

COORDINATED MULTI-LANE CHANGING
PROCESS FOR CONNECTED AND
AUTOMATED VEHICLES IN MIXED
ENVIRONMENT

BY

ABDULLAH ALI ALSHAKHS

A Thesis Presented to the
COLLEGE OF GRADUATE AND INTERDISCIPLINARY STUDIES
KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

SYSTEMS AND CONTROL ENGINEERING

11/24

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

This thesis, written by **ABDULLAH ALI ALSHAKHS** under the direction of his thesis adviser and approved by his thesis committee, has been presented to and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN SYSTEMS AND CONTROL ENGINEERING**.

Thesis Committee

am. Jaizan 25/12/24

Dr. Muhammad Mysorewala (Adviser)

Ali Nasir

Dr. Ali Nasir (Member)

25/12/24
Dr. Nezar AL-Yazidi (Member)

25/12/24
Dr. Mujahed Al-Dhaifallah
Department Chairman

Prof. Suliman Saleh Al-Homidan
Dean of Graduate Studies

Date



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I dedicate this thesis to my family. To my mother and father, for their endless support; and to my wife, for her patience, understanding and encouragement. Thank you all for always being there for me.

ACKNOWLEDGMENTS

I would also like to thank my friends, whose assistance and encouragement have been invaluable throughout this journey. Lastly, I want to express my heartfelt thanks to my family, especially my mother, father, and wife, for their continuous support and understanding during my work. *I would like to begin by thanking Allah, the Merciful, for blessing me with the enthusiasm and patience needed to complete this thesis. I am also grateful to King Fahd University of Petroleum and Minerals, along with the Control and Instrumentation Department, for providing an outstanding environment for study and research. My sincere appreciation goes to my advisor, Dr. Muhammed Mysorewala, for his unwavering guidance and support. I extend my gratitude to the committee members, Dr. Ali Nasir and Dr. Nezar Al-Yazidi, for their valuable feedback and encouragement. I would also like to thank my friends, whose assistance and encouragement have been invaluable throughout this journey. Lastly, I want to express my heartfelt thanks to my family, especially my mother, father, and wife, for their continuous support and understanding during my work.*

TABLE OF CONTENTS

ACKNOWLEDGMENTS	v
LIST OF TABLES	ix
LIST OF FIGURES	x
LIST OF SYMBOLS	xiii
LIST OF ABBREVIATIONS	xvi
ABSTRACT (ENGLISH)	xviii
ABSTRACT (ARABIC)	xx
CHAPTER 1 INTRODUCTION	1
1.1 Background and Motivation	1
1.2 Thesis Contribution	3
1.3 Assumptions	4
1.4 Approach	6
CHAPTER 2 LITERATURE REVIEW	8
2.1 General Overview of Lane Changing Algorithms	8
2.2 Trajectory Generation Methods	12
2.3 MDP and Intelligent Techniques	15
2.4 Existing Dynamic Lane-Changing Schemes	21
2.4.1 A Single Ego Vehicle Approach	21

2.4.2	A Multi-CAV Lane-Changing Approach	25
CHAPTER 3 METHODOLOGY		29
3.1	MDP-Based Framework for Lane-Changing Decision-Making	29
3.1.1	State Representation	29
3.1.2	Reward Function	31
3.1.3	Transition Probability	34
3.1.4	Value Iteration and Discount Factor Selection	36
3.1.5	Decision-Making Process for Lane Changes	38
3.2	Gap Detection	43
3.3	Cooperation Strategy	44
3.3.1	Cooperation Request Initiation	44
3.3.2	Cooperation Strategy	46
3.4	Target Lane	47
3.5	Priority Mechanism for Collision Avoidance	48
3.6	Trajectory Planning Model	50
3.6.1	Smooth Path Calculation	51
3.6.2	Speed Control using PID	58
3.7	Combined Scheme	62
CHAPTER 4 RESULTS AND DISCUSSION		65
4.1	Independent Lane Change	65
4.1.1	Avoiding Stationary Vehicles	65
4.1.2	Avoid a Fast Rear Vehicle	70
4.2	Cooperative Lane Change	74
4.2.1	Single-Attempt Cooperation	74
4.2.2	Multi-Attempt Cooperation	80
4.3	Multi-Vehicle Lane Change	85
4.3.1	Priority-Based Lane Change Coordination	85
4.3.2	Simultaneous Lane Change Coordination	91

CHAPTER 5 CONCLUSION	102
5.1 Summary of Findings and Implications	102
5.2 Future Work	104
REFERENCES	107
VITAE	112

LIST OF TABLES

2.1	Lane Change Algorithms	10
2.2	Comparison of MDP Methods for Autonomous Vehicle Decision-Making	19
2.3	Traffic density modes [10].	27
3.1	Example of decision-making based on current and next state reward. .	39
3.2	Lateral Position Adjustments Based on Lane Transitions	56
3.3	Vehicle Speed Categories	61
4.1	Performance Metrics for Double LCP in Low-Traffic Conditions	69
4.2	Performance Metrics for Single LCP in Low-Traffic Conditions	73
4.3	Performance Metrics for Single Lane-Change Phase with Cooperation .	79
4.4	Performance Metrics for LCP with Two Cooperating CAVs	84
4.5	Performance Metrics for Lane-Change Phase with Priority Coordination	90
4.6	Performance Metrics for Vehicle v1 across LCP Phases	99
4.7	Performance Metrics for Vehicle v2 across LCP Phases	99
4.8	Performance Metrics for Vehicle v3 during LCP	100

LIST OF FIGURES

2.1	Components of a Markov Decision Process (MDP) [20].	15
2.2	Three decisions states [9].	22
2.3	AV trajectory during LCP [9].	23
2.4	Effect of driver aggressiveness [9].	24
2.5	The architecture of the MA2C network [10].	26
2.6	Performance comparison of various MARL algorithms [10].	27
3.1	State representation of the ego vehicle in a multi-lane traffic scenario. The diagram shows the ego vehicle in lane L2, with nearby vehicles in adjacent lanes and relative speed and safety indicators.	30
3.2	State transition diagram showing the reward structure for various actions.	38
3.3	Flowchart of the reward-based lane change decision process.	42
3.4	Illustration of lane-changing gap assessment. The top part shows a sce- nario with sufficient gap space, while the bottom part shows insufficient gap space for a safe lane change.	43
3.5	Illustration of cooperation in lane-changing: blue vehicles represent Connected Automated Vehicles (CAVs) capable of cooperation, while red vehicles represent Human-Driven Vehicles (HDVs) that cannot co- ordinate.	45
3.6	Default Trajectory Time $t(k)$ vs PID Controller Trajectory Time $t_c(k)$.	55
3.7	Default Generated Trajectory (red) vs The Final Applied Trajectory (black).	57
3.8	PID Control Response for Speed Transition between Levels (L, M, H, VH)	61

3.9	Overall Scheme for Lane-Changing Decision-Making	64
4.1	Phase 1: Start of First Lane Change Maneuver ($t = 3.78s$)	66
4.2	Phase 1: Completion of First Lane Change Maneuver ($t = 8.77s$) . . .	67
4.3	Phase 2: Start and Completion of Second Lane Change Maneuver ($t = 8.80s$ to $t = 14s$)	67
4.4	Single Lane Change Maneuver: Ego vehicle ($v1$) transitioning in response to faster approaching rear vehicle ($v2$).	71
4.5	Speed profiles of all vehicles across the duration of the lane change maneuver.	72
4.6	Phase 1: Slowing Down ($t = 2.98s$ to $t = 8s$) and Completion ($t = 8s$). . .	75
4.7	Phase 2: Gap Detection and Speeding Up ($t = 8s$ to $t = 11.68s$) and Completion ($t = 11.68s$).	75
4.8	Phase 3: Performing the Lane Change ($t = 11.68s$ to $t = 16.67s$) and Final Position ($t = 16.67s$).	76
4.9	Speed Profiles of Ego Vehicle and Surrounding Vehicles Across Time. . .	77
4.10	Phase 1: Initial Cooperation Attempt from First CAV and Ego Vehicle Adjustment ($t = 2.98s$ to $t = 2.99s$)	80
4.11	Continued Cooperation Attempt, Adjustments in Position ($t = 4.85s$ to $t = 6.85s$)	81
4.12	Phase 2: Additional Cooperation from Second CAV and Ego Vehicle Preparation ($t = 11.85s$ to $t = 17.07s$)	81
4.13	Phase 2: Ego Vehicle Completing Lane Change ($t = 17.07s$ to $t = 22.06s$) . . .	82
4.14	Speed Profiles of All Vehicles During Lane Change Scenario	83
4.15	Lane Change Scenario: Vehicle 1 ($v1$) Initiates Lane Change with Priority ($t = 3 s$ to $t = 13 s$)	86
4.16	Speed Profiles for Lane Change Priority Scenario	87
4.17	Phase of Single Overtaking: Position of Vehicles at $t = 1.2s$	91
4.18	Phase of Necessary Speed Control and Stability at $t = 3.71s$	92
4.19	Phase of Necessary Speed Control and Stability at $t = 4.24s$	92
4.20	Phase of Necessary Speed Control and Stability at $t = 6.2s$	93

4.21 Multi-Simultaneous Lane Change Initiation at $t = 9.27\text{s}$ 94

4.22 v1 Sequential Overtaking Maneuver at $t = 16.83\text{s}$ 94

4.23 v2 Sequential Overtaking Maneuver at $t = 25.93\text{s}$ 95

4.24 CAVs Speed Profiles. 95

4.25 HDVs Speed Profiles. 96

LIST OF SYMBOLS

$v_i(t)$: Velocity of particle i at time t in Particle Swarm Optimization (PSO)

$x_i(t)$: Position of particle i at time t in PSO

w : Inertia weight in PSO

c_1, c_2 : Cognitive and social coefficients in PSO

$V(s)$: Value function for state s in RL and MDP contexts

γ : Discount factor in RL and MDP

r_t : Reward at time step t in RL

J : Cost function in MPC

x_t : Vehicle state at time step t in MPC

x_{desired} : Target state in MPC

u_t : Control input in MPC

λ : Weighting factor in MPC

$R(s, a)$: Reward function in MDP

$P(s' \mid s, a)$: Transition probability in MDP

S : State vector describing the situation of the ego vehicle in lane and speed

t_{init} : Time of lane change initiation for determining priority

P_i : Priority level of vehicle i

Pr: Probability

k : index variable ranging from 0 to N

L : Lane width

R : Scale factor

P_{lat} : Lateral position during lane change

v_{lat} : Lateral velocity component during lane change

v_{long} : Longitudinal velocity component during lane change

D_{min} : Minimum Distance at

P_{long} : Longitudinal position

$t(k)$: A time variable representing a normalized time parameter ranging from 0 to 1.

t_{PID} : The time taken for the PID controller to compute and apply its control action.

$t_c(k)$: A normalized time variable defined as the ratio $t_{\text{pid}}(k)/t_{\text{pid}}(N)$.

T_m : Engine torque

η : Efficiency factor of drivetrain

C_r : Rolling resistance coefficient

C_d : Aerodynamic drag coefficient

b : Damping force

g : Gravitational force

D : Air density

A : Frontal Vehicle Area

$G(s)$: Transfer function relating engine torque to vehicle speed

$C(s)$: PID controller

ΔL : Shift value for lane transitions

LIST OF ABBREVIATIONS

CAVs: Connected and Automated Vehicles

V2V: Vehicle-to-Vehicle communication

AVs: Autonomous Vehicles

HDVs: Human-Driven Vehicles

LCP: Lane Change Process

MDP: Markov Decision Process

POMDP: Partially Observable Markov Decision Process

MPC: Model Predictive Control

RL: Reinforcement Learning

GP: Gaussian Process

CBS: Conflict-Based Search

MARL: Multi-Agent Reinforcement Learning

MA2C: Multi-Agent Advantage Actor-Critic

IDM: Intelligent Driver Model

MOBIL: Minimizing Overall Braking Induced by Lane Changes (lateral control model)

MADQN: Multi-agent Deep Q-Network

MAACKTR: Multi-agent ACKTR (Trust Region Policy Optimization)

MAPPO: Multi-Agent Proximal Policy Optimization

UCLF: Uncertainty-Aware Cooperative Lane-Changing Framework

L, M, H, and VH: Low, Medium, High, and Very High (speed categories)

THESIS ABSTRACT

NAME: Abdullah Ali Alshakhs
TITLE OF STUDY: Coordinated Multi Lane-Changing Process for Connected and Automated Vehicles in Mixed Traffic
MAJOR FIELD: Systems and Control engineering
DATE OF DEGREE: 11/2024

This thesis develops a novel algorithm of decentralized coordinated multi-vehicle lane-changing processes for Connected and Automated Vehicles (CAVs) in a mixed traffic with Human-Driven Vehicles (HDVs). The study enhances road safety and traffic efficiency through advanced lane-changing maneuvers, facilitated by MATLAB-based simulations. Central to this research is the development of Markov Decision Processes (MDPs) for adaptive decision-making, enabling CAVs to assess their surroundings and predict the behavior of nearby vehicles. The system incorporates robust gap detection mechanisms, allowing CAVs to identify and evaluate safe spaces for lane transitions. Additionally, a priority-based strategy manages trajectory overlapping, ensuring that vehicles coordinate their actions to avoid conflicts during simultaneous maneuvers. Cooperation strategies enable CAVs to communicate and adjust their movements, creating smooth and synchronized lane changes even when interacting with unpredictable HDVs. The research combines these intelligent decision-making approaches with precise speed regulation using Proportional-Integral-Derivative (PID) mechanisms. Simulation results demonstrate that coordinated actions among CAVs can significantly improve traffic flow, reduce collision risks, and adapt to dynamic road conditions. The findings provide valuable insights into the practical implementation of autonomous driving systems, emphasizing the role of real-time cooperation and communication be-

tween vehicles in enhancing road safety and efficiency. Ultimately, this research lays a solid foundation for future advancements in CAV technology, paving the way for smarter, safer, and more integrated autonomous driving solutions.

ملخص الرسالة

الاسم: عبدالله علي الشخص

عنوان الدراسة: عملية تغيير المسارات المتعددة بطريقة منسقة ولا مركزية للمركبات المتصلة وذاتية القيادة في بيئة مرور مختلطة

التخصص: هندسة نظم التحكم

تاريخ الدرجة العلمية: نوفمبر 2024

تستكشف هذه الأطروحة محاكاة ديناميكية لعمليات تغيير المسارات المتعددة المنسقة و المستقلة للمركبات المتصلة وذاتية القيادة في بيئة مختلطة تضم مركبات يقودها بشر. يعزز البحث السلامة المرورية وكفاءة الحركة عبر مناورات متقدمة لتغيير المسارات. يتمحور هذا البحث حول تطوير عمليات اتخاذ القرار التكيفية باستخدام عمليات اتخاذ القرار القائمة على ماركوف، مما يمكن المركبات ذاتية القيادة من تقييم البيئة المحيطة وتوقع سلوك المركبات المجاورة. يتضمن النظام آليات فعالة للكشف عن الفراغات، مما يسمح للمركبات بتحديد وتقييم المساحات الآمنة للانتقال بين المسارات. علاوة على ذلك، تُدار تداخلات المسارات باستخدام استراتيجية تعتمد على الأولويات، مما يضمن تنسيق المركبات لتحركاتها لتجنب النزاعات أثناء المناورات المتزامنة. تتيح استراتيجيات التعاون للمركبات ذاتية القيادة التواصل وتعديل حركاتها، مما يؤدي إلى تغييرات مسار سلسة ومتزامنة حتى عند التفاعل مع المركبات التي يقودها بشر. يدمج البحث هذه الأساليب الذكية لاتخاذ القرارات مع التحكم الدقيق في السرعة باستخدام آليات التحكم التناسبي-التكاملي-التفاضلي. أظهرت نتائج المحاكاة أن التنسيق بين المركبات ذاتية القيادة يمكن أن يحسن تدفق الحركة بشكل كبير، ويقلل من مخاطر الاصطدام، ويتكيف مع الظروف المتغيرة للطريق. تقدم هذه النتائج رؤى قيمة حول التطبيق العملي لأنظمة القيادة الذاتية، مع التأكيد على دور التعاون والتواصل في الوقت الفعلي بين المركبات لتعزيز السلامة والكفاءة المرورية. وفي النهاية، تضع هذه الدراسة أساساً قوياً لتطوير تكنولوجيا المركبات ذاتية القيادة، مما يمهد الطريق لحلول قيادة ذاتية أكثر ذكاءً وأماناً وتكاملاً.

