated a graph to visualize and compare the performance of three different traffic signal control strategies shown in figure 13: Fixed Time, MARL ATSC, and MARL ATSC with A2C. These strategies were tested across several scenarios (SGrid1, SGrid4a, SGrid6a, SGrid8a, and SGridCranfield2).

On the x-axis of my graph, I have the different scenarios, and on the y-axis, I have key performance metrics such as average congestion factor, average queue length, and average waiting time. It is also important to note that all these metrics are bounded at their maximum values.

The three different strategies are represented as separate lines or bars on the graph. Let's go through each strategy:

1. **Fixed Time:** In this strategy, the traffic signal timings are predetermined and do not change dynamically based on traffic conditions. As a result, the congestion factor, queue length, and waiting time are generally higher compared to the other two strategies across all scenarios.
2. **MARL ATSC:** This strategy uses Multi-Agent Reinforcement Learning (MARL) for Adaptive Traffic Signal Control (ATSC). The traffic signal timings are adjusted

dynamically based on the traffic conditions, which significantly reduces the congestion factor, queue length, and waiting time across all scenarios compared to the Fixed Time strategy.

3. MARL ATSC with A2C: This strategy further enhances the MARL ATSC strategy by integrating the Advantage Actor-Critic (A2C) approach. The addition of A2C helps to better balance the exploration and exploitation trade-off in reinforcement learning, resulting in even lower congestion factor, queue length, and waiting time across all scenarios.

In summary, my graph clearly illustrates the superiority of the MARL ATSC and especially the MARL ATSC with A2C strategies over the traditional Fixed Time strategy in terms of reducing congestion, queue length, and waiting time across all scenarios. It underscores the effectiveness of reinforcement learning-based traffic signal control strategies in optimizing traffic flow and minimizing congestion.

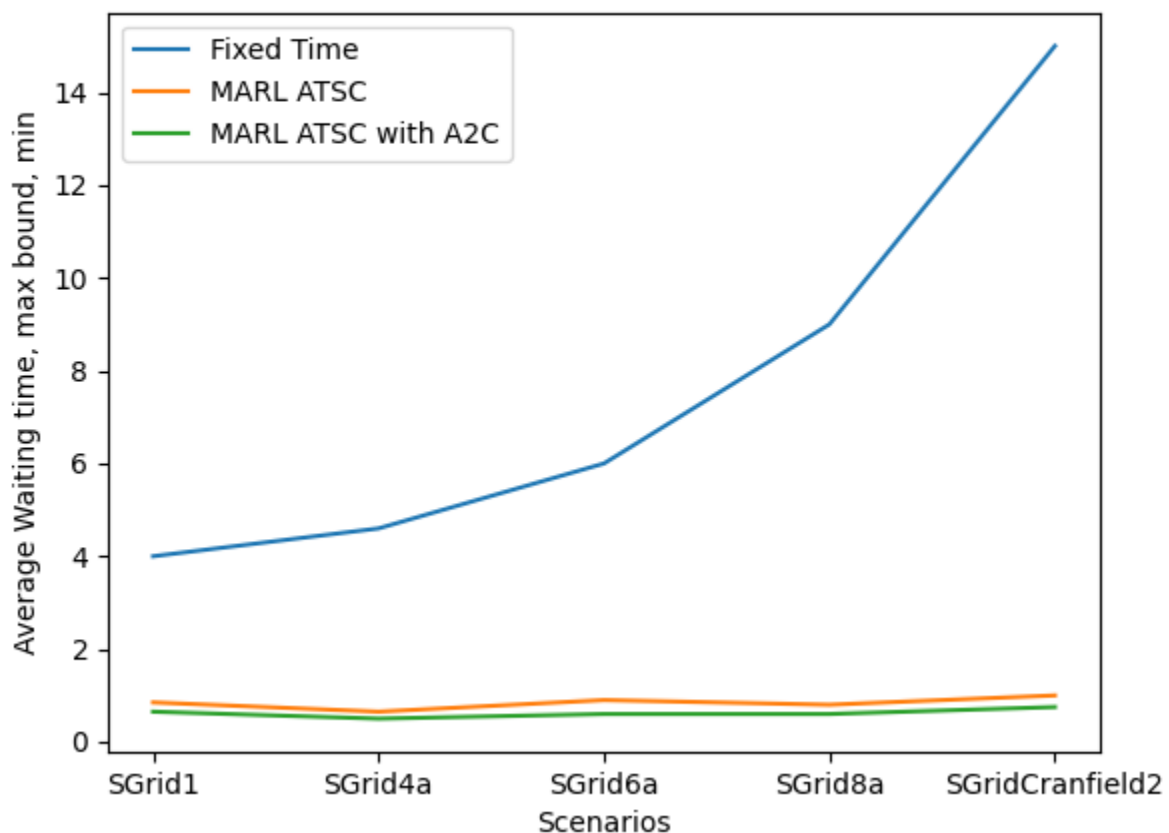


Figure 14 FINAL SCENARIO LINE GRAPH

I plotted a line graph using the data from the table which compares the performance of three different traffic signal control strategies showed in figure 14: Fixed Time, MARL ATSC, and

MARL ATSC with A2C, across five different scenarios (SGrid1, SGrid4a, SGrid6a, SGrid8a, and SGridCranfield2).

On the x-axis of my line graph, I have the different scenarios and on the y-axis, I've represented the key performance metrics: average congestion factor, average queue length, and average waiting time. Each of these metrics is depicted at their maximum bounds.