CHAPTER 1

INTRODUCTION

The integration of Connected and Automated Vehicles (CAVs) into mainstream traffic systems presents a revolutionary step towards enhancing road safety, traffic efficiency, and overall transportation dynamics. This project explores the development of a MATLAB-based simulation aimed at facilitating sophisticated multi-vehicle lane-changing maneuvers. The focus is on designing a system that allows multiple vehicles to change lanes in coordination, enhancing traffic flow and reducing the likelihood of congestion or collisions.

1.1 Background and Motivation

The development of connected and automated vehicles (CAVs) has notably enhanced road capacity, improved mobility, and reduced fuel consumption [1]. Key technologies within CAV research include cooperative cruise control, platooning, cooperative collision avoidance, and lane-changing maneuvers, with lane-changing being particularly complex due to its reliance on calculated decisions and precise execution. This process

integrates vehicle-to-vehicle (V2V) communication, optimal decision-making, maneuver planning, and control algorithms [2][3]. CAVs can operate either autonomously or within a platoon, and studies have shown that they generally outperform autonomous vehicles (AVs) in terms of safety and travel time, with fewer accidents and a smoother driving experience. CAVs' ability to address sensor limitations and create networked vehicular environments makes them more reliable compared to AVs [4]. These advancements highlight the potential of CAVs to significantly improve road safety and driving efficiency. As the future of self-driven vehicles draws nearer with technological advancements, companies like Tesla are actively working toward developing fully autonomous cars for public use. However, several challenges still need to be addressed before autonomous vehicles can be considered practically superior to human-driven ones. One promising approach is to organize cars into platoons, allowing them to navigate roads more efficiently. In this work, we focus on a scenario where connected and automated vehicles (CAVs) must avoid unexpected obstacles on the road. The motivation behind this idea stems from several key factors:

1. Autonomous vehicles must exhibit human-like reactions when faced with unexpected road accidents or emergencies.
2. Realistically, various obstacles, such as rocks or other accidents, can suddenly appear on the road.
3. To address this issue, decentralized decision-making algorithm and control with cooperation potential is implemented for each vehicle, enabling them to change lanes based on the positions recommended and coordinate the process.

4. Effective coordination during lane changes enhances traffic flow and minimizes disruptions caused by sudden braking or swerving.

This approach aims to enhance the adaptability and safety of CAVs in dynamic driving environments.

1.2 Thesis Contribution

This research contributes to the design, development, simulation, testing, refinement of a decentralized coordinated lane-changing strategy for multiple connected and automated vehicles (CAVs) operating alongside human-driven vehicles (HDVs). By addressing the complexities of mixed traffic environments, this work aims to enhance safety, efficiency, and adaptability of lane-changing maneuvers for CAVs in the presence of HDVs, thereby optimizing road space usage and reducing traffic disruptions. The objectives can be summarized as:

1. Algorithm Development:

- (a) Developing a decentralized coordinated-LCP model that is more effective than a single-LCP.
- (b) Dividing the model into decision-making and trajectory control levels.
- (c) Factoring in cooperation from other CAVs.
- (d) Introducing a coordination algorithm to perform multiple lane changes effectively.

- (e) Incorporating a priority and simultaneous lane-change mechanism to manage situations where multiple vehicles need to change lanes at the same time, ensuring safety and efficiency.

2. Simulation and Validation:

- (a) Applying the scheme in a mixed environment of CAVs and HDVs.
- (b) Conducting simulations to validate performance.

1.3 Assumptions

The effectiveness of the lane change protocol in our autonomous vehicle system is predicated on several key assumptions that define the operational environment and system capabilities. These assumptions are crucial for simplifying the model while ensuring reliable functionality within these defined parameters.

1. Sensor Data Processing:

- All data collected from onboard sensors is processed in real-time. This data forms the basis for all decision-making processes related to vehicle navigation and maneuvering.
- CAVs can detect a maximum of four neighboring vehicles, identifying the nearest one in each of the left, right, front, and rear directions. They are not capable of detecting multiple vehicles in the same direction.
- The maximum detection range extends up to 200 meters in the longitudinal direction, while in the lateral direction, it fully covers the adjacent lane.

- Gaps are detected within a range of 200 meters and are assumed not to decrease once the lane-changing process is initiated.

2. Vehicle Dynamics and Road Structure:

- Velocity Considerations: The protocol accounts for changes in velocity of surrounding vehicles, which is critical for assessing the safety and necessity of lane changes.
- Road Configuration: The model is designed for roads consisting of three lanes with each lane width being 5 meters. This specific structure is essential for standardizing the lane change strategy.
- collision avoidance techniques improve overall safety, reducing the likelihood of collisions and ensuring smoother maneuvers in unpredictable environments.
- lane change time is set to 5 seconds for all cases.
- for acceleration duration, it is set to 3 seconds if its in the same lane and 5 seconds during a lane change.
- deceleration is done in 2 seconds, assuming a brake system without failures.

3. Exclusions from the Model:

- Communication and Weather: The current model does not take into account communication failures or weather disturbances. These factors are considered externalities that are not covered under the standard operational parameters.

- Human-Driven Vehicles (HDVs): It is assumed that HDVs maintain their lane positions during the lane change process (LCP), providing predictability of their behavior on the road.

These assumptions are integral to the design and implementation of the lane change algorithm. They provide a clear framework within which the system operates, ensuring that the autonomous vehicle behaves predictably and safely under normal traffic conditions. However, it is important to note that scenarios outside these assumptions may require additional strategies or modifications to the existing protocol to ensure safety and efficiency.

1.4 Approach

1. Ego Vehicle State Monitoring: Continuously monitor the ego vehicle's speed, position, and surrounding vehicles' data.
2. Lane Changing Decision Algorithm (MDP): Use a Markov Decision Process (MDP) to determine whether to change lanes or stay based on the vehicle's position, speed, and proximity to other vehicles.
3. Gap Detection and Feasibility: Evaluate the feasibility of a lane change by detecting gaps in the target lane, ensuring sufficient space for a safe maneuver.
4. Cooperation and Priority Strategies: If needed, initiate cooperation requests with surrounding vehicles to create space.

5. Coordination: Prevent potential collisions caused by multiple vehicles intersecting during a lane change by employing a priority-based technique.
6. Trajectory Planning and PID Control: Plan a smooth trajectory for the lane change and use a PID controller to manage speed adjustments throughout the maneuver.
7. Lane Change Execution: Execute the lane change based on the calculated trajectory, ensuring no overlapping regions with other vehicles.
8. Continuous Monitoring and Adaptation: Continuously update the ego vehicle's decisions based on real-time traffic conditions, ensuring adaptability to changes in the environment.

CHAPTER 2

LITERATURE REVIEW

2.1 General Overview of Lane Changing Algorithms

Lane-changing decision-making and trajectory planning have been widely researched in recent years, focusing on improving both safety and efficiency in mixed traffic environments. One approach to this problem involves cooperative control frameworks, which focus on enhancing CAV lane-changing by facilitating coordination between CAVs and HDVs. This cooperative approach ensures smoother traffic flow and improves lane-changing safety, as discussed in [5]. Such frameworks are critical, especially when considering dense, high-speed traffic scenarios where uncooperative behaviors from human-driven vehicles (HDVs) could jeopardize CAV safety. In contrast, more dynamic models like those in [6] focus on optimizing lane-changing decisions using game-theory-based approaches. By considering the real-time status of surrounding vehicles and dynamically updating lane-change trajectories, this method provides a flexible and

adaptable solution for AVs in mixed traffic environments. This is particularly useful when navigating complex road conditions where static models fall short. Additionally, trajectory planning has evolved to address the real-time variability of traffic, as seen in [7]. Unlike earlier static models that assume constant velocities of surrounding vehicles, this dynamic model incorporates real-time adjustments in speed and position, offering a more accurate and reliable solution for AVs to perform lane changes safely. The importance of real-time adaptation in trajectory planning cannot be overstated, especially when human-driven vehicles can behave unpredictably. Further research, such as in [8], has shifted towards optimizing CAV merging into dedicated lanes by using centralized control strategies. These strategies optimize lane-changing sequences and trajectories, ensuring that CAVs can transition smoothly into dedicated lanes without disrupting overall traffic flow. This is particularly relevant for future roadway designs where dedicated CAV lanes are expected to coexist with traditional lanes. Another promising direction in lane-changing research involves learning-based approaches that incorporate human driver behavior into AV control systems. By combining Gaussian process learning with model predictive control strategies, the work in [9] aims to predict human-driven vehicle behaviors more accurately, thereby enhancing safety and operational efficiency in mixed traffic. This approach addresses a critical gap in traditional models that often overlook the variability and uncertainty of human driving. Reinforcement learning has also been explored for cooperative lane-changing, particularly in scenarios where multiple AVs must interact with HDVs. The work in [10] leverages multi-agent reinforcement learning (MARL) to enable AVs to collaborate and safely perform lane changes, enhancing both safety and traffic effi-

ciency. This approach introduces a novel multi-objective reward system that balances fuel efficiency, driving comfort, and safety, which is crucial for real-world applications. Lastly, conflict-based search (CBS) models, as detailed in [11], tackle the challenges of coordinating lane changes between CAVs and HDVs in dense traffic. This model provides a structured method for resolving conflicts in lane-changing decisions, ensuring that both CAVs and HDVs can safely navigate complex traffic environments. Similarly, uncertainty-aware frameworks like the one in [12] use partially observable Markov decision processes (POMDP) to handle the unpredictability of human drivers, further improving CAV performance in mixed traffic.

Table 2.1: Lane Change Algorithms

Paper	Mixed Traffic	Trajectory Planning	Learning-Based Approach	Decision-Making Method	Real-Time Operation	Collision Avoidance	Applicable to
[5]	Yes	Yes	No	Rule-based co-operative	No	No	Single Ego Vehicle with CAVs Co-operation
[6]	Yes	Yes	No	Rule-based	No	No	Single Ego Vehicle
[7]	Yes	Yes	No	Game-theory	Yes	Yes	Single Ego Vehicle
[8]	Yes	Yes	No	Centralized merging	No	No	Single Ego Vehicle with CAVs Co-operation
[9]	Yes	No	Yes	Gaussian Process (GP)	Yes	Yes	Single Ego Vehicle
[10]	Yes	Yes	Yes	Multi-Agent Reinforcement Learning	Yes	Yes	Multiple CAVs
[11]	Yes	Yes	No	Conflict-based search (CBS)	Yes	Yes	Single Ego Vehicle with CAVs Co-operation
[12]	Yes	Yes	No	UCLF	Yes	Yes	Multiple CAVs
This Work	Yes	Yes	No	Markov Decision Process	Yes	Yes	Multiple CAVs with Coordination

The comparison in Table 2.1 highlights distinct approaches to lane-changing decision-making models, especially in mixed traffic environments involving both autonomous vehicles (AVs) and human-driven vehicles (HDVs). A key distinction between the papers is their focus on either single vehicle decision-making or multi-vehicle coordination. Papers such as [6], [7], and [9] concentrate on single vehicle scenarios, where the ego vehicle makes decisions based on its environment, using methods like game theory [7] or Gaussian Process learning [9]. In contrast, multi-vehicle approaches, including [5], [8], and [10], explore scenarios where multiple vehicles interact either to facilitate the lane change of one vehicle or to collaboratively perform lane changes.

Trajectory planning is another significant factor across the papers. Most papers, like [5], [6], and [7], incorporate trajectory planning to ensure smooth and safe lane changes. However, [9] stands out by focusing more on predictive decision-making using Gaussian Processes rather than detailed trajectory planning. Meanwhile, the real-time operation of these models is essential for practical applications. Papers such as [7], [9], [10], [11], and [12] (the Uncertainty-Aware Cooperative Lane-Changing Framework) include real-time decision-making, which is crucial for adapting to dynamic traffic environments, ensuring collision avoidance, and optimizing vehicle behavior based on current traffic conditions. In contrast, papers like [5], [6], and [8] lack real-time adaptation, making them potentially less responsive in dynamic scenarios.

The collision avoidance strategies differ significantly across the models. More advanced approaches like game theory [7], Gaussian Process learning [9], and Multi-Agent Reinforcement Learning [10] incorporate mechanisms to avoid collisions by dy-

namically adjusting vehicle trajectories or predicting potential hazards. However, simpler rule-based systems like those in [5] and [6] do not provide explicit collision avoidance mechanisms, which could limit their effectiveness in high-risk situations. Multi-vehicle interactions are especially critical in papers like [5], [8], and [11], where other vehicles assist in creating gaps or facilitating the lane change of the ego vehicle, enhancing safety and traffic flow.

In conclusion, the decision-making models reviewed offer a range of strategies for handling lane changes in mixed traffic. The more sophisticated real-time, learning-based models offer significant advantages in safety and efficiency by dynamically adapting to the environment. On the other hand, simpler rule-based and non-real-time models may have limited application in complex or rapidly changing traffic scenarios, where unexpected events require immediate responses. However, this thesis, as stated in Section 1.2, contributes by adding interactive coordination between the CAVs such that it is possible to coordinate a Multi-LCP simultaneously. Also, the CAVs consider changing speeds to facilitate lane changing process of there vehicles. Furthermore, this is done in real-time indicating practicality of the decision making and trajectory planning.

2.2 Trajectory Generation Methods

Trajectory generation methods for autonomous vehicles (AVs) are essential in navigating dynamic environments safely and efficiently. Conventional trajectory planning treats the task as an optimization problem and often employs numerical methods, such

as dynamic programming, direct methods, and indirect methods. These methods are used to derive solutions to control variables that minimize a defined cost function across a given trajectory horizon. However, such approaches can be computationally intensive, especially in real-time applications, making heuristic and bio-inspired methods attractive alternatives [13].

Bio-inspired algorithms offer an adaptive solution, relying on models of natural behaviors. For instance, Genetic Algorithms (GA) apply evolutionary principles such as selection and mutation to iteratively improve trajectory solutions, balancing computational efficiency with optimality. Particle Swarm Optimization (PSO), modeled on flocking behavior, updates particles based on their own experience and the best-known solutions of the swarm. This provides faster convergence than GA but sometimes lacks adaptability to dynamic changes. This adaptive balance is often represented by updating velocities and positions using the equations:

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot (p_{\text{best},i} - x_i(t)) + c_2 \cdot r_2 \cdot (g_{\text{best}} - x_i(t)) \quad (2.1)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2.2)$$

where $v_i(t)$ and $x_i(t)$ denote the velocity and position, w represents the inertia weight, and c_1 and c_2 are cognitive and social coefficients [14].