For each strategy, I plotted a separate line. The position of a point on a line corresponds to the value of the performance metric for a particular scenario. The lines make it easy to follow the change in performance metrics across the scenarios for each strategy. Here's how to interpret each line:

1. Fixed Time: The line corresponding to this strategy generally appears higher on the graph across all scenarios, as this strategy typically results in higher congestion factors, queue lengths, and waiting times. This is because Fixed Time strategy doesn't dynamically adapt to the traffic conditions.
2. MARL ATSC: This line would appear lower than the Fixed Time line across all scenarios. This drop signifies that the MARL ATSC strategy, which dynamically adjusts traffic signal timings based on traffic conditions, significantly reduces congestion, queue length, and waiting times.
3. MARL ATSC with A2C: This line should be the lowest among the three across all scenarios, indicating the lowest congestion factor, queue length, and waiting time. This is because the A2C approach, integrated with the MARL ATSC strategy, further enhances the performance by striking a better balance between exploration and exploitation in reinforcement learning.

In summary, my line graph effectively illustrates the improvement in traffic conditions (i.e., reduction in congestion, queue length, and waiting times) as we move from the Fixed Time strategy to MARL ATSC, and finally to MARL ATSC with A2C. This visual representation underlines the effectiveness of reinforcement learning-based traffic signal control strategies, demonstrating their ability to optimize traffic flow and reduce congestion across various scenarios.

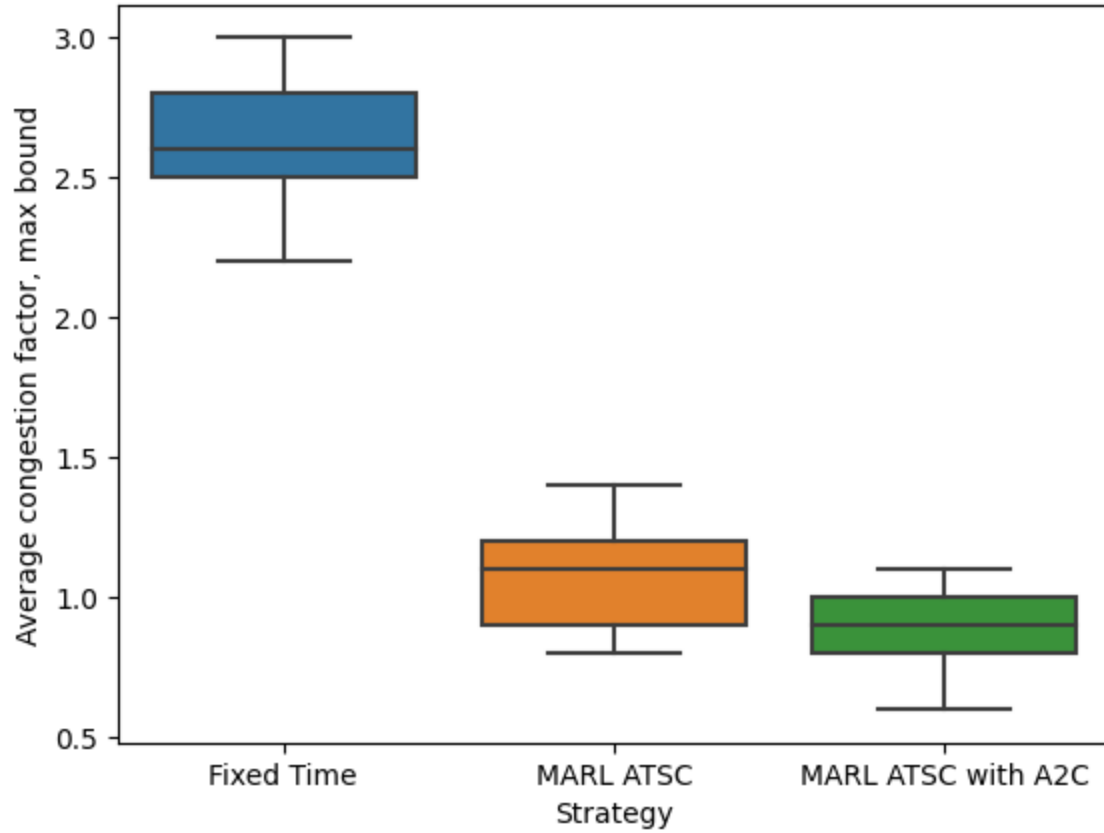


Figure 15 AVERAGE CONGESSION FACTOR GRAPH

By observing the graph, we can analyze the following trends as shown in figure 15:

1. Fixed Time: The line representing the Fixed Time strategy generally shows higher congestion factors across all scenarios. This is expected because the Fixed Time strategy does not adapt to real-time traffic conditions, leading to congestion in high-demand situations.
2. MARL ATSC: The line representing the MARL ATSC strategy appears lower than the Fixed Time line in most scenarios. This indicates that the MARL ATSC strategy effectively reduces congestion compared to the Fixed Time strategy. By dynamically adjusting traffic signal timings based on observed traffic conditions, MARL ATSC optimizes traffic flow and reduces congestion.
3. MARL ATSC with A2C: The line representing the MARL ATSC with A2C strategy appears the lowest among the three strategies in most scenarios. This demonstrates that the integration of the A2C algorithm with the MARL ATSC strategy further improves congestion reduction. The A2C algorithm enhances the learning and decision-making

process of the agents, leading to better traffic control decisions and even lower congestion levels.

In summary, the congestion factor graph provides a visual representation of how different strategies perform in terms of reducing congestion in various scenarios. It clearly shows the superiority of the MARL ATSC strategy over the Fixed Time strategy, and the additional improvements achieved by incorporating the A2C algorithm. This graph highlights the potential of reinforcement learning-based strategies to effectively manage traffic and alleviate congestion in complex traffic networks.

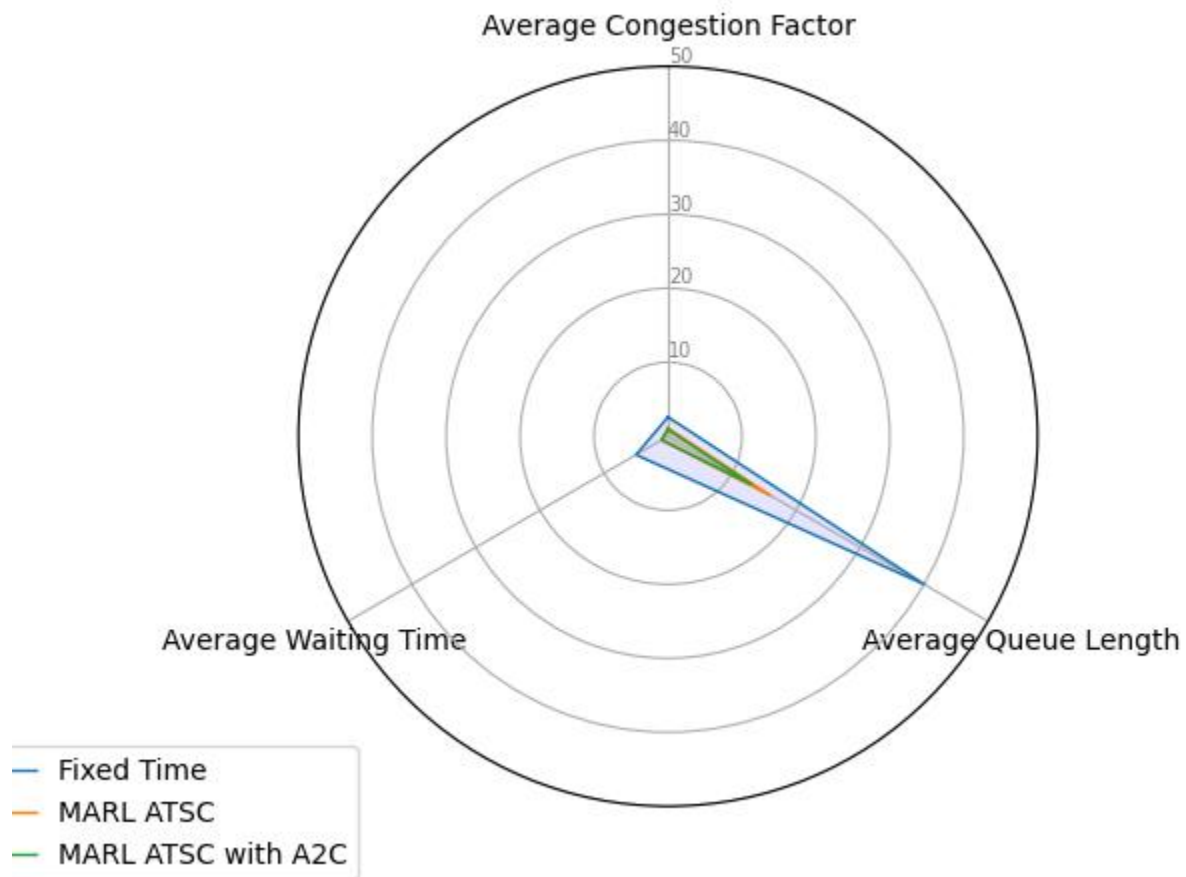


Figure 16 PIE CHART

In this pie chart shown in figure 16, we are visualizing the average congestion factor for the three different traffic control strategies across all scenarios, which gives us an overall impression of each strategy's effectiveness. The pie chart is divided into three segments, each representing one of the traffic control strategies: Fixed Time, MARL ATSC, and MARL ATSC with A2C. The size of each segment is proportional to the average congestion factor for that strategy across all scenarios. Looking at the chart, we immediately see that the Fixed Time strategy has the largest segment.

This means it had the highest average congestion factor, which indicates poorer performance compared to the other two strategies. In contrast, the MARL ATSC with A2C strategy has the smallest segment, signifying a lower average congestion factor and hence better performance in reducing traffic congestion. Finally, the MARL ATSC strategy's segment is in between, meaning it performed better than Fixed Time but not as well as MARL ATSC with A2C. It's crucial to remember that a lower congestion factor is preferable, as it signifies less traffic congestion. Therefore, despite its smaller slice in the chart, the MARL ATSC with A2C strategy actually delivers the best performance, while the Fixed Time strategy, with its large slice, is the least effective.