With advances in machine learning, Reinforcement Learning (RL) has gained popularity as a method for adaptive trajectory generation. RL formulates the planning

task as a Markov Decision Process (MDP), where an agent learns to maximize cumulative rewards by interacting with the environment, thus enabling adaptability to changing conditions. This adaptability is crucial in multi-agent or dense traffic scenarios where AVs need to predict and respond to the behavior of surrounding vehicles. The agent's expected reward can be described by:

$$V(s) = E \left[\sum_{t=0}^T \gamma^t r_t \right] \quad (2.3)$$

where $V(s)$ is the value function for state s , γ is the discount factor, and r_t is the reward at each step [15].

Another effective approach, Model Predictive Control (MPC), integrates future state predictions into the current decision-making process. MPC iteratively solves an optimization problem over a finite horizon to minimize tracking error, control effort, and smoothness. Its cost function, typically structured as:

$$J = \sum_{t=0}^T (x_t - x_{\text{desired}})^2 + \lambda \sum_{t=0}^T u_t^2 \quad (2.4)$$

where x_t denotes the vehicle state, x_{desired} the target state, u_t the control input, and λ a weighting factor, allows the system to adjust dynamically, making MPC well-suited for high-speed and mixed-traffic environments [16].

Hybrid models combine multiple methods, such as RL with MPC or GA with PSO, to create robust, adaptable systems that take advantage of each method's strengths. For example, RL's adaptability is complemented by MPC's predictive capabilities, which can provide smoother trajectories for AVs by adjusting continuously based on

real-time sensor data. Emerging techniques like the Aquila Optimizer (AO) further enhance adaptability by balancing exploration and exploitation without excessive parameter tuning, making it suitable for real-time trajectory adjustments in complex scenarios [17].

In summary, trajectory generation methods have evolved from purely numerical models to include bio-inspired, reinforcement learning, and hybrid approaches. This evolution reflects the increasing complexity of AV environments and the need for more adaptable and computationally efficient solutions [18], [19].

2.3 MDP and Intelligent Techniques

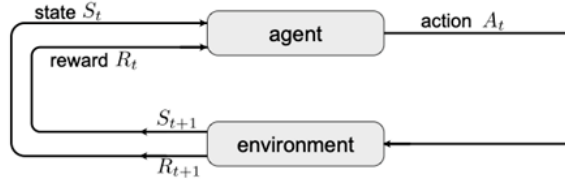


Figure 2.1: Components of a Markov Decision Process (MDP) [20].

as illustrated in Figure 2.1, The main components of a Markov Decision Process (MDP) are [20] :

- **States (S):** The set of all possible states in which the agent can find itself. In the context of the diagram, S_t represents the state of the agent at time t .
- **Actions (A):** The set of all actions the agent can take while in a particular state. A_t in the diagram refers to the action taken by the agent at time t .

- **Transition Function (P):** This function defines the probability distribution over what state results from taking an action in a particular state. It captures the dynamics of the environment.
- **Reward Function (R):** A reward function specifies the immediate payoff received after transitioning from one state to another due to an action. In the diagram, R_t indicates the reward received at time t .
- **Policy (π):** A policy is a strategy used by the decision-maker. It specifies the action to take in each state. A policy can be deterministic, where a specific action is chosen in each state, or stochastic, where a probability distribution over actions is specified.

Markov Decision Processes (MDPs) provide a formal framework for modeling decision-making in environments where outcomes are partly random and partly under the influence of a decision-maker. MDPs are widely used in various fields, including robotics, automated control, economics, and manufacturing.

Markov Decision Processes (MDPs) and Partially Observable MDPs (POMDPs) are powerful frameworks for autonomous vehicle (AV) decision-making, allowing AVs to navigate complex, uncertain environments by optimizing sequential actions. These frameworks focus on deriving policies that maximize expected cumulative rewards through a set of states, actions, and transitions, accounting for probabilistic outcomes and rewards. The Bellman equation [20] serves as a foundational element in MDPs, enabling recursive optimization of the expected rewards :

$$V(s) = \max_{a \in A} \left[R(s, a) + \gamma \sum_{s' \in S} P(s' | s, a) V(s') \right] \quad (2.5)$$

where $V(s)$ represents the value of each state, $R(s, a)$ is the reward function, and γ is a discount factor that balances immediate versus future rewards.

Various studies have applied these frameworks to AV lane-changing and decision-making challenges in complex, uncertain environments. For instance, in highly uncertain urban settings where sensor noise is prevalent, one approach leverages a POMDP for lane-changing decisions, employing a probabilistic online method that operates in a hierarchical structure. This model breaks down the lane-changing task into layers, such as situational analysis, maneuver planning, and trajectory generation, and prioritizes actions to minimize risks associated with urban traffic [21]. This approach incorporates policy iteration to accommodate noisy sensor data, enhancing robustness in real-time.

Another study develops a Bayesian-influenced MDP framework that integrates Bayesian inference to improve situational awareness and predict the behavior of surrounding vehicles. This model updates its beliefs about traffic dynamics, allowing the vehicle to adapt its actions based on probabilistic predictions of other vehicles' movements. By employing value iteration for optimization, the model adjusts its decisions dynamically, which is especially beneficial for mitigating risks in unpredictable urban environments [22].

Extending these frameworks further, a Mixed Observability MDP (MOMDP) approach has been introduced to separate observable vehicle states from hidden driver

intentions. This model, which accounts for hidden states such as human drivers’ intentions, enables a more adaptable decision-making process. By using approximate policy iteration, the MOMDP is able to consider both observable and unobservable factors, making it particularly useful in scenarios with unpredictable human behavior. This allows the model to support complex maneuvers like lane changes by incorporating both observable and hidden information [23].

In addition to these MDP-based models, Bayesian networks within an MDP framework have also been applied to assess lane-change feasibility. By focusing on deceleration-to-safety distance metrics, this approach enables vehicles to calculate safe passing distances in real time, dynamically adjusting to vehicle dynamics and surrounding traffic. This model applies dynamic programming for optimization, ensuring safety in high-density traffic scenarios where precise safety margins are necessary for smooth lane transitions [24].

For environments like freeways where sudden changes are less frequent, a point-based MDP approach has been explored. This model focuses on maintaining lane stability and responding to environmental changes, such as nearby vehicles shifting lanes. Optimized through point-based value iteration, the model prioritizes computational efficiency while maintaining adaptability, making it particularly effective for high-speed, low-variability scenarios [25].

In applications beyond terrestrial AVs, continuous-state POMDPs have been employed for unmanned aerial vehicle (UAV) collision avoidance, which could be adapted to AV lane-changing in certain high-speed scenarios. Using branch-and-bound search in a continuous state space, this model precisely adjusts velocity and acceleration,

enabling nuanced collision avoidance strategies in dynamic environments. Unlike discrete-state MDPs, this continuous-state model is well-suited for applications requiring fine-grained control over speed and position, supporting safe operation in environments with rapid and continuous changes [26].

Overall, MDP and POMDP frameworks provide versatile tools for decision-making in AVs, with approaches ranging from Bayesian-enhanced situational awareness to mixed observability for handling hidden human intentions. Each method offers unique advantages in balancing computational efficiency, real-time adaptability, and safety across diverse traffic scenarios.

Table 2.2: Comparison of MDP Methods for Autonomous Vehicle Decision-Making

Paper	Type	Key Features	Optimization Method	Application Focus	Strengths
[21]	POMDP	Probabilistic, hierarchical decision layers	Policy iteration	Urban lane-changing	Real-time noise handling, reduced computation
[22]	MDP with Bayesian	Bayesian updates for predicting vehicle behavior	Value iteration	General urban driving	Adaptive risk assessment, Bayesian integration
[23]	MOMDP	Mixed observability for human intention modeling	Approximate policy iteration	General driving	Robust with hidden variables
[24]	MDP with Bayesian	Safety metrics like deceleration-to-safety distance	Dynamic programming	Lane-change safety assessment	Real-time safety adjustments
[25]	Point-based MDP	Lane stability in single-lane freeway driving	Point-based value iteration	High-speed freeway driving	Computational efficiency, robust for freeways
[26]	Continuous POMDP	Continuous state modeling with lookahead	Branch-and-bound search	UAV collision avoidance	Precision in dynamic, high-speed conditions

The comparison in Table 2.2 highlights various decision-making frameworks used

in autonomous vehicle (AV) applications, focusing on MDP and POMDP-based approaches. Each method has been tailored to address specific challenges in AV environments, ranging from urban lane-changing to high-speed freeway driving and UAV collision avoidance.

One key distinction between the methods lies in the type of decision framework used—whether it is an MDP, POMDP, or an adaptation like MOMDP. POMDPs, as seen in [21], excel in handling uncertainty in urban settings where noisy sensor data can impact decision-making, benefiting from hierarchical probabilistic decision layers. Bayesian-enhanced MDPs (e.g., [22] and [24]) add predictive capabilities, allowing for dynamic updates based on observed traffic behavior, which is especially valuable in general urban driving and lane-change safety assessment.

The optimization methods employed also vary according to application needs. For instance, policy iteration and value iteration are commonly used for AVs in urban environments (e.g., [21] and [22]) due to their effectiveness in sequential decision-making. In contrast, dynamic programming and point-based value iteration (e.g., [24] and [25]) are employed in freeway driving where the focus shifts to stability and computational efficiency in structured, less-variable environments.

In terms of application focus, most of these methods target urban and freeway driving, with a few focusing on specialized applications like UAV collision avoidance [26]. Notably, methods that use continuous-state modeling and lookahead capabilities, such as the continuous POMDP in [26], are particularly well-suited for dynamic, high-speed conditions where precision is critical.

Finally, each approach’s strengths align with its intended environment. For in-

stance, the real-time noise handling in the POMDP model [21] and the adaptive risk assessment in the Bayesian MDP [22] are crucial for urban settings. Meanwhile, computational efficiency and robustness in high-speed conditions are highlighted in point-based MDPs, making them well-suited for freeway scenarios [25].

In summary, the table demonstrates that the choice of decision-making framework, optimization method, and specific features must align closely with the AV’s operational context. While urban scenarios benefit from approaches that handle noise and unpredictability, structured environments like freeways favor computationally efficient models that prioritize stability.

2.4 Existing Dynamic Lane-Changing Schemes

2.4.1 A Single Ego Vehicle Approach

2.4.1.1 Method

The methodology introduces a dynamic lane-changing decision model [9] based on multi-player game theory and polynomial trajectory planning. This system operates in real-time to facilitate safe and efficient lane changes for autonomous vehicles (AVs) in mixed traffic.

1. Lane-Changing Decision Module:

- The multi-player game theory model calculates the interactions between the AV (vehicle A) and surrounding human-driven vehicles (HVs, vehicles B and C). The model estimates driver aggressiveness and evaluates poten-

tial lane-change outcomes based on safety (space headway) and efficiency (time).

- The decision process is divided into three stages (see Figure 2.2). These stages involve intention generation, returning to the original lane if the game fails, multi-player game dynamics, and final lane-changing completion.

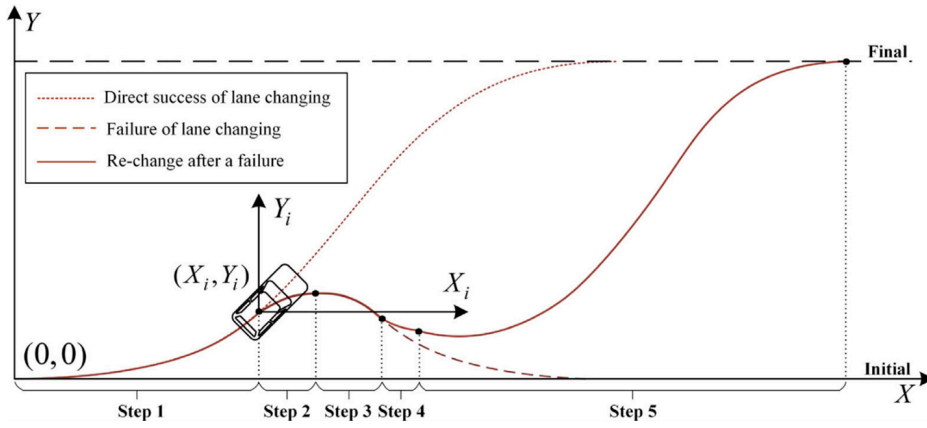


Figure 2.2: Three decisions states [9].

2. Trajectory Generation Module:

- The lane-changing trajectory is generated using a quintic polynomial curve that updates every 0.1 seconds. This trajectory ensures smooth transitions in speed and acceleration.
- Figure 3.7 shows the dynamic trajectory planning process. Constraints like maximum allowable acceleration and speed ensure vehicle stability and prevent collisions.

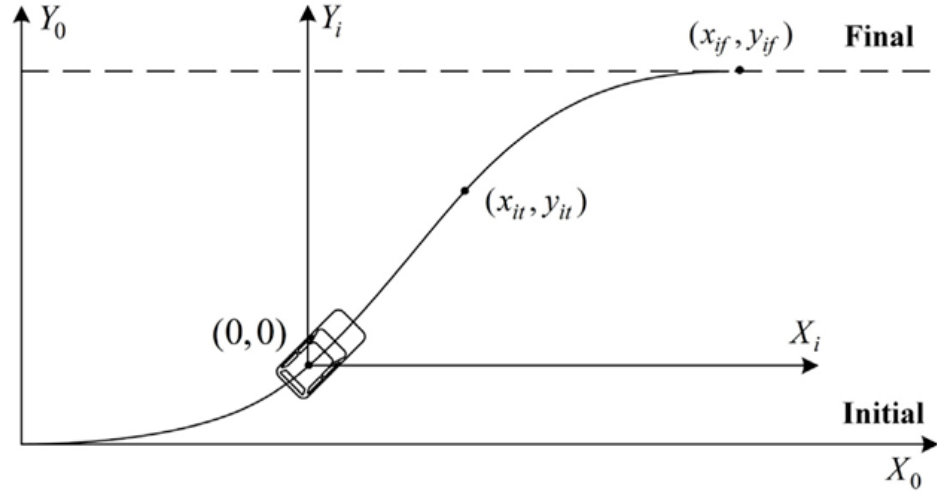


Figure 2.3: AV trajectory during LCP [9].

3. Optimization Objective:

- The model minimizes lane-changing time while ensuring comfort and safety.

A balance between lateral speed and overall time is achieved, with regular updates to the trajectory based on game outcomes. The final trajectory optimally adapts to real-time traffic conditions.

2.4.1.2 Discussion

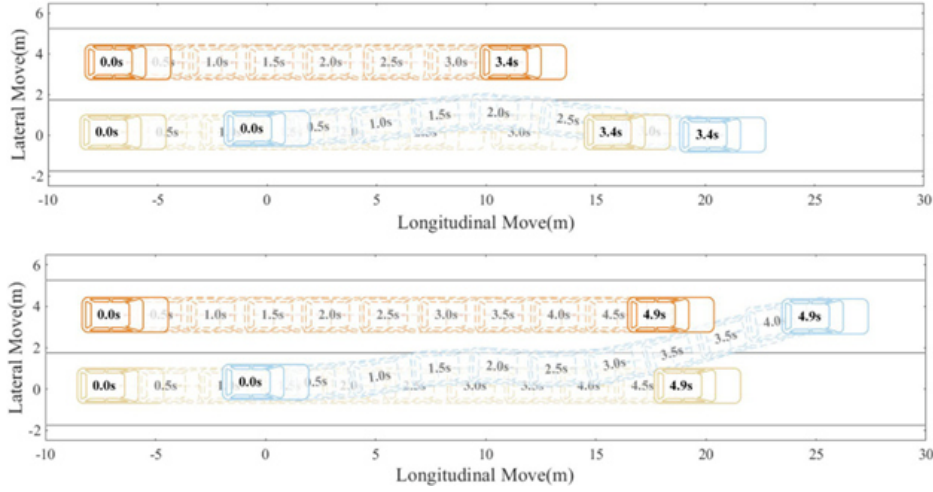


Figure 2.4: Effect of driver aggressiveness [9].