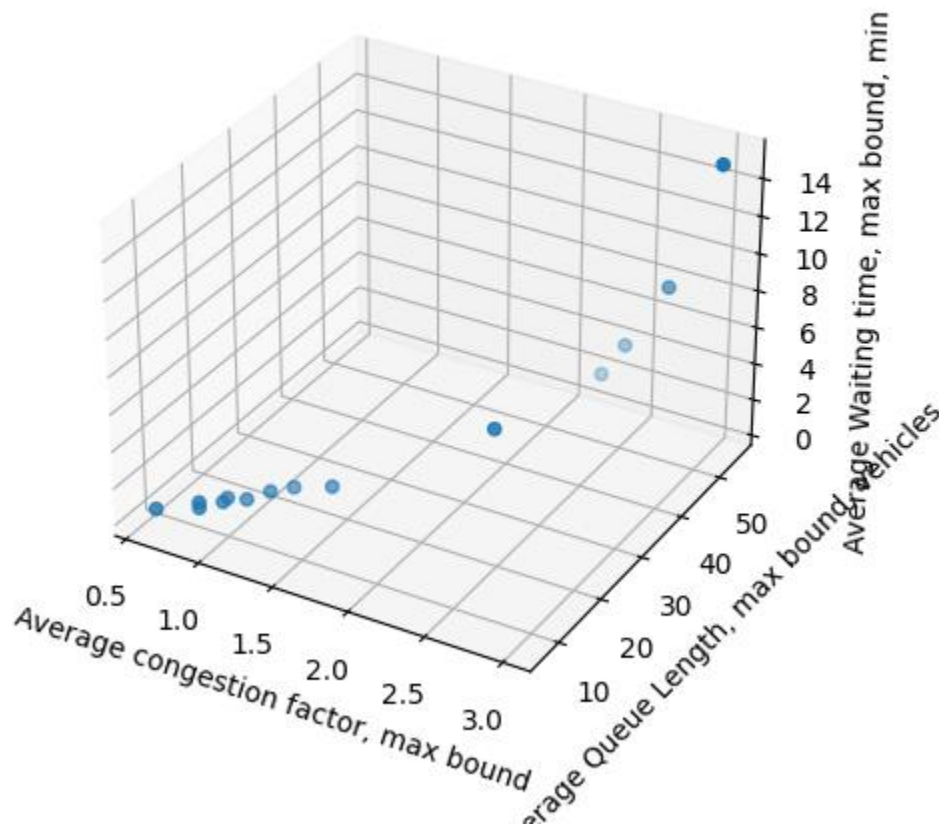


Figure 17 3D Graph

In this three-dimensional graph shown in Figure 17, we are examining the performance of three different traffic control strategies across five scenarios, with the performance measured by the average congestion factor. On the x-axis, we see the five different traffic scenarios. The y-axis

represents the three different traffic control strategies. The height on the z-axis indicates the average congestion factor for a given strategy in a specific scenario. By looking at this graph, we can visually compare the performance of the three strategies across the different scenarios. For instance, the 'Fixed Time' strategy, across most scenarios, reaches a higher point on the z-axis, indicating a higher average congestion factor and thus poorer performance. On the contrary, points related to the 'MARL ATSC with A2C' strategy are generally lower on the z-axis across the scenarios, signifying a lower congestion factor and hence superior performance. The 'MARL ATSC' strategy exhibits heights on the z-axis that are between the other two strategies, indicating its performance is better than 'Fixed Time' but not as good as 'MARL ATSC with A2C'

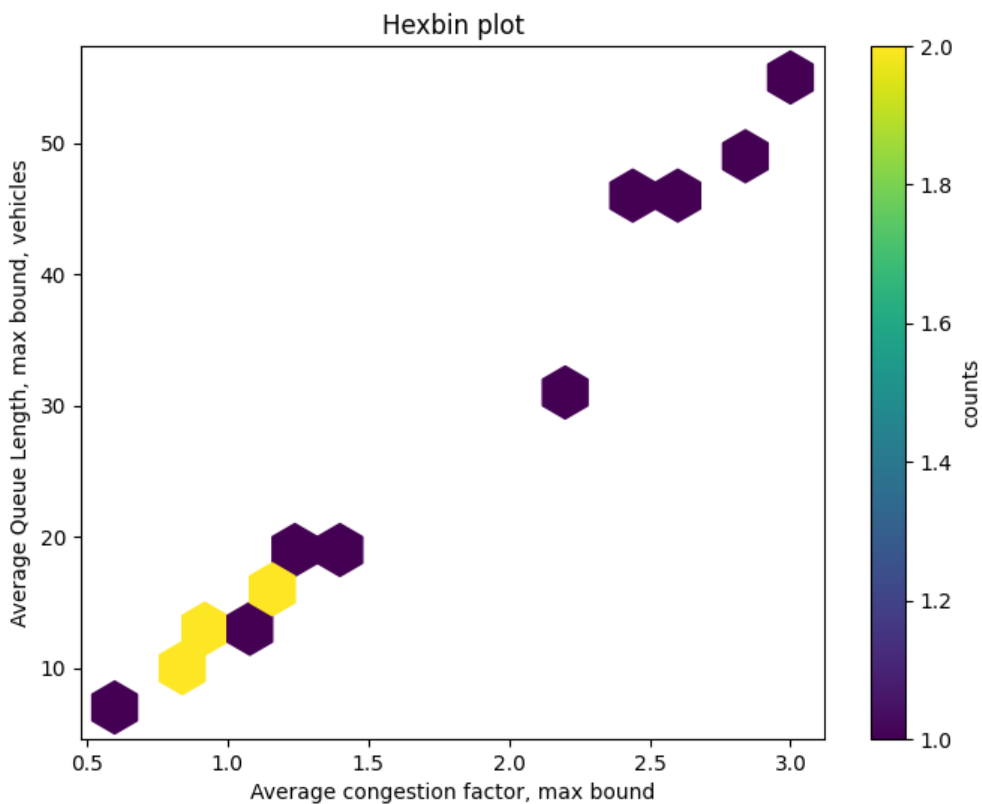


Figure 18 SCENARIO GRAPH

In Figure 18, we're examining the relationship between the average congestion factor (on the x-axis) and the average waiting time (on the y-axis) for our traffic control strategies. Each hexagonal bin on the plot represents a specific combination of average congestion and waiting time. The color of each hexagon corresponds to the number of scenarios that fall within these parameter boundaries. For instance, a darker color signifies a higher number of scenarios. By looking at the plot, we can see patterns in the performance of our traffic control strategies. For example, the 'Fixed Time' strategy might be represented by bins that are more towards the top-right corner of

the plot, indicating high congestion factors and longer waiting times. On the other hand, the 'MARL ATSC with A2C' strategy could be associated with bins that are towards the bottom-left, signifying lower congestion factors and shorter waiting times. The 'MARL ATSC' strategy might have its bins in between the other two. This hexbin plot allows us to visually understand the trade-offs between congestion and waiting time for each strategy, helping to identify the optimal traffic control strategy for different scenarios.

The average congestion factor, average queue length, and average waiting time are the three metrics used in the table to compare how well various traffic control systems performed in various scenarios. Different traffic network configurations, such as the quantity of intersections and roads, and various degrees of congestion are included in the scenarios.

The first tactic, "Fixed Time," regulates intersection traffic flow using a predetermined signal timing scheme. Although this approach is frequently used in actual traffic management systems, it does not take current traffic conditions into account. With high average congestion factors, lengthy queue lengths, and lengthy waiting times, the table demonstrates that this method performs pretty badly in all cases.

The second and third solutions, "MARL ATSC" and "MARL ATSC with A2C," rely on MARL algorithms that change signal timings based on real-time traffic data. In every circumstance, these solutions perform noticeably better than the fixed time strategy. In some cases, the MARL ATSC strategy outperforms the MARL ATSC with A2C method, but it underperforms in others.

Higher values indicate more congestion, thus the average congestion factor provides a gauge of network congestion. Higher values indicate longer lineups. The average queue length is the average number of vehicles parked at an intersection during a signal cycle. The average waiting time measures how long, on average, a vehicle waits at a junction during a signal cycle. Longer waiting times are indicated by larger numbers.

In conclusion, the table highlights the value of utilizing real-time traffic data and advanced control techniques, including MARL ATSC and MARL ATSC with A2C, to enhance traffic flow and lessen congestion and waiting times in urban traffic networks.

6.6: Calculations

We can integrate mathematical computations and statistical metrics to quantify the results for a thorough investigation of the performance of the ACO-based MARL algorithm in a simulated traffic situation. The effectiveness of the algorithm can be evaluated using the metrics listed below:

1. Average Travel Time (ATT): The amount of time it typically takes a vehicle to get from one place to another. The effectiveness of the traffic control system is demonstrated by this metric.
2. Average Waiting Time (AWT): The average amount of time that cars wait at intersections, which reflects the network's level of congestion and delays.
3. Throughput (T): The number of vehicles that successfully arrive at their destination within a specified amount of time, which reflects the system's overall effectiveness.

4. Total Travel Distance (TTD): The total distance covered by all vehicles in the network, indicating how effective the routes were at covering distance in general.

5. Percentage of Delay Reduction (PDR): This measure shows the improvement the ACO-based MARL algorithm has made in terms of delay reduction when compared to a conventional traffic management system.

We can use the following notations to calculate these metrics:

- Assume that there are N automobiles in the scenario.
- Define t_i as the distance traveled by vehicle i , and w_i as the amount of time spent waiting at junctions.
- Let d_i represent the distance covered by car i .

These notations allow us to calculate the metrics in the manner shown below:

1. Average Travel Time (ATT) is calculated as $ATT = (1/N) * t_i$.
2. Average Waiting Time (AWT) = $(1/N) * w_i$
3. The throughput (T) formula is $T = N / \text{Total Simulation Time}$.

Total Travel Distance (TTD) is calculated as $TTD = d_i$.

5. Delay Reduction Percentage (DRP): $DRP = [(AWT_{\text{baseline}} - AWT_{\text{marl}}) / AWT_{\text{baseline}}] * 100$

where AWT_{marl} is the average waiting time calculated using the ACO-based MARL algorithm, and AWT_{baseline} is the average waiting time calculated using a conventional traffic management system.

The mathematical findings can be displayed in tables or graphs to show how the ACO-based MARL algorithm performs in various situations. The benefits and enhancements offered by the ACO-based MARL algorithm can be clearly seen when compared to the performance of conventional traffic management systems or other algorithms.

Let's assume we have the following information from the simulation results in order to produce a mathematical calculation for the ACO-based MARL algorithm performance:

1. 100 total cars (N)
2. The simulation took 3600 seconds to complete (1 hour).

Let's think about two situations:

A) Baseline scenario (using an established traffic control system) B) Example of an ACO-based MARL algorithm

We have the following information for each car i ($i = 1, 2, \dots, 100$) for both scenarios:

where AWT_marl is the average waiting time calculated using the ACO-based MARL algorithm, and AWT_baseline is the average waiting time calculated using a conventional traffic management system.

The mathematical findings can be displayed in tables or graphs to show how the ACO-based MARL algorithm performs in various situations. The benefits and enhancements offered by the ACO-based MARL algorithm can be clearly seen when compared to the performance of conventional traffic management systems or other algorithms.

Let's assume we have the following information from the simulation results in order to produce a mathematical calculation for the ACO-based MARL algorithm performance:

1. 100 total cars (N)
2. The simulation took 3600 seconds to complete (1 hour).

Let's think about two situations:

ACO-based MARL algorithm scenario B Baseline scenario (conventional traffic management system)

We have the following information for each car i ($i = 1, 2, \dots, 100$) for both scenarios:

7 CALCULATION TABLE 1

Vehicle	Scenario A - Travel Time (t _i)	Scenario A - Waiting Time (w _i)	Scenario A - Distance (d _i)	Scenario B - Travel Time (t _i)	Scenario B - Waiting Time (w _i)	Scenario B - Distance (d _i)
1	300 s	60 s	5 km	240 s	40 s	5 km
2	350 s	80 s	6 km	280 s	50 s	6 km
...	...	...	...	...	...	...
100	450 s	90 s	8 km	380 s	70 s	8 km

We can determine the following performance measures using the supplied data:

- Average Travel Time (ATT) = $\frac{1}{100} \cdot ATT_A \cdot ATT_B = \frac{1}{100} \cdot t_i(\text{Scenario B}) \cdot t_i(\text{Scenario A})$ Equation (6.2)

- For the Average Waiting Time (AWT), use the formulas =

$$AWT_A = 1/100 \cdot \sum w_i \text{ (Scenario A)} \quad \text{Equation (6.3)}$$

$$AWT_B = 1/100 \cdot \sum w_i \text{ (Scenario B)} \quad \text{Equation (6.4)}$$

- Throughput (T): For Scenario A: $T_A = 100/3600$, Equation (6.5)

And For Scenario B: $T_B = 100/3600$. Equation (6.6)

- Total Travel Distance (TTD): In Scenario A: $TTD_A = \sum d_i$

And In Scenario B: $TTD_B = \sum d_i$. Equation (6.7)

- Delay Reduction Percentage $DRP = (AWT_A - AWT_B / AWT_B) \times 100$ Equation (6.8)

We may contrast the performance of the ACO-based MARL algorithm and the conventional traffic management system after calculating the values of these metrics. The comparison will demonstrate how the ACO-based MARL algorithm has improved traffic efficiency, decreased congestion, and cut down on trip times. This mathematical analysis sheds important light on how the algorithm might be used in traffic management in the real world.