1. Performance Evaluation:

- The proposed model's real-time adaptability allows the AV to handle aggressive behavior from human drivers. The lane-change process was tested using the NGSIM dataset, and the AV consistently avoided collisions by adjusting its trajectory in real-time.
- Figure 2.4 demonstrates the lane-changing process under different aggressiveness levels. In the top subplot, the AV completes the lane change in 3.4 seconds, while the bottom subplot shows a longer 4.9-second lane change due to more aggressive drivers in the surrounding lanes.

2. Limitations and Future Work:

- While the model handles simple lane changes effectively, it does not yet address more complex scenarios like multi-lane changes or full route plan-

ning. Future work could also include AV-to-AV communication to enhance decision-making.

2.4.2 A Multi-CAV Lane-Changing Approach

The paper [10] proposes a multi-agent reinforcement learning (MARL) framework to enable cooperative lane-changing for connected autonomous vehicles (CAVs) in mixed traffic. The primary method used is a multi-agent advantage actor-critic (MA2C) algorithm, with a focus on improving safety, efficiency, and comfort during lane changes.

2.4.2.1 Method

The lane-changing problem is modeled as a partially observable Markov decision process (POMDP). Each autonomous vehicle (AV) acts as an agent and observes its neighboring vehicles, both AVs and human-driven vehicles (HDVs), to make real-time lane-changing decisions.

- The action space for each AV includes decisions such as speeding up, slowing down, cruising, or changing lanes.
- A multi-objective reward function is used to guide decision-making, factoring in safety (avoiding collisions), driving comfort (minimizing abrupt acceleration and deceleration), and efficiency (maintaining high speeds).

Below, Equation 2.6 defines the reward function that balances these metrics:

$$r_{i,t} = \omega_s r_s + \omega_d r_d + \omega_v r_v - \omega_c r_c \quad (2.6)$$

The MA2C algorithm incorporates parameter sharing, allowing agents to share the same actor-critic network, which improves training efficiency. The agents still make individualized decisions based on their observations.

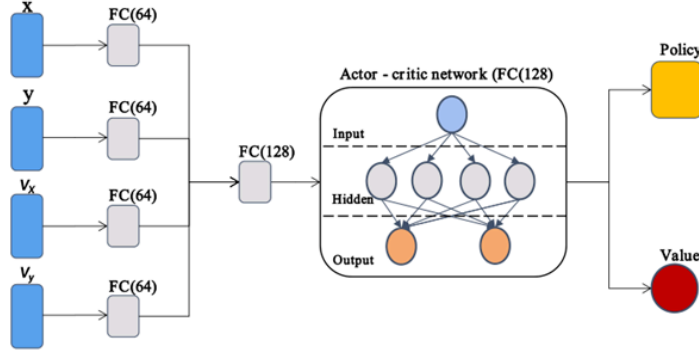


Figure 2.5: The architecture of the MA2C network [10].

The experiments are conducted in a simulated highway environment, modified from the gym-based highway-env simulator. The highway consists of two lanes, and vehicles are randomly initialized with different speeds.

- The model is tested across three traffic density levels (low, medium, and high) with varying numbers of AVs and HDVs (see Table 2.3 for traffic mode details).
- The HDVs' behavior is modeled using the Intelligent Driver Model (IDM) for longitudinal control and the MOBIL model for lateral control, which simulates different levels of aggressiveness in driving styles.

Table 2.3: Traffic density modes [10].

Traffic Density Modes	AVs	HDVs	Explanation
1	1–3	1–3	Low level
2	2–4	2–4	Middle level
3	4–6	4–6	High level

2.4.2.2 Discussion

The MA2C framework outperforms several state-of-the-art MARL methods in terms of driving safety, efficiency, and comfort. The comparison is made against Multi-agent DQN (MADQN), MAACKTR, and MAPPO.

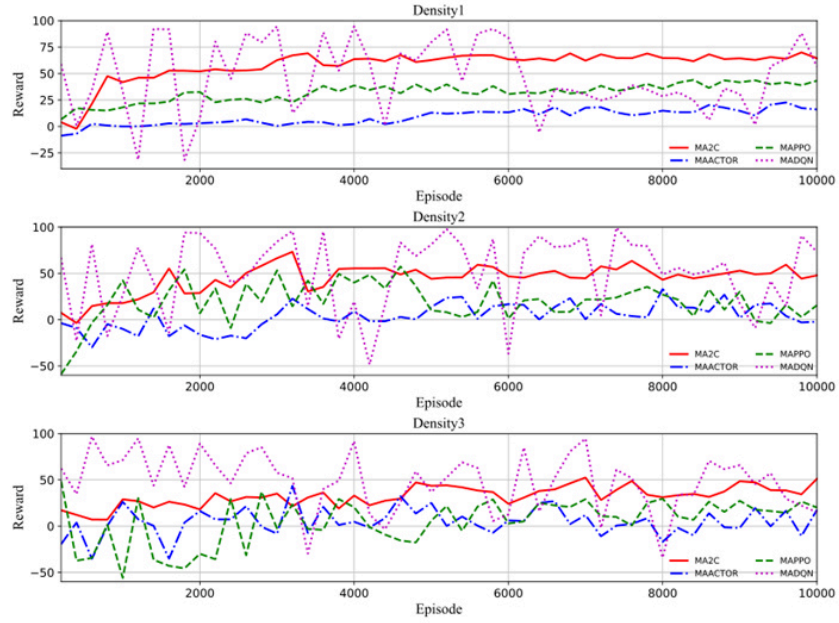


Figure 2.6: Performance comparison of various MARL algorithms [10].

The MA2C algorithm successfully adapts to various traffic conditions and human driving behaviors, including both aggressive and polite drivers. By promoting co-

operative lane-changing, the framework ensures that AVs can adjust their actions in real-time to prevent collisions and maintain traffic flow.

The model's ability to perform well under different driver behaviors and traffic densities makes it robust and scalable for real-world applications.

CHAPTER 3

METHODOLOGY

3.1 MDP-Based Framework for Lane-Changing Decision-Making

3.1.1 State Representation

The state of the system at any given time is given by:

$$\begin{aligned} S = \{ & \text{Ego Vehicle Lane, Ego Vehicle Speed,} \\ & \text{Left Vehicle Status, Right Vehicle Status,} \\ & \text{Front Vehicle Status, Rear Vehicle Status} \} \end{aligned} \tag{3.1}$$

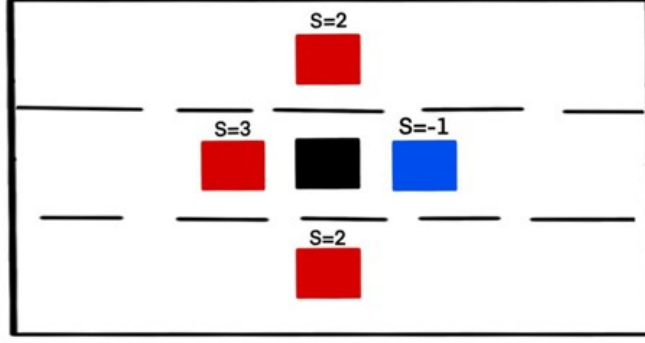


Figure 3.1: State representation of the ego vehicle in a multi-lane traffic scenario. The diagram shows the ego vehicle in lane L2, with nearby vehicles in adjacent lanes and relative speed and safety indicators.

which is critical for decision-making, as shown in Figure 3.1. The state consists of variables that fully describe the situation of the ego vehicle (the vehicle controlled by the algorithm) within its environment:

- **Lane:** Indicates the current lane of the ego vehicle. In this example, there are three lanes: L1, L2, and L3. The state shows that the ego vehicle is in lane L2, represented by the first element of the state vector $S = \{2, \dots\}$.
- **Speed:** Specifies the speed category of the ego vehicle, categorized into Low (1), Medium (2), and High (3) speed levels. Here, the ego vehicle's speed is Medium.
- **Adjacent Vehicles:** The state includes positions relative to other vehicles in neighboring lanes. which in this case is as following:
 - **Left (S=2):** The vehicle in the lane to the left of the ego vehicle, at a safe

distance and low speed.

- **Right (S=-1)**: The vehicle in the lane to the right, indicating unsafe proximity with low speed.
- **Front (S=3)**: The vehicle directly in front of the ego vehicle, at a safe distance and high speed.
- **Rear (S=-3)**: The vehicle directly behind the ego vehicle, at an unsafe distance and high speed.

By evaluating its current state as represented by the state vector $S = \{2, 1, 2, -1, 3, -3\}$, the ego vehicle can decide whether to change lanes, adjust speed, or maintain its current path. In this scenario, the vehicle is in a challenging position, with a fast-moving vehicle close behind and limited safe distance from the vehicle in front. If the rear vehicle’s intentions are unclear, the MDP will decide to change lanes which is necessary to avoid potential collisions. The ego vehicle could either request cooperation from the front vehicle to speed up or wait for the side lanes to clear, as those vehicles are moving faster.

The state indicator S captures relative safety and speed but does not distinguish between HDVs and CAVs—it represents the situation based on position and speed alone.

3.1.2 Reward Function

The reward function is a critical component of the decision-making process for autonomous vehicle lane changes. This function systematically evaluates the vehicle’s

state and surroundings, assigning reward values that guide the vehicle's actions. The function processes each state by validating its feasibility and then quantifies rewards based on the vehicle's position and speed parameters relative to nearby vehicles. The following is the reward assignment logic:

- **Lateral Proximity:**

- *Safe Distance (positive value)*: The vehicle gains a reward of +1 for each side (left or right) where another vehicle is at a safe distance, indicating favorable conditions for a lane change.
- *No Vehicle (zero value)*: A higher reward of +1.5 is assigned when there are no vehicles on either side, suggesting optimal conditions for changing lanes without risk.
- *Unsafe Distance (negative value)*: An unsafe proximity to another vehicle on either side results in a penalty of -1 , reflecting the increased risk of collision.

- **Longitudinal Proximity:**

- *Front Vehicle*:
 - *Safe Distance*: A reward of +1 is granted for maintaining a safe distance to the vehicle ahead.
 - *No Vehicle*: The absence of a vehicle directly in front increases the reward by +2, promoting faster travel and overtaking maneuvers.
 - *Unsafe Distance*: A significant penalty of -10 is imposed for being

too close to the front vehicle, emphasizing the critical need to avoid forward collisions.

- *Rear Vehicle:*

- *Safe Distance:* A reward of +1 is given for maintaining a safe following distance from the rear vehicle.
- *No Vehicle:* An additional reward of +2 is awarded if there is no vehicle close behind, reducing concerns about being rear-ended.
- *Unsafe Distance:* A smaller penalty of -2 is applied for an unsafely close rear vehicle, indicating a less critical but still important safety concern.

- **Relative Speed Differences:**

- *Front Vehicle Speed Greater than Ego Vehicle:* A reward of +1 encourages maintaining a slower speed than the vehicle ahead when safe, aligning with defensive driving principles.
- *Front Vehicle Speed Less than Ego Vehicle:* Penalties scaled by -2 times the speed difference are imposed for approaching a slower vehicle too rapidly, with increasing penalties as the speed discrepancy grows.
- *Rear Vehicle Speed Less than Ego Vehicle:* A reward of +1 supports scenarios where the ego vehicle is outpacing the following vehicle safely.
- *Rear Vehicle Speed Greater than Ego Vehicle:* Penalties calculated as -2 times the difference in speed are applied in situations where a faster rear vehicle may pose a risk of collision.

This structured reward system enables the autonomous vehicle to make calculated decisions regarding lane changes, prioritizing safety and efficiency based on real-time evaluations of the surrounding vehicles' state.

3.1.3 Transition Probability

In autonomous vehicle systems, deciding when and how to change lanes or continue on the same path involves more than just a flip of a switch. This is where the transition probability function comes into play. It's the essence behind the probability calculations that help the vehicle predict and navigate the road ahead.

The process can be described as follows:

- The function starts by setting up a matrix that matches all the possible driving scenario states that the vehicle might encounter, as defined in Equation 3.1.
- This matrix accounts for scenarios where the vehicle might stay in its lane or switch to another. Probabilities are assigned to each potential move:
 - Common moves are assigned higher probabilities.
 - Less likely moves are assigned lower probabilities.
 - Impossible states are ruled out by assigning them a probability of zero, ensuring safety.
- To calculate the total number of valid states, the state vector S is used. The vector, defined in Equation 3.1, includes components such as lane, speed, and

statuses of nearby vehicles. The total states for each lane type are computed as follows:

- For the left lane, the left vehicle status is always zero, reducing the possibilities:

$$\text{Left lane possible states: } 3 \times 3 \times 1 \times 7 \times 7 \times 7 = 1029 \quad (3.2)$$

- Similarly, for the right lane, the right vehicle status is always zero:

$$\text{Right lane possible states: } 3 \times 3 \times 7 \times 1 \times 7 \times 7 = 1029 \quad (3.3)$$

- For the middle lane, all nearby vehicles are considered:

$$\text{Middle lane possible states: } 3 \times 3 \times 7 \times 7 \times 7 \times 7 = 7203 \quad (3.4)$$

- Adding these values gives the total number of states:

$$\text{Total number of states: } 1029 + 1029 + 7203 = 9261 \quad (3.5)$$

- The transition probability for each state depends on the current lane:
 - When the vehicle is in the middle lane and transitioning to either the left

or right lane, the probability of each state is:

$$\text{Pr} = \frac{1}{1029} \quad (3.6)$$

- When the vehicle is in either the left or right lane and transitioning to the middle lane, the probability of each state is:

$$\text{Pr} = \frac{1}{7203} \quad (3.7)$$

This structured representation ensures that the vehicle evaluates 9261 possible states, each with probabilities assigned based on feasibility and likelihood. The probabilities adapt dynamically based on the current lane, allowing the system to prioritize realistic and safe transitions.

3.1.4 Value Iteration and Discount Factor Selection

In this study, we employ the *Value Iteration* [21] algorithm to solve the Markov Decision Process (MDP) governing the lane-changing decisions for the autonomous vehicle. Value Iteration is an iterative method for computing the optimal value function $V^*(s)$ for each state s , allowing the agent to determine the best possible actions in each state to maximize cumulative rewards.

As shown in Equation (3.8), the Value Iteration update rule is defined as:

$$V(s) \leftarrow \max_{a \in A} \left[R(s, a) + \gamma \sum_{s' \in S} P(s'|s, a) V(s') \right] \quad (3.8)$$

The discount factor γ plays a critical role in Value Iteration, as it determines how much the agent values immediate rewards relative to future rewards. For this system, we have chosen a discount factor of $\gamma = 0.1$. This low value is strategically selected to emphasize short-term gains, which is crucial in a dynamic traffic environment where timely responses to nearby vehicles and immediate surroundings are paramount.

By setting $\gamma = 0.1$, the agent focuses on optimizing for immediate safety and efficiency, rather than planning far ahead. This is particularly important in lane-changing scenarios, where the primary objective is to make quick, responsive maneuvers that adapt to the current traffic situation. High discount factors (e.g., γ closer to 1) would prioritize long-term outcomes, which may be less relevant in these rapid decision-making scenarios.

A lower discount factor like $\gamma = 0.1$ also accelerates the convergence of the Value Iteration algorithm. Since future rewards contribute less to the value function, the algorithm requires fewer iterations to stabilize. This efficiency is advantageous in real-time applications, allowing the vehicle to compute optimal policies quickly and make timely lane-changing decisions.