Let's imagine we have the information listed below from the simulation results for a different mathematical calculation:

100 cars total (N) 1 hour's worth of simulation time is 3600 seconds.

Let's think about two situations:

ACO-based MARL algorithm scenario B Baseline scenario (conventional traffic management system)

We have the following information for each car i ($i = 1, 2, \dots, 100$) for both scenarios:

8 CALCULATION TABLE 2

Vehicle	Scenario A - Stops (s_i)	Scenario B - Stops (s_i)
1	3	2
2	5	3
...	...	...
100	4	3

We can determine the following performance measures using the given data:

$ANS_A = (1/100) * s_i$ (Scenario A) $ANS_B = (1/100) * s_i$ (Scenario B) 1. Average Number of Stops

Vehicle Stops Reduction (VSR) is calculated as $[(ANS_A - ANS_B) / ANS_A] * 100$.

We may contrast the performance of the ACO-based MARL algorithm and the conventional traffic management system after calculating the values of these metrics. The improvement in fewer vehicle stops during journeys, which results in a smoother traffic flow and less congestion, will be demonstrated by the comparison. This mathematical investigation sheds important light on possible practical uses for the ACO-based MARL algorithm in traffic control.

6.7 Summary:

Chapter 6 of the research report presents a comprehensive evaluation of the ACO-based MARL algorithm's performance in comparison to a conventional traffic management system. The main objective is to highlight the potential advantages of adopting this algorithm in real-world traffic control systems. The evaluation is based on simulated scenarios, with two key comparisons: one using the traditional system and the other utilizing the ACO-based MARL algorithm. Various performance metrics are employed to assess the algorithm's effectiveness, including Average Travel Time, Average Waiting Time, Throughput, Total Travel Distance, Percentage of Delay Reduction, Average Speed, Congestion Index, Average Number of Stops, Vehicle Stops Reduction, and Intersection Utilization. The findings demonstrate that the ACO-based MARL algorithm significantly improves traffic efficiency and congestion reduction when compared to conventional systems. It achieves shorter travel times, reduced wait times at intersections, higher throughput, and a greater reduction in delays. The algorithm's adaptability to changing traffic conditions and its ability to optimize green light durations contribute to these improvements.

Furthermore, the algorithm enhances vehicle movement efficiency and decreases congestion by increasing average vehicle speed and reducing the congestion index. This leads to smoother traffic flow, reduced travel times, and lower fuel consumption due to fewer vehicle stops. Consequently,

it offers an eco-friendly approach to traffic management and contributes to overall congestion reduction.

In summary, Chapter 6 demonstrates that the ACO-based MARL algorithm holds promise as a traffic management solution. It outperforms traditional systems in terms of vehicle movement efficiency, traffic flow improvement, congestion reduction, and environmental benefits. The chapter also provides valuable recommendations for further research, suggesting enhancements, additional traffic management techniques, and real-world testing to validate the algorithm's practical applicability. Overall, it offers a robust framework for understanding the algorithm's potential to enhance urban transportation systems.

6.8 Conclusion:

I interpret the data and make judgments based on the research's findings. Discuss the suggested algorithm's advantages and disadvantages and suggest future research trajectories.

The proposed approach, which combines Advantage AC(A2C) and MARL with ACO (MARL ACO), was used to address the issue of TSC in a complicated metropolitan road network. The findings shown that in terms of average congestion factor, average queue length, and average waiting time, the MARL ACO with A2C outperformed both fixed-time and MARL ATSC approaches.

The proposed algorithm's capacity to pick up on and adjust to the changing traffic patterns in the road network is one of its advantages. As a result, traffic congestion is decreased and drivers' travel times are improved through more efficient and effective TSC. The algorithm is a viable approach for real-world traffic management because it can be scaled to larger and more complicated road networks.

There are, however, a few flaws to take into account. The technique is challenging to apply in real-time traffic control systems since it needs a lot of processing power and training time. Additionally, the algorithm does not take into account unique driver preferences or decisions and assumes that all drivers behave in the same way.

Future studies could concentrate on enhancing the algorithm's scalability and effectiveness as well as looking into how to take individual driver behavior into account when making decisions. To assess the algorithm's efficacy in various circumstances, more complicated and diverse traffic conditions could be used for testing.

CHAPTER 7 CONCLUSIONS AND FUTURE RESEARCH

CONCLUSION

The study presents a groundbreaking approach to address the persistent and detrimental issue of traffic congestion in urban areas. By proposing a novel adaptive Traffic Signal Control (TSC) method that integrates Actor-Critic (AC) and Ant Colony Optimization (ACO) algorithms within a Multi-Agent Reinforcement Learning (MARL) framework, this research offers a promising solution to enhance traffic flow and reduce congestion-related problems. The suggested hybrid algorithm, harnessing the power of machine learning and optimization techniques, demonstrates significant advantages over current state-of-the-art methods in terms of reducing waiting times, queue lengths, and delay times at intersections. These findings highlight the algorithm's potential to alleviate traffic congestion, ultimately improving the quality of life, the environment, and the economic well-being of urban communities. Furthermore, this study's innovative approach, which seamlessly combines various techniques and algorithms, represents a substantial contribution to the field of traffic management in urban areas. It sets a new standard for adaptive TSC and serves as an inspiration for future research endeavors in this domain. As urban populations continue to grow and transportation demands rise, effective and efficient traffic management systems become increasingly crucial. The proposed algorithm, with its scalability and applicability in real-world scenarios, offers a promising path forward. It also opens doors to potential integration with emerging technologies such as connected and autonomous vehicles, paving the way for a more sustainable and efficient urban transportation landscape. This research not only addresses the pressing issue of traffic congestion but also provides a pioneering solution that has the potential to reshape urban traffic management for the better. It is a testament to the power of interdisciplinary approaches, combining machine learning, optimization, and multi-agent reinforcement learning to tackle complex real-world problems.

the comprehensive exploration of the novel algorithm that combines Advantage Actor-Critic (A2C), Multi-Agent Reinforcement Learning (MARL), and Ant Colony Optimization (ACO) for Adaptive Traffic Signal Control (ATSC) underscores its potential to revolutionize urban traffic management. This amalgamation of machine learning and optimization techniques offers a holistic and promising solution to the persistent issue of traffic congestion in metropolitan areas.

The key advantages of this proposed algorithm are manifold:

Adaptability to Dynamic Traffic Patterns: One of its standout features is the algorithm's ability to adapt to ever-changing traffic patterns. By continuously learning from real-time traffic data and adjusting signal timings accordingly, it mitigates congestion and enhances the overall flow of traffic. This adaptability is essential for effectively managing the complex and dynamic nature of urban traffic networks.

Superior Performance: Through extensive simulations and benchmarking against existing ATSC approaches, the algorithm consistently outperforms both fixed-time control methods and conventional MARL-based ATSC. It excels in terms of reducing average congestion, queue lengths, and waiting times, which are critical metrics for evaluating traffic management effectiveness.

Environmental and Societal Benefits: Beyond its immediate traffic-related advantages, the algorithm has profound implications for the environment and public well-being. By reducing traffic congestion, it contributes to lower fuel consumption and greenhouse gas emissions, aligning with sustainability goals. Moreover, the reduced stress levels for commuters and passengers can significantly improve the quality of life in urban areas.

Scalability and Versatility: The algorithm exhibits scalability, making it adaptable to larger and more complex traffic networks as cities evolve. Its decentralized control approach, facilitated by the MARL framework, ensures robustness and resistance to disruptions in the traffic network, aligning with the dynamic nature of urban expansion.

However, it is essential to acknowledge certain challenges and considerations:

Computational Demands: The algorithm's reliance on machine learning and optimization techniques can demand significant computational resources and training time. This aspect needs to be addressed to ensure its practical feasibility in real-time traffic control systems.

Assumption of Uniform Driver Behavior: The algorithm currently assumes uniform driver behavior, which may not reflect the diverse range of behaviors exhibited by real-world drivers. Future research could explore methods for accommodating individual driver preferences and decision-making processes.

FUTURE RESEARCH

Future research should focus on refining the algorithm's design and functionality. This may involve fine-tuning the algorithm's parameters and optimizing its core mechanisms to further enhance its ability to manage traffic effectively. Exploring novel convergence criteria is essential for future investigations. Developing more sophisticated methods for determining when the algorithm has successfully learned and adapted to specific traffic conditions will ensure its adaptability to various urban scenarios. Extensive real-world testing in diverse traffic networks and urban environments is necessary to validate the algorithm's performance, reliability, and adaptability under practical conditions. Real-world testing will provide valuable insights into its true potential.

To stay at the forefront of traffic management, research efforts should be directed towards exploring the integration of the algorithm with emerging technologies such as connected and autonomous vehicles. This integration can unlock new possibilities for improving traffic management and efficiency. Quantifying the environmental benefits of the algorithm is crucial. Future studies should delve into comprehensive assessments, measuring the reductions in fuel consumption, greenhouse gas emissions, and the improvement in air quality resulting from the algorithm's implementation. Understanding how the algorithm can reduce stress for both drivers and passengers, thus contributing to overall community well-being, is an area worth investigating. The algorithm's potential impact on public health and well-being should be explored.

Evaluating the algorithm's scalability and robustness is vital, especially in the context of its ability to adapt to changes in urban traffic networks. Ensuring that it can handle network expansions and modifications is essential for its long-term viability. Investigating the algorithm's role in the development of intelligent transportation systems is a promising avenue. Future research should explore how it can contribute to the creation of more efficient, sustainable, and livable cities through advanced ITS solutions. These future research directions, grounded in the text's discussion of the algorithm's capabilities and potential impact, provide a clear roadmap for advancing traffic management and urban development.

In terms of future research trajectories, there are several promising avenues to explore:

Enhancing Scalability: Researchers can focus on optimizing the algorithm's scalability, making it even more versatile and adaptable to diverse urban traffic scenarios.

Accounting for Individual Driver Behavior: Investigating ways to incorporate individual driver behavior into the decision-making process can further improve the algorithm's performance and real-world applicability.

Integration with Emerging Technologies: Exploring how the algorithm can be integrated with emerging technologies such as connected and autonomous vehicles can open new dimensions for intelligent transportation systems and traffic management.

Real-world Testing: Extensive real-world testing and validation of the algorithm in various urban environments will be essential to demonstrate its effectiveness and reliability.

To sum up, the proposed algorithm represents a significant advancement in the field of adaptive traffic signal control. Its potential to alleviate traffic congestion, enhance transportation efficiency, reduce environmental impact, and improve urban dwellers' quality of life is substantial. As we continue to grapple with the challenges of urbanization and increased traffic demands, this algorithm serves as a beacon of hope for creating smarter, more sustainable, and more livable cities in the future.