In summary, using Value Iteration with a discount factor of $\gamma = 0.1$ aligns well with the goals of the system, ensuring both rapid convergence and a focus on immediate rewards that enhance safety and responsiveness in dynamic traffic conditions.

3.1.5 Decision-Making Process for Lane Changes

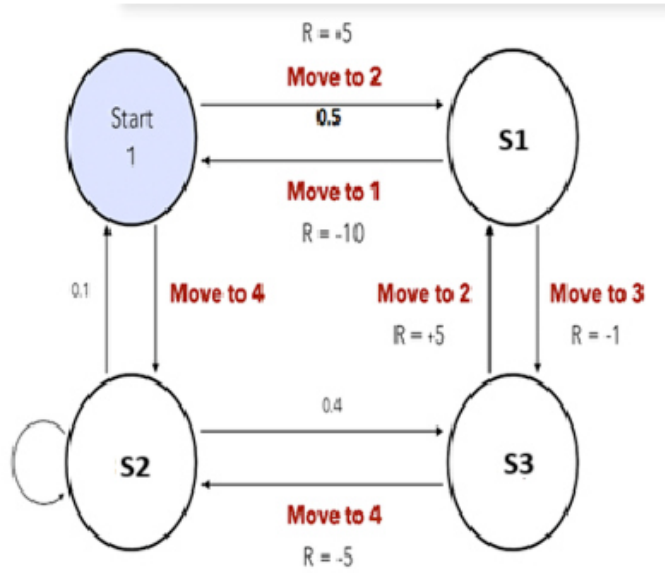


Figure 3.2: State transition diagram showing the reward structure for various actions.

A core aspect of our approach to enhancing autonomous driving decision-making involves comparing the rewards associated with the vehicle's current state against the average rewards of all possible next states. This method helps determine whether it is more beneficial for the vehicle to stay in its current lane or make a lane change. At any given moment, the vehicle evaluates its current state and calculates the associated reward based on specific criteria. Simultaneously, the system forecasts potential future states, each representing a different scenario—such as maintaining the current trajectory or moving to an adjacent lane.

As illustrated in Figure 3.2, each state transition is labeled with the possible actions (e.g., Move to 2) and the corresponding rewards. Since future outcomes are uncertain, the system considers multiple possible next states and calculates an average reward

across these states:

$$R(t+1) = R(t)_{\text{NextStates}} \cdot T(t)_{\text{NextStates}} \quad (3.9)$$

where n is the number of states in this work, $R_{\text{NextStates}}$ is a $1 \times n$ matrix representing the rewards of possible next states, and $T_{\text{NextStates}}$ is an $n \times 1$ matrix representing transition probabilities. This average provides a robust estimate of the expected reward if the vehicle were to change its current behavior. The decision to change lanes or stay is then based on a straightforward comparison: if the average reward for the possible next states is higher than the current state's reward, a lane change is considered beneficial, and vice versa.

Table 3.1: Example of decision-making based on current and next state reward.

Action	Current State Reward	Average Next State Reward	Decision
Change Lane	-10	3.3	Change Lane

For example, Table 3.1 illustrates a scenario where the decision is based on the current and next state reward where current state is assumed to be:

$$S = \{2, 3, 3, 1, -1, -2, 3\} \quad (3.10)$$

Based on the reward algorithm explained in Section 3.1.2, the current reward $R(t)$ is initialized as zero. The state reward is calculated as follows:

- **Left vehicle**, $S(3)$, is at high speed and safe proximity:

$$R(t) = R(t) + 1 \quad (3.11)$$

- **Right vehicle**, $S(4)$, is at low speed and unsafe proximity:

$$R(t) = R(t) - 1 \quad (3.12)$$

- **Front vehicle**, $S(5)$, is at medium speed and unsafe proximity:

$$\text{One level speed difference} \rightarrow R(t) = R(t) - 2 \quad (3.13)$$

$$\text{Unsafe proximity} \rightarrow R(t) = R(t) - 10 \quad (3.14)$$

Therefore, the total reward from the front vehicle is:

$$R(t) = R(t) - 12 \quad (3.15)$$

- **Rear vehicle**, $S(6)$, is at low speed and safe proximity:

$$\text{Same speed level} \rightarrow R(t) = R(t) + 1 \quad (3.16)$$

$$\text{Safe proximity} \rightarrow R(t) = R(t) + 1 \quad (3.17)$$

Therefore, the total reward from the rear vehicle is:

$$R(t) = R(t) + 2 \quad (3.18)$$

Thus, the overall reward is:

$$R(t) = -10 \quad (3.19)$$

Even though the current reward indicates a high risk by staying in the lane, the algorithm will first predict the next reward in case of a lane change before making its decision:

According to Equation 3.8, the next predictable reward is a sum of all possible next states' rewards, accounting for their probabilities. Using a small discount factor for fast convergence, $R(t + 1)$ is calculated as follows:

- First, each possible next state S reward is evaluated.
- The probability is uniformly distributed, as explained in Section 3.6.
- γ is set at 0.1, as per Section 3.1.4.

The calculation for the next reward is:

$$R(t + 1) = -10 + 0.1 \sum [5 + 4 + 0 + (-2) + \dots] = 3.3 \quad (3.20)$$

In this case, it can be shown that lane changing is encouraged, which is logical due to the inevitable danger of colliding with the front vehicle if no action is taken.

To implement this decision-making framework, the system follows the flowchart in Figure 3.3. This flowchart outlines the MDP-based process for determining whether the vehicle should remain in its current lane or initiate a lane change.

In this process, the current state $S(t)$ is evaluated to determine the current reward $R(t)$, which represents the reward associated with staying in the current lane under

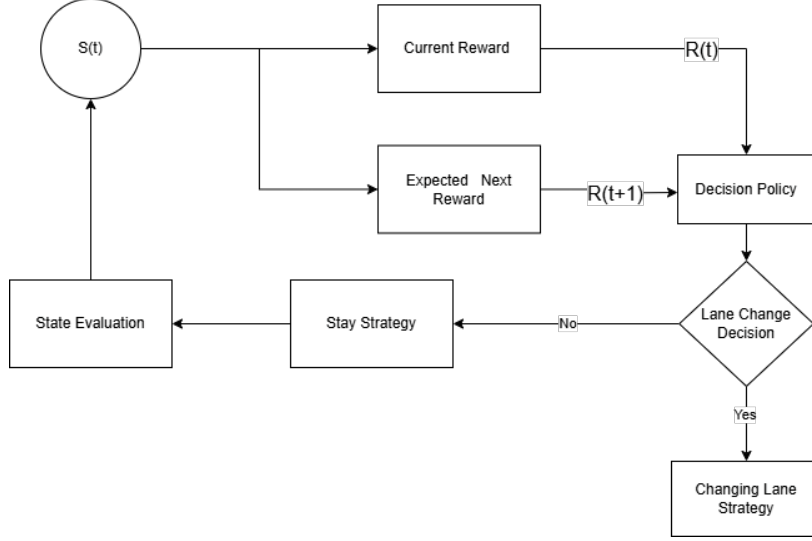


Figure 3.3: Flowchart of the reward-based lane change decision process.

present traffic conditions. Simultaneously, the system calculates the speculated next reward $R(t + 1)$, which is an estimate of the average reward for adopting a different lane-changing strategy. This reward is calculated as shown above using $R_{\text{NextStates}}$ and $T_{\text{NextStates}}$.

The decision policy then compares the current reward and speculated next reward:

- If $R(t + 1) > R(t)$, indicating that changing lanes would yield a higher reward, the system makes a lane change decision and moves to a changing lane strategy. Conversely, if $R(t + 1) \leq R(t)$, the system decides to remain in its current lane, implementing the stay strategy.

This strategy ensures each maneuver decision is based on a thorough analysis of potential outcomes, optimizing for safety and efficiency. By continuously evaluating both the current and possible next states, the vehicle adapts its behavior in real-time to maximize expected rewards, thus enhancing safety, adaptability, and responsiveness to dynamic road conditions.

3.2 Gap Detection

A function to calculate the gap between nearby vehicles, such as the front and left vehicle, is an essential component in the decision-making process for executing lane changes. By utilizing the positional data, it calculates the gap in real-time to determine if a lane change is feasible.

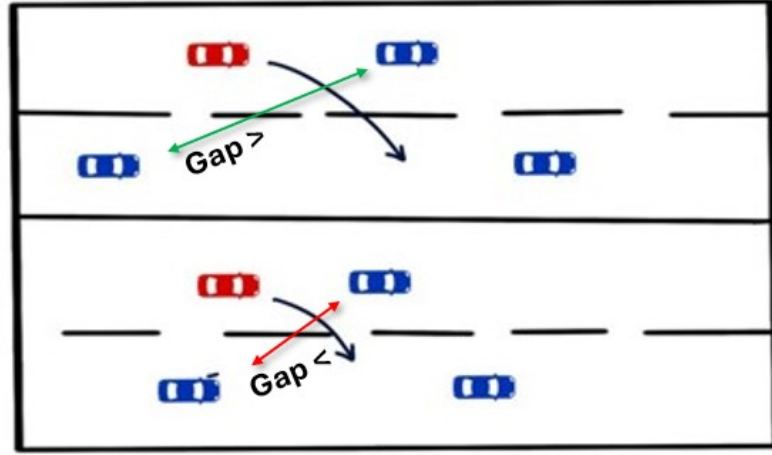


Figure 3.4: Illustration of lane-changing gap assessment. The top part shows a scenario with sufficient gap space, while the bottom part shows insufficient gap space for a safe lane change.

After evaluating the state as described in Section 3.1.1 and Figure 3.1. The minimum safety distance has to be determined according to the three-seconds rule [27]. Disregarding the difference in speed for maximum safety, the minimum distance is determined by:

$$D_{\min}(t) = 3 \times v_{\text{long}}(t) \quad (3.21)$$

where $v(t)_{\text{long}}$ is the longitudinal velocity component of the ego vehicle, measured in meters per second (m/s).

The gap detection begins by extracting the positions of the front and adjacent lane vehicles. A predefined vehicle width of 2 meters and a safety gap of three vehicles (15 meters) is used to ensure safe maneuvering. The gap calculation is given by:

$$\text{Gap} = ||P_{\text{front}} - P_{\text{adjacent}}|| \quad (3.22)$$

This formula ensures a safety gap of 17 meters, which is approximately three vehicle lengths, between the ego vehicle and the adjacent vehicle.

If the condition is met, indicating a safe gap, the function returns a value of 1, signifying that the lane change is feasible. Otherwise, it returns 0, indicating that the lane change should not be attempted. This function thus plays a critical role in enhancing road safety by preventing unsafe lane changes, ensuring that the system adheres to strict safety standards in a mixed traffic environment.

Overall, as shown in Figure 3.4, the top part of the figure illustrates a scenario where the gap between the vehicles is sufficient for a safe lane change. In contrast, the bottom part of the figure shows a scenario with an inadequate gap, where a lane change would not be safe.

3.3 Cooperation Strategy

3.3.1 Cooperation Request Initiation

The process of cooperation begins when the ego vehicle identifies the need to change lanes but finds itself in a situation where the surrounding traffic poses a constraint.

As shown in Figure 3.5, the ego vehicle (in black) first evaluates its surroundings, identifying nearby vehicles and their relative positions. The blue vehicles represent Connected Automated Vehicles (CAVs), which are capable of cooperative behavior, while the red vehicles represent Human-Driven Vehicles (HDVs), which lack the communication capabilities required for coordination.

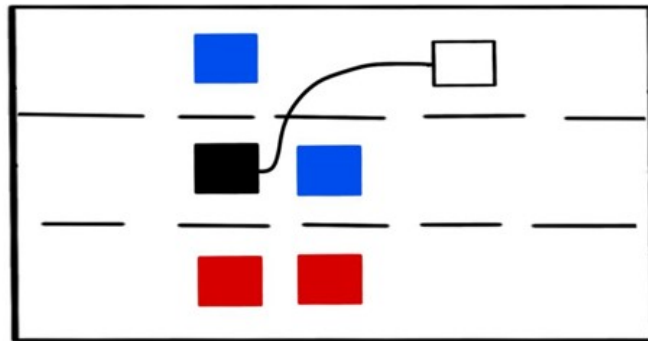


Figure 3.5: Illustration of cooperation in lane-changing: blue vehicles represent Connected Automated Vehicles (CAVs) capable of cooperation, while red vehicles represent Human-Driven Vehicles (HDVs) that cannot coordinate.

Upon detecting the need to change lanes, the ego vehicle first decelerates to avoid potential collisions by matching the speed of the vehicle directly in front of it. This initial action helps maintain a safe following distance and prevents any abrupt or dangerous maneuvers. Simultaneously, the ego vehicle begins analyzing the environment, identifying which of the surrounding vehicles are CAVs. The system distinguishes between CAVs and HDVs based on vehicle communication capabilities, signaling which vehicles can cooperate.

The ego vehicle then sends out a cooperation request to the nearby CAVs. This

request is communicated through vehicle-to-vehicle (V2V) communication protocols, with the ego vehicle asking for either acceleration or deceleration from the neighboring CAVs to create enough space for a safe lane change. The HDVs, being human-driven, are not included in this communication since they do not possess the necessary technology for coordination.

3.3.2 Cooperation Strategy

Once the cooperation request is initiated, the ego vehicle and the surrounding CAVs engage in a coordinated maneuver to facilitate the lane change. The cooperation strategy involves two primary objectives: creating adequate space for the ego vehicle to change lanes and ensuring that all involved vehicles maintain safe speeds and distances. After receiving the request, the nearby CAVs (blue vehicles in the diagram) assess their own speeds and relative positions. Based on the ego vehicle's request, the CAVs may either accelerate or decelerate to create a gap in the traffic. The ego vehicle continuously monitors the space generated between the vehicles and adjusts its speed to align with the lane change requirements. The cooperation strategy also ensures that the deceleration or acceleration actions performed by the CAVs do not disrupt the overall traffic flow or cause collisions with any HDVs (red vehicles), which cannot participate in the cooperative process. When a sufficient gap is formed, the ego vehicle verifies that the conditions for a safe lane change have been met. The system evaluates both the lateral and longitudinal space, ensuring that the gap is wide enough to accommodate the vehicle's dimensions, and that the lane change can be performed without affecting the speed and safety of other vehicles. Once these conditions are

satisfied, the ego vehicle executes the lane change, smoothly transitioning into the adjacent lane. This strategy leverages the cooperative capabilities of CAVs while ensuring that HDVs, which cannot participate in the coordination, are considered during the maneuver. The entire process—from the initiation of the cooperation request to the execution of the lane change—ensures that road safety and traffic flow efficiency are maintained. These sections describe the approach used by the ego vehicle to initiate and implement cooperative lane changes in a mixed traffic environment, ensuring safe and efficient maneuvers by leveraging CAV cooperation and avoiding disruptions from HDVs.

3.4 Target Lane

This algorithm plays a critical role in determining the target lane for a vehicle in our coordinated multi-lane-changing system. It considers the state the vehicle is in and the possible target point. The function first computes the desired positions for the vehicle’s lane change maneuvers, including transitions from lane 3 to 2, lane 1 to 2, lane 2 to 1, and lane 2 to 3. For each vehicle in the scenario, it retrieves their position and dimensions, then takes into account all vehicles’ dimensions (which is fixed) in the sensory range. By using the function, it checks if there is any vehicle occupying the desired lane change positions. Thus, ensuring no collision avoidance possibility. As the environment consists of 3 lanes, the obvious lane change target to both when the ego vehicle is in the farthest left and right lanes are the middle one. However, When the vehicle is in middle. The function considers both left and right lane as

a potential target for the lane change. Considering the universal rules of overtaking vehicles, changing lane to the left side is prioritized in all cases and if only it's not available the ego vehicle will try to overtake from the right. This careful consideration of vehicle positions and lane clearances ensures safe and efficient lane changes in the mixed traffic environment.