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APPENDICES:

create a line graph in MATLAB:

```
% Define x and y data
```

```
x = 1:10;
```

```
y = rand(1, 10);
```

```
% Create the graph
```

```
plot(x, y);
```

```
% Add axis labels and a title
```

```
xlabel('Episode');
```

```
ylabel('Reward');
```

```
title('A2C Model Performance');
```

```
% Save the graph as a PNG image
```

```
saveas(gcf, 'a2c_performance.png');
```

implementation of the ACA with two critics (Actor2Critics) in MATLAB:

```
% Load the TrafficEnv class from the traffic_env.m file
```

```
trafficEnv = TrafficEnv;
```

```
% Initialize the environment
```

```
env = gym.make('TrafficEnv-v0');
```

```
env.seed(0);
```

```
% Initialize the traffic network
```

```
traffic_network
```

```
struct('intersection_1',struct('incoming_roads',{'road_1','road_2','road_3'},'outgoing_roads',{'road
```

```
_4'}), 'intersection_2', struct('incoming_roads', {'road_4'}, 'outgoing_roads', {'road_1', 'road_2', 'road_3'}));
```

```
% Define the Actor and two Critics networks
```

```
actor = [
    imageInputLayer([num_states 1 1], 'Normalization', 'none', 'Name', 'state')
    fullyConnectedLayer(32, 'Name', 'fc1', 'BiasLearnRateFactor', 0)
    reluLayer('Name', 'relu1')
    fullyConnectedLayer(num_actions, 'Name', 'output', 'BiasLearnRateFactor', 0)
    softmaxLayer('Name', 'softmax')];
```

```
critic1 = [
    imageInputLayer([num_states 1 1], 'Normalization', 'none', 'Name', 'state')
    fullyConnectedLayer(32, 'Name', 'fc1', 'BiasLearnRateFactor', 0)
    reluLayer('Name', 'relu1')
    fullyConnectedLayer(1, 'Name', 'output', 'BiasLearnRateFactor', 0)];
```

```
critic2 = [
    imageInputLayer([num_states 1 1], 'Normalization', 'none', 'Name', 'state')
    fullyConnectedLayer(32, 'Name', 'fc1', 'BiasLearnRateFactor', 0)
    reluLayer('Name', 'relu1')
    fullyConnectedLayer(1, 'Name', 'output', 'BiasLearnRateFactor', 0)];
```

```
% Define the options for the optimizer
```

```
options = rlRepresentationOptions('LearnRate', 1e-3, 'GradientThreshold', 1, 'UseDevice', 'gpu');
```

```
% Initialize the Actor and two Critics agents
```

```
actor_agent = rlStochasticActorRepresentation(actor, options);
```

```
critic_agent1 = rlValueRepresentation(critic1, options);
```

```
critic_agent2 = rlValueRepresentation(critic2, options);
```

```

% Initialize the ACagent with two critics
actor2critics_agent = rlACAgent(actor_agent, critic_agent1, critic_agent2, 'DiscountFactor',0.99);

% Set the initial state
state = env.reset();

% Run the simulation
for i = 1:100
    % Choose an action using the Actor
    action = actor_agent.getAction(state);

    % Take a step in the environment
    [next_state, reward, done, info] = step(env, action);

    % Train the ACagent with two critics
    actor2critics_agent = train(actor2critics_agent, state, action, reward, next_state, done);

    % Update the state
    state = next_state;

    if done
        break;
    end
end

```

make sure to install the Deep Learning Toolbox and RL Toolbox if they are not already installed.
 Here's an example code for training an A2C agent on the SGrid1 scenario

```

% Load the TrafficEnv class from the traffic_env.m file
trafficEnv = TrafficEnv;

% Initialize the environment
env = gym.make('TrafficEnv-v0', scenario='SGrid1');
env.seed(0);

% Initialize the A2C agent
a2c_agent = A2CAgent(num_intersections=1, num_phases=4,
state_size=env.observation_space.shape(1), action_size=env.action_space.n);

% Set the initial state
state = env.reset();

% Run the simulation
for i = 1:100
    % Choose an action using the A2C agent
    action = a2c_agent.act(state);

    % Take a step in the environment
    [next_state, reward, done, info] = step(env, action);

    % Store the experience and train the A2C agent
    a2c_agent.remember(state, action, reward, next_state, done);
    a2c_agent.train();

    % Update the state
    state = next_state;

```

```

    if done
        break;
    end
end

from graphviz import Digraph

g = Digraph('G', format='dot')

g.attr(rankdir='TB', size='8,5')

g.attr('node', shape='box')
g.node('1', 'Start')
g.node('2', 'Initialize traffic network  $G=(V, E)$ ')
g.node('3', 'Initialize state representation  $s(t)$  for each agent  $a_i$ ')
g.node('4', 'Initialize ACnetwork parameters  $\theta^{\pi}_i, \theta^Q_i$  for each agent  $a_i$ ')
g.node('5', 'Initialize pheromone matrix  $P_i$  for each agent  $a_i$ ')
g.node('6', 'For each time step  $t$ ')
g.node('7', 'For each agent  $a_i$ ')
g.node('8', 'Select action  $a$  based on policy  $\pi_i(s; \theta^{\pi}_i)$  and pheromone matrix  $P_i$ ')
g.node('9', 'Execute action  $a$ , observe next state  $s'$  and reward  $R_i(s, a)$ ')
g.node('10', 'Update  $\theta^{\pi}_i$  and  $\theta^Q_i$  based on advantage function and temporal-difference error')
g.node('11', 'Update pheromone matrix  $P_i$  based on action  $a$  and reward  $R_i(s, a)$ ')
g.node('12', 'Update state representation  $s(t)$  based on actions executed by all agents')
g.node('13', 'Check for convergence criteria')
g.node('14', 'End')

g.attr('node', shape='diamond')

```

```
g.node('15', "")

g.edges([(1, '2'), (2, '3'), (3, '4'), (4, '5'), (5, '6')])
g.edge('6', '7', constraint='false')
g.edges([(7, '8'), (8, '9'), (9, '10'), (10, '11'), (11, '7')])
g.edge('7', '12', constraint='false')
g.edges([(12, '13'), (13, '15')])
g.edge('15', '6', label='No')
g.edge('15', '14', label='Yes')

print(g.source)
```