3.5 Priority Mechanism for Collision Avoidance

In the proposed system, a priority-based coordination mechanism is used to prevent collisions when vehicle trajectories intersect during lane changes. This mechanism ensures that vehicles adjust their behavior based on the priority of other vehicles performing similar maneuvers. The process is divided into the following steps:

1. **Lane Change Signal Broadcast:** When a vehicle (referred to as the ego vehicle) initiates a lane change, it sends out a priority signal to all nearby Connected and Autonomous Vehicles (CAVs). This signal serves as a notification that the vehicle is executing a lane change and requires priority. The signal includes the time of initiation, denoted as t_{init} , which is used to determine priority among multiple vehicles.

2. **Priority Assignment:** Priority is determined based on the earliest initiation time of the lane change. The vehicle with the earliest initiation time gets the highest priority. We define the priority level of vehicle i as P_i , which is inversely proportional to the initiation time:

$$P_i = \frac{1}{t_{\text{init},i}} \quad (3.23)$$

The vehicle with the highest priority (i.e., smallest t_{init}) is given precedence in lane-changing decisions. All other vehicles must adjust their behavior, either by delaying their lane change or reducing speed, to avoid trajectory conflicts.

3. Trajectory Conflict Detection: Upon receiving a signal from another vehicle, each CAV checks whether its intended lane-change trajectory overlaps with the ego vehicle's. If a conflict is detected, the vehicle compares its priority with the ego vehicle's priority using the following condition:

$$P_{\text{ego}} > P_{\text{other}} \quad (3.24)$$

If the ego vehicle has a higher priority, the other vehicles must yield and adjust their trajectories accordingly. Conversely, if the other vehicle has a higher priority, the ego vehicle defers its maneuver.

4. Collision Avoidance Through Adjustment: Vehicles with lower priority adjust their speed or delay their lane change to avoid collision. This ensures smooth coordination and avoids abrupt lane changes in multi-vehicle scenarios. The system continuously monitors the environment and recalculates priorities dynamically as new lane change signals are received, ensuring real-time adaptability.

5. Signal Reception and Reaction: Every vehicle receiving a signal interprets it as a request for priority. Based on the signal's time of initiation and comparison with its own t_{init} , each vehicle dynamically updates its behavior. Priority signals are processed in real-time, and vehicles react within milliseconds to avoid collisions and ensure that lane changes are performed efficiently without interruption.

This priority mechanism ensures that lane changes are coordinated among multiple vehicles, especially in high-density traffic scenarios, where multiple vehicles may attempt simultaneous maneuvers. By assigning priority based on the time of initiation and adjusting vehicle behavior accordingly, the system minimizes the risk of collisions and maintains smooth traffic flow.

3.6 Trajectory Planning Model

Trajectory generation in this simulation involves calculating the paths that vehicles will follow when executing lane changes. This component is crucial for ensuring that movements are not only planned in accordance with vehicle dynamics and road constraints but are also executed in a manner that minimizes risk to the vehicle and its surroundings. The road setup is designed to simulate a multi-lane highway environment. The road consists of three lanes, each having a width of 5 meters, resulting in a total road width of 15 meters. This lane structure allows for dynamic vehicle maneuvers, including lane changes and forward motion. The dimensions of vehicles are uniform and carefully chosen to replicate realistic driving conditions. Each vehicle is modeled with a length of 5 meters and a width of 2 meters, ensuring that lane positioning and lateral movements remain within practical limits. The simulation also accounts for visual markers that define the lane boundaries and separators. Solid lines demarcate the road's edges, while dashed lines separate the lanes, ensuring clear guidance for vehicle transitions between lanes. Before any lane change, vehicles are assumed to be at the center of each road initially, and the lateral position is

changed only when a vehicle is changing lane. Otherwise, scenario is considered free of accidents or vehicles deviations. This configuration provides a robust framework for simulating various driving scenarios, ensuring the vehicles operate within realistic spatial constraints while testing lane-change behaviors and vehicle dynamics. The use of precise values for road width and vehicle dimensions ensures that the simulation closely mirrors real-world driving conditions.

3.6.1 Smooth Path Calculation

The lane change path generation algorithm is designed to ensure smooth and controlled transitions between lanes during vehicle maneuvers, particularly in connected and automated vehicle systems. The algorithm is rooted in a mathematical approach that leverages a modified inverse tangent function to generate a continuous and differentiable trajectory. This ensures that the vehicle moves between lanes without abrupt shifts in lateral velocity or acceleration, which could compromise stability and passenger comfort.

The lateral position points, $P_{\text{lat}}(k)$, are defined as a weighted combination of the initial position, $P_{\text{lat}}(0)$, and the final position, $P_{\text{lat}}(N)$, at a given time step. This relationship is represented by the equation:

$$P_{\text{lat}}(k) = t(k)P(0) + (1 - t(k))P(N) \quad (3.25)$$

Where $t(k)$ denotes the weighting time factor that varies between 0 and 1, effectively interpolating between $P_{\text{lat}}(0)$ and $P_{\text{lat}}(N)$. This formulation allows for a

continuous transition across the lateral positions within the specified interval.

However, in order to achieve a smoother and more physically consistent transition, the time-weighted interpolation equation will be modified to incorporate the $\tan^{-1}$ function [28]. This change ensures that the transition follows the smooth and nonlinear characteristics of the $\tan^{-1}$ function rather than a simple linear interpolation. The updated equation is given as:

$$P_{\text{lat}}(k) = \tan^{-1} \left(t(k) \tan(P_{\text{lat}}(0)) + (1 - t(k)) \tan(P_{\text{lat}}(N)) \right) \quad (3.26)$$

Equation 3.26 produces an S-shaped curve, which is particularly suitable for lane changes as it begins with a gradual rise, smoothly reaches a peak, and then tapers off. However, the standard function $\tan^{-1}(x)$ inherently outputs values within the range $[-\pi/2, \pi/2]$, necessitating a mathematical modification to adapt it to our requirements.

The modification ensures that the desired S-shaped curve smoothly transitions from $P_{\text{lat}}(0)$ to $P_{\text{lat}}(N)$, while remaining in the range $[-\pi/2, \pi/2]$. For a lane width of 5 meters, the lateral position points $P_{\text{lat}}(k)$ must span from one lane center to another. This requires that the S-shaped curve adheres to the lateral bounds $[-L/2, L/2]$.

To ensure compliance, $P_{\text{lat}}(k)$ is constrained by the following range:

$$P_{\text{lat}}(0) \leq P_{\text{lat}}(k) \leq P_{\text{lat}}(N) \quad (3.27)$$

Here, $P_{\text{lat}}(0)$ and $P_{\text{lat}}(N)$ represent the lateral positions at the start and end of the maneuver, respectively, with L denoting the lane width. Specifically, $P_{\text{lat}}(0) = -L/2$

and $P_{\text{lat}}(N) = L/2$.

To satisfy Equation 3.27, the argument of $\tan$ in Equation 3.26 is divided by a scale variable R . This ensures that the argument remains within the boundaries of $-\pi/2$ to $\pi/2$ for the $\tan^{-1}$ function. For this condition to hold, R must satisfy $R \geq L/\pi$.

Subsequently, R is selected as $L/2$ to ensure that the lateral position starts at the center of one lane, which is -2.5 , and transitions smoothly to the center of the target lane, which is 2.5 . This choice of R satisfies the condition $R \geq L/\pi$ while aligning the trajectory with the desired lane centers.

The modified equation is expressed as:

$$P_{\text{lat}}(k) = \tan^{-1} \left(t(k) \tan \left(\frac{-L}{2R} \right) + (1 - t(k)) \tan \left(\frac{L}{2R} \right) \right) \quad (3.28)$$

where R represents the scaling factor ensuring compliance with both the boundary conditions and the alignment of the trajectory with the lane centers.

With the introduction of the division by R , $P_{\text{lat}}(k)$ is now confined to the range $[-L/4, L/4]$. This occurs because the scaling factor R reduces the effective range of the argument within the tangent function, compressing the lateral position values.

To ensure compliance with the constraint defined in Equation 3.27, Equation 3.28 is scaled up externally by the same factor R . This external scaling preserves the conditions while restoring the lateral position range to span from $P_{\text{lat}}(0)$ to $P_{\text{lat}}(N)$:

$$P_{\text{lat}}(k) = R \cdot \tan^{-1} \left(t(k) \tan \left(\frac{-L}{2R} \right) + (1 - t(k)) \tan \left(\frac{L}{2R} \right) \right), \quad (3.29)$$

Here, the external multiplication by R ensures that $P_{\text{lat}}(k)$ adheres to the lateral

bounds specified in Equation 3.27. By applying R outside the arguments of the $\tan^{-1}$ function, the scaled equation maintains both the desired trajectory and the required boundary conditions.

After accounting for the range limits, time is modified to generate points over a specific duration. This duration aligns with the controlled speed generated from the PID controller, which is introduced later to implement successful motion and speed control during the lane change:

$$P_{\text{lat}}(k) = R \tan^{-1} \left(t_c(k) \tan\left(\frac{-L}{2R}\right) + (1 - t_c(k)) \tan\left(\frac{L}{2R}\right) \right) \quad (3.30)$$

where

$$t_c(k) = \frac{t_{\text{PID}}(k)}{t_{\text{PID}}(N)} \quad (3.31)$$

where $t_{\text{PID}}(k)$ is the time from the controller and $t_{\text{PID}}(N)$ represents the full duration.

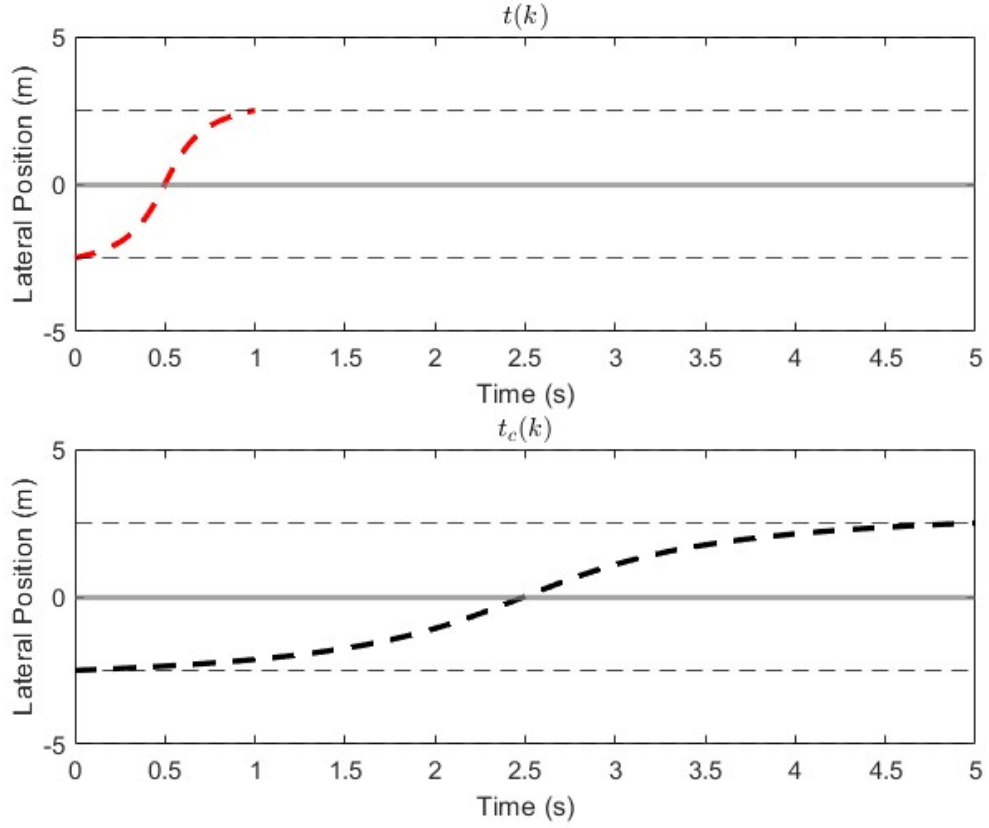


Figure 3.6: Default Trajectory Time $t(k)$ vs PID Controller Trajectory Time $t_c(k)$.

By the trajectory shapes illustrated in 3.6, the trajectory of Equation 3.29 (red) indicates discomfort and rigidity while the smooth trajectory of Equation 3.30 (black) is more realistic and considers passenger comfort. Thus, incorporating the practical PID controller time is a necessary step.

Lastly, the lateral position values generated by this method are in the range $[-L/2, L/2]$. Given that this environment consists of three lanes with different lane centers but a unified width, a shift in values is applied according to the start and end lanes of the operation. For instance, if the vehicle begins in the rightmost lane and moves to the middle lane, the center of the starting lane would be at -5 and the

center of the target lane at 0. Conversely, if the vehicle transitions from the middle lane to the left lane, the center of the starting lane would be at 0, while the center of the target lane would be at +5.

To accommodate this, a shift is applied to the lateral position equation based on the start and end lanes. The lateral position points $P_{\text{lat}}(k)$, which originally range from $[-L/2, L/2]$, are shifted as follows:

$$P_{\text{lat}}(k) = P_{\text{lat}}(k) + \Delta L \quad (3.32)$$

where ΔL is the shift applied based on the lane centers. It is calculated as the difference between the target lane's center and the starting lane's center.

The following table provides details of the final correct position, ensuring that the S-shape curve points match the desired trajectory:

Table 3.2: Lateral Position Adjustments Based on Lane Transitions

Start Lane	End Lane	Shift Direction	Shift Value ΔL	Equation for Lateral Position
+5 (Left)	0 (Middle)	Right	+2.5 m	$P_{\text{lat}}(k) = -P_{\text{lat}}(k) + \Delta L$
0 (Middle)	+5 (Left)	Left	+2.5 m	$P_{\text{lat}}(k) = P_{\text{lat}}(k) + \Delta L$
-5 (Right)	0 (Middle)	Left	-2.5 m	$P_{\text{lat}}(k) = P_{\text{lat}}(k) + \Delta L$
0 (Middle)	-5 (Right)	Right	-2.5 m	$P_{\text{lat}}(k) = -P_{\text{lat}}(k) + \Delta L$

To illustrate how Table 3.2 works, Figure 3.7 shows the default generated trajectory (red) and the actual tuned trajectory after applying the change (black):

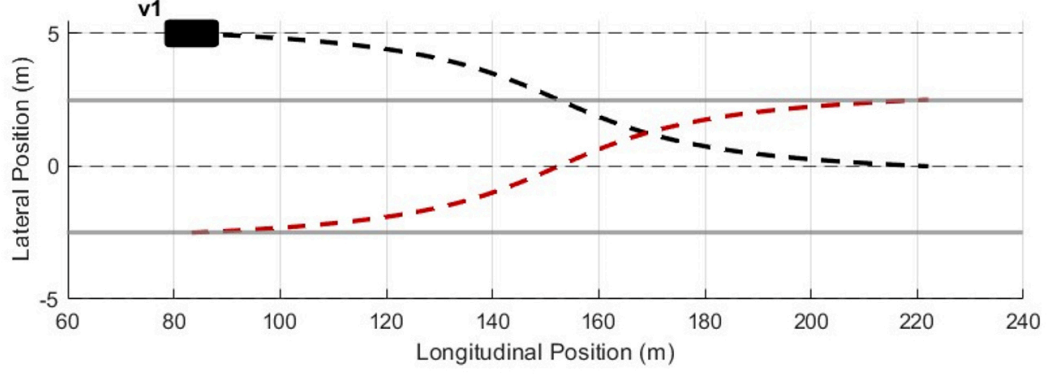


Figure 3.7: Default Generated Trajectory (red) vs The Final Applied Trajectory (black).

In Figure 3.7, the duration of the lateral shift, as mentioned in Section 1.3, is always set to 5 seconds. The default trajectory is generated via Equation 3.30 and it is always the same for all cases. However, depending on the initial and final lane destination of the LCP, the actual trajectory is generated by applying the necessary calculations indicated in Table 3.2 first case making the vehicle able to navigate successfully. As for the longitudinal position component, it is affected by the vehicle's longitudinal velocity. To calculate the longitudinal velocity, the lateral velocity component $v_{\text{lat}}(k)$ is first determined by:

$$v_{\text{lat}}(k) = \frac{P_{\text{lat}}(k) - P_{\text{lat}}(k-1)}{t_c(k) - t_c(k-1)} \quad (3.33)$$

Therefore, the longitudinal velocity $v_{\text{long}}(k)$ is computed as:

$$v_{\text{long}}(k) = \sqrt{v(k)^2 - v_{\text{lat}}(k)^2} \quad (3.34)$$

Finally, the new longitudinal position is given by:

$$P_{\text{long}}(k) = P_{\text{long}}(k - 1) + v_{\text{long}}(k) \times \text{SampleTime} \quad (3.35)$$

In this work, the sample time used is set to 0.01 seconds.

3.6.2 Speed Control using PID

According to [29], the algorithm models the vehicle's speed response based on its physical characteristics and external forces. The following parameters are considered:

- **Vehicle Mass (m):** A mass of 1500 kg, representing a standard passenger vehicle, is used in this model. The mass is essential for calculating inertia and how the vehicle responds to torque.
- **Engine Torque (T_m):** The maximum engine torque is set to 250 Nm, which drives the acceleration of the vehicle.
- **Efficiency Factor (η):** The drivetrain efficiency is modeled with a factor of 0.85, accounting for power losses during energy transfer from the engine to the wheels.
- **Rolling Resistance Coefficient (C_r) and Aerodynamic Drag Coefficient (C_d):** The rolling resistance coefficient is set to 0.015, and the drag coefficient is 0.32, representing typical values for a standard vehicle. These factors, along with the vehicle's frontal area and air density, contribute to the forces resisting motion.

The damping forces acting on the vehicle are calculated using the equation:

$$b = C_r \times m \times g + 0.5 \times C_d \times A \times D \times v \quad (3.36)$$

where:

- g is the gravitational acceleration, $g = 9.81m/s^2$
- D is the air density, $D = 1.225kg/m^3$
- v is the vehicle speed. $v = 22m/s$
- A is area of the vehicle front, $A = 2m^2$

The initial speed introduced in this calculation is a typical average speed. However, Since vehicle speed is dynamic, the model is recalculated for each control attempt, with the initial speed defined as:

$$v = \text{Initial Speed (m/s)} \quad (3.37)$$

The vehicle's dynamic response is modeled using a second-order transfer function. The system relates engine torque to the resulting vehicle speed. The transfer function $G(s)$ is expressed as:

$$G(s) = \frac{\eta \times T_m}{m \times s \times (s + \frac{b}{m})} \quad (3.38)$$

After applying the introduced vehicle parameters:

$$G(s) = \frac{0.1417}{s^2 + 0.2736s} \quad (3.39)$$

This transfer function models how the vehicle accelerates based on the applied engine torque, taking into account the resisting forces of rolling friction and aerodynamic drag.

A PID controller is implemented to manage the transition between the initial speed and the desired speed. To ensure a well-tuned controller that minimizes overshoot and ensures a fast response, the controller is tuned to achieve a desired closed-loop bandwidth, resulting in a settling time of approximately 3-4 seconds.

The PID controller $C(s)$ is designed to meet the following objectives:

- **Minimize Settling Time:** The controller is tuned to achieve rapid convergence to the desired speed, $T_S \leq 3$ seconds.
- **Avoid Overshoot:** The controller minimizes excessive acceleration or deceleration beyond the target speed, $\text{Overshoot} \leq 5\%$.
- **Steady State:** A maximum settling error is ensured to avoid collisions due to inaccuracy, $\text{Tolerance} \leq 2\%$.

The closed-loop system is represented by the following equation:

$$\text{Sys} = \frac{G(s) \times C(s)}{1 + G(s) \times C(s)} \quad (3.40)$$

After tuning the controller to meet the above requirements:

$$C(s) = 35.1 + \frac{11.2}{s} + 27.6s^2 \quad (3.41)$$

Overall, the current controlled system in closed loop is:

$$\text{System} = \frac{3.912s^2 + 4.976s + 1.582}{s^3 + 4.201s^2 + 4.98s + 1.6} \quad (3.42)$$

Considering that vehicles can be in only 4 different velocities, Table 3.3 demonstrates the velocities introduced in this work:

Table 3.3: Vehicle Speed Categories

Velocity Indication	Value in km/h	Value in m/s
Low (L)	60	16.67
Medium (M)	80	22.22
High (H)	100	27.78
Very High (VH)	120	33.33

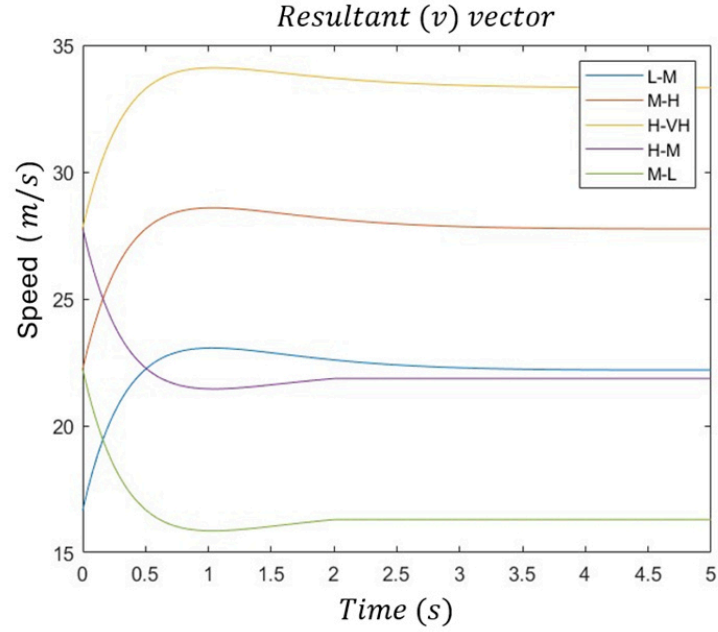


Figure 3.8: PID Control Response for Speed Transition between Levels (L, M, H, VH)

Figure 3.8 illustrates the PID control response when transitioning from one speed level to a higher one. The labels L, M, H, and VH represent Low, Medium, High, and Very High speeds, respectively. This response shows the PID control behavior during

acceleration, and the same PID algorithm can be applied to deceleration or transitions between any two speed levels within the same time duration.

The PID controller works on the velocity magnitude as illustrated in Figure 3.8. For velocity components, Section 3.6.1 demonstrates how the lateral and longitudinal velocities are calculated. Specifically in Equation 3.33 and Equation 3.34.

This method ensures that the speed transition is smooth, minimizing abrupt changes and enhancing both safety and passenger comfort in connected and automated vehicle systems.

3.7 Combined Scheme

The flowchart presented in Figure 3.9 illustrates the comprehensive process for lane-changing decision-making in an autonomous vehicle. This process is structured to ensure a safe and efficient lane change, coordinating multiple elements like gap detection, trajectory planning, priority checks, and cooperation requests with nearby vehicles.

The decision-making process begins with an assessment of the ego vehicle's current state. Using a Markov Decision Process (MDP), the system determines whether a lane change is required based on the vehicle's surroundings and target objectives.

If a gap is detected and sufficient space is available in the target lane, the vehicle sets the target lane as its goal and initiates trajectory planning. In cases where the space is deemed insufficient for a safe maneuver, the system initiates a cooperation request with nearby vehicles, asking them to adjust their speed or position to create

adequate space.

The priority mechanism then evaluates each vehicle’s priority level, ensuring that vehicles with higher priority proceed first. If there are any overlaps in planned trajectories, the system checks to confirm that these have been resolved before the lane change is executed.

Once all conditions are met—sufficient gap, cooperation established, and overlaps cleared—the PID velocity control executes the lane change, ensuring a smooth transition without abrupt speed changes. If cooperation with other vehicles is not possible, the vehicle adopts a waiting strategy, holding its position until conditions become favorable for a safe lane change.

Additionally, if multiple vehicles are running the algorithm simultaneously and no conflicts are detected, the priority mechanism is not going to take action allowing all vehicles to perform the lane change simultaneously, thus minimizing disruptions to traffic flow.

This overall scheme ensures a robust, adaptable approach to lane-changing in complex traffic scenarios, balancing safety, efficiency, and cooperation with surrounding vehicles.

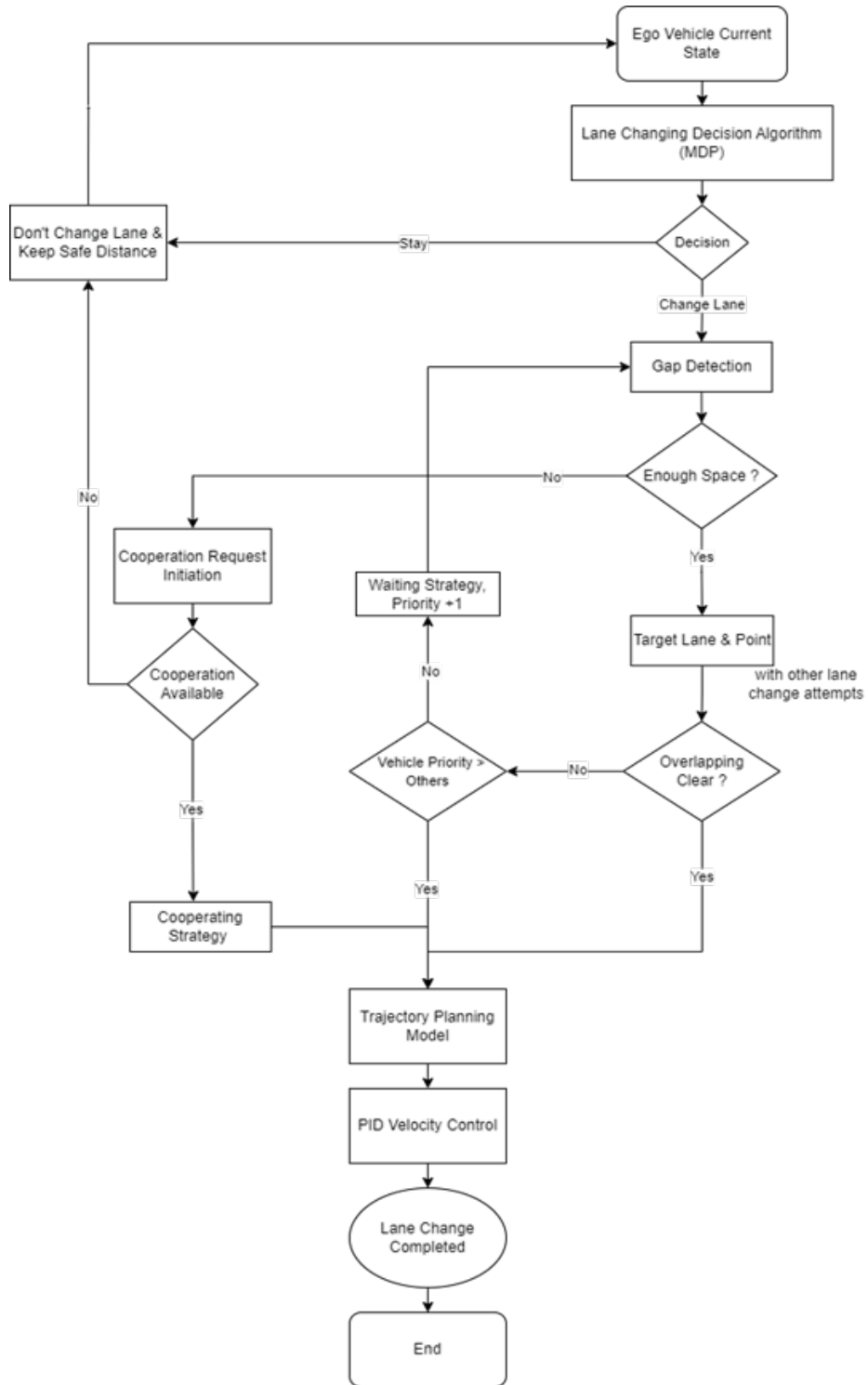


Figure 3.9: Overall Scheme for Lane-Changing Decision-Making

CHAPTER 4

RESULTS AND DISCUSSION

This chapter presents the outcomes of the developed approach in various traffic scenarios, emphasizing its performance in ensuring safe and efficient lane-changing maneuvers. The analysis focuses on key aspects such as independent lane changes, cooperative interactions, and multi-vehicle coordination, with performance evaluated using metrics like safety, adaptability, and efficiency.

The discussion delves into the system’s ability to handle challenges, including stationary obstacles, interactions with fast-approaching vehicles, and coordinated movements in complex situations. The results demonstrate the adaptability and robustness of the approach in addressing dynamic and unpredictable traffic conditions.

4.1 Independent Lane Change

4.1.1 Avoiding Stationary Vehicles

Objective: The objective of this analysis is to evaluate the lane-changing behavior of an autonomous ego vehicle in a low-traffic environment, focusing on its interactions

with nearby human-driven vehicles (HDVs). The aim is to assess how the ego vehicle adapts its maneuvers based on the spatial positioning and movement of surrounding vehicles, ensuring safety, stability, and efficiency during lane changes. This scenario demonstrates the system's capability to handle multiple lane changes independently, without requiring cooperation from other vehicles.

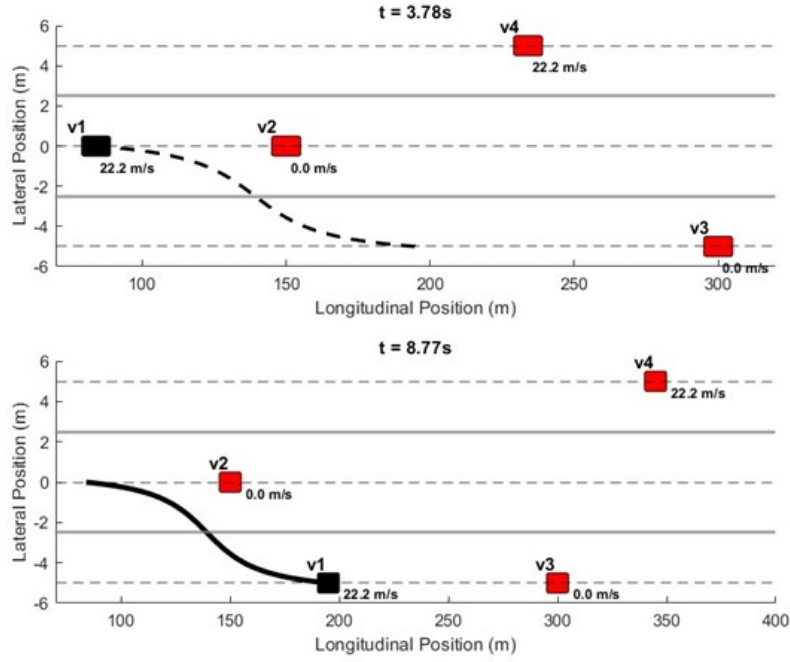


Figure 4.1: Phase 1: Start of First Lane Change Maneuver ($t = 3.78s$)

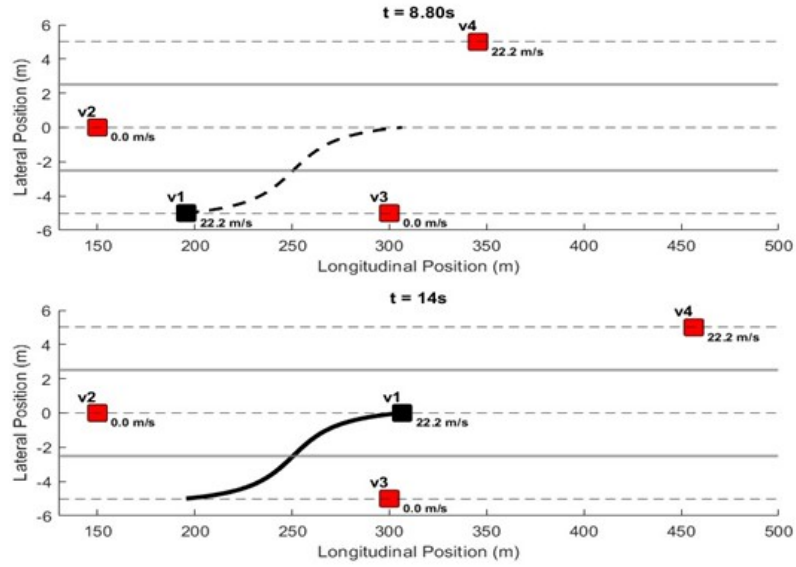


Figure 4.2: Phase 1: Completion of First Lane Change Maneuver ($t = 8.77s$)

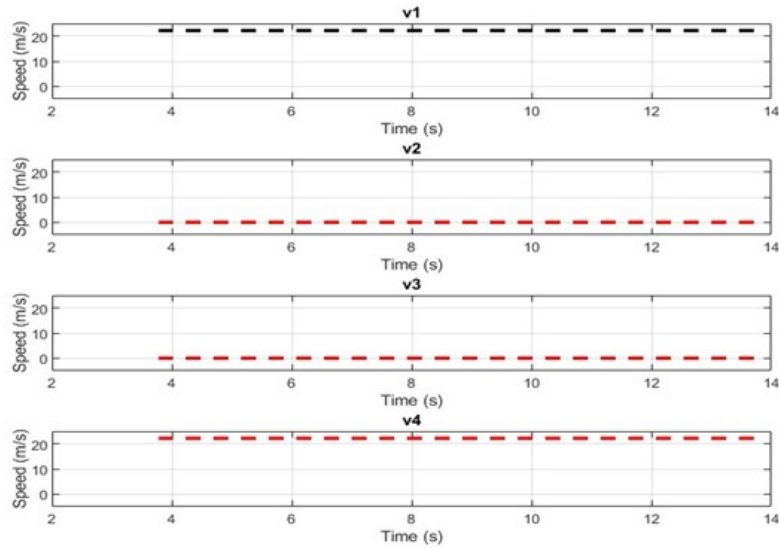


Figure 4.3: Phase 2: Start and Completion of Second Lane Change Maneuver ($t = 8.80s$ to $t = 14s$)

The lane-changing scenario is depicted across three distinct phases, as shown in

Figures 4.1, 4.2, and 4.3.

In Phase 1 (Figure 4.1), which spans from $t = 3.78$ seconds to $t = 8.77$ seconds, the ego vehicle ($v1$) maintains a speed of 22.2 m/s while preparing for a lane change. It adjusts its trajectory and speed to initiate a smooth transition into the target lane. The intended path is represented by a dashed line, illustrating the controlled maneuver. By $t = 8.77$ seconds, the ego vehicle successfully completes the lane change, reaching its target position. During this phase, HDVs $v2$ and $v3$ are stationary (0.0 m/s), positioned ahead of $v1$'s intended path, posing no immediate obstacle. HDV $v4$, in a separate lane, maintains a constant speed of 22.2 m/s and remains unaffected by $v1$'s maneuvers.

In Phase 2 (Figure 4.2), occurring between $t = 8.80$ seconds and $t = 14$ seconds, the ego vehicle initiates a second lane change due to the presence of a stationary vehicle in its newly occupied lane. This unexpected obstacle requires $v1$ to execute another lane transition to maintain its path unobstructed. The vehicle continuously adjusts its speed and position to ensure a smooth maneuver, completing the lane change by $t = 14$ seconds. The solid line in the figure denotes the completed trajectory. Throughout this phase, HDVs $v2$ and $v3$ remain stationary, with no interaction with $v1$, while HDV $v4$ continues at a constant speed of 22.2 m/s, unaffected by the maneuvers of the ego vehicle.

Additionally, (Figure 4.3) shows that no speed adjustments were required during the entire process.

Table 4.1: Performance Metrics for Double LCP in Low-Traffic Conditions

Metric/Scenario	$v1$ First LCP	$v1$ Second LCP
Gap Distance (m)	Inf	Inf
Average Acceleration Magnitude (m/s^2)	0	0
Long Distance Crossed During LCP (m)	110.94	110.94
Cooperation (true/false)	False	False
Current Distance Detected (m)	66	104.39
Minimum Distance to Maintain (m)	66	66
Current Reward Value, $R(t)$	-6	4.5
Next Estimated Reward Value, $R(t + 1)$	2.22	5

Table 4.1 analyzes the performance of lane-changing maneuvers by the ego vehicle in low-traffic conditions, focusing on metrics such as gap detection, average acceleration, distance crossed, and cooperation. Both lane-change phases demonstrated infinite gap detection, indicating no nearby vehicles during the maneuvers. The ego vehicle maintained zero acceleration throughout, reflecting a smooth, stable transition without speed adjustments. Additionally, the long distance crossed (110.94 m) suggests substantial lateral movement, while the lack of required cooperation emphasizes the independence of each maneuver. These results highlight the vehicle’s ability to execute safe and efficient lane changes in unchallenged, low-density traffic scenarios.

Furthermore, the current distance detected was 66 meters in first case which should be maintained according to the threshold stated in Equation 3.21. The risk is illustrated in the current reward value, $R(t)$, was -6 during the maneuvers, while the next

estimated reward value, $R(t+1)$, improved to 2.22. Nonetheless, the second LCP was initiated purely to the small difference in reward reflecting the algorithm method of continuously searching for best state to be in. These results underline the vehicle’s capability to execute safe and efficient lane changes in unchallenged, low-density traffic scenarios.

4.1.2 Avoid a Fast Rear Vehicle

Objective: The objective of this scenario is to analyze the lane-changing behavior of an autonomous ego vehicle (v1) as it responds to a rear vehicle (v2) approaching at a significantly higher speed. By employing a Markov Decision Process (MDP), the ego vehicle detects potential conflicts and initiates a lane change to ensure safety and smoother traffic flow. This scenario highlights the system’s capability to proactively manage lane changes without requiring cooperation from other vehicles.

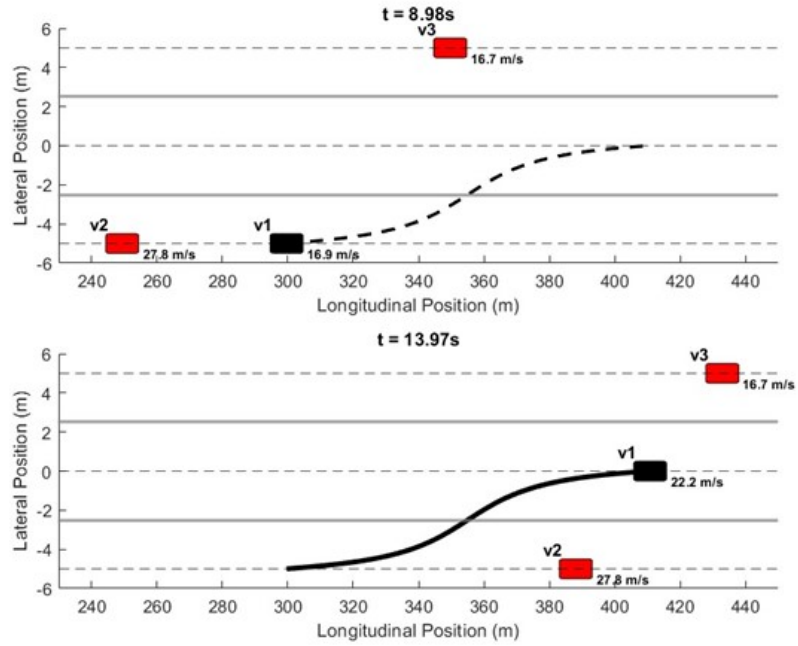


Figure 4.4: Single Lane Change Maneuver: Ego vehicle (v1) transitioning in response to faster approaching rear vehicle (v2).

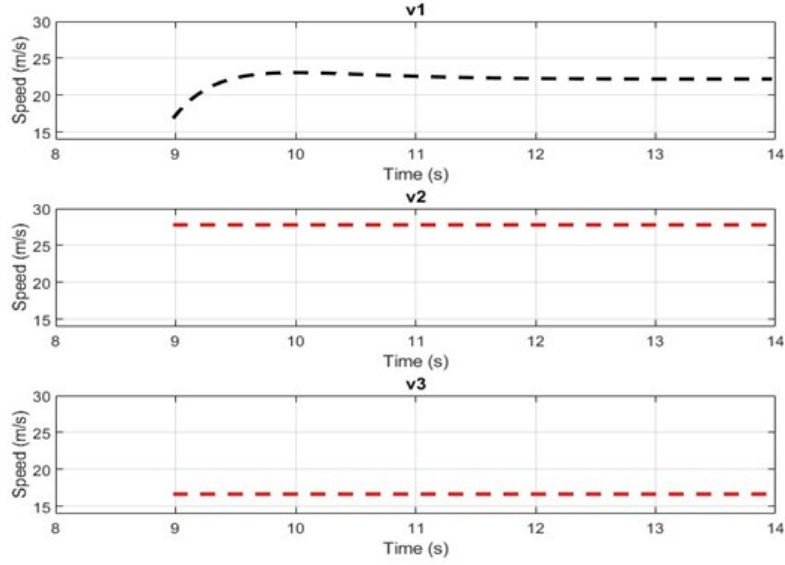


Figure 4.5: Speed profiles of all vehicles across the duration of the lane change maneuver.

The lane-changing process in this scenario is illustrated in Figures 4.4 and 4.5.

At the start of this maneuver, the Markov Decision Process (MDP) continuously monitors the ego vehicle's surroundings, focusing on the positions and speeds of nearby vehicles. As shown in Figure 4.4, the MDP detects a rear vehicle, v2, approaching at a speed of 27.8 m/s at $t = 8.98$ seconds, which is considerably faster than the ego vehicle's current speed of 16.9 m/s. Given this speed difference and the potential risk of collision if v1 remains in its lane, the MDP decides to initiate a lane change.

The lane change is executed in a controlled manner. The ego vehicle (v1) starts its maneuver at $t = 8.98$ seconds, as represented by the dashed line in Figure 4.4. Initially, v1 maintains a speed of 16.9 m/s, adjusting its trajectory for a smooth transition. By $t = 13.97$ seconds, the lane change is completed, marked by the solid line, with the ego

vehicle’s speed increasing to 22.2 m/s as it merges into the adjacent lane, adapting to the traffic flow.

In this scenario, v2 continues at a high speed of 27.8 m/s, unaffected by the lane change of v1, demonstrating the MDP’s proactive decision-making to avoid any interference. Other vehicles, such as v3 (moving at a steady speed of 16.7 m/s in a separate lane), are also unaffected by the maneuver, maintaining their courses without interaction.

Figure 4.5 displays the speed dynamics of all vehicles. The ego vehicle (v1) initially increases its speed to mitigate collision risk upon detecting the fast-approaching vehicle from the rear. Meanwhile, v2 maintains a constant high speed of 27.8 m/s, illustrating that no cooperation was requested or needed from v2. Vehicle v3, unaffected by the ego vehicle’s actions, continues steadily at 16.7 m/s.

Table 4.2: Performance Metrics for Single LCP in Low-Traffic Conditions

Metric/Scenario	<i>v1</i> Single LCP to the Middle Lane
Gap Distance (m)	Inf
Average Acceleration Magnitude (m/s ²)	1.0627
Long Distance Crossed During LCP (m)	111.09
Cooperation (true/false)	False
Current Distance Detected (m)	50.3
Minimum Distance to Maintain (m)	83.4
Current Reward Value, $R(t)$	-3
Next Estimated Reward Value, $R(t + 1)$	2.9

Table 4.2 summarizes the single lane-change phase (LCP) to the middle lane, executed under low-traffic conditions with no nearby vehicles detected, allowing for an independent maneuver. The ego vehicle maintained an average acceleration of 1.0627 m/s^2 , ensuring a smooth and controlled transition. Covering a lateral distance of 111.09 meters, the vehicle demonstrated significant repositioning across lanes, a typical scenario in highway driving. No cooperation was required from other vehicles, reinforcing the ego vehicle’s ability to complete the lane change autonomously in an unobstructed environment.

Additionally, the current distance detected was 50.3 meters, with a minimum distance to maintain of 83.4 meters. The current reward value, $R(t)$, was -3, indicating the severity of the situation due to crossing the safety threshold. However, the next estimated reward value, $R(t+1)$, improved to 2.9, reflecting the maneuver’s successful execution and its anticipated future benefits.

4.2 Cooperative Lane Change

4.2.1 Single-Attempt Cooperation

Objective: The objective of this scenario is to analyze the lane-changing behavior of an ego vehicle (v1) in a mixed traffic environment, where it interacts with both Connected and Autonomous Vehicles (CAVs) and Human-Driven Vehicles (HDVs). This case specifically demonstrates the role of cooperative behavior in facilitating safe and efficient lane changes, especially in scenarios involving both cooperating and non-cooperating vehicles.

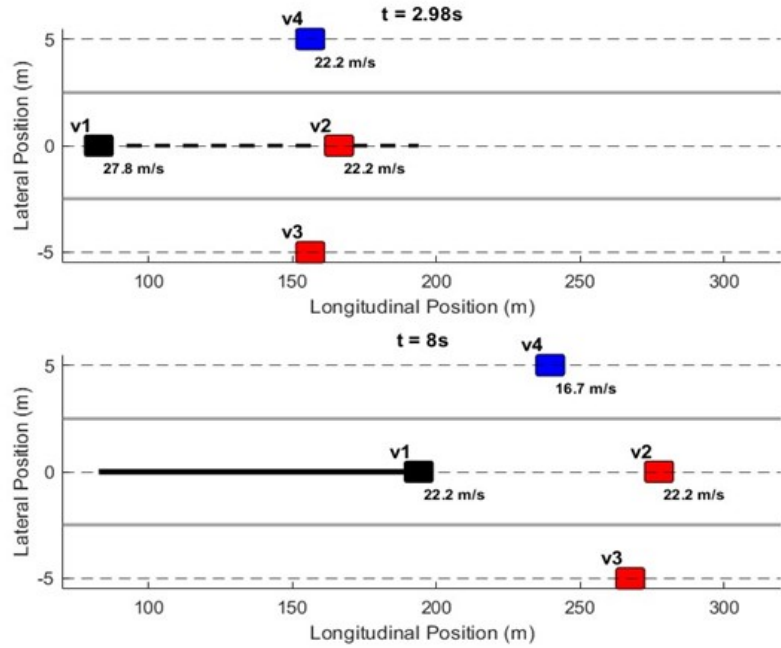


Figure 4.6: Phase 1: Slowing Down ($t = 2.98s$ to $t = 8s$) and Completion ($t = 8s$).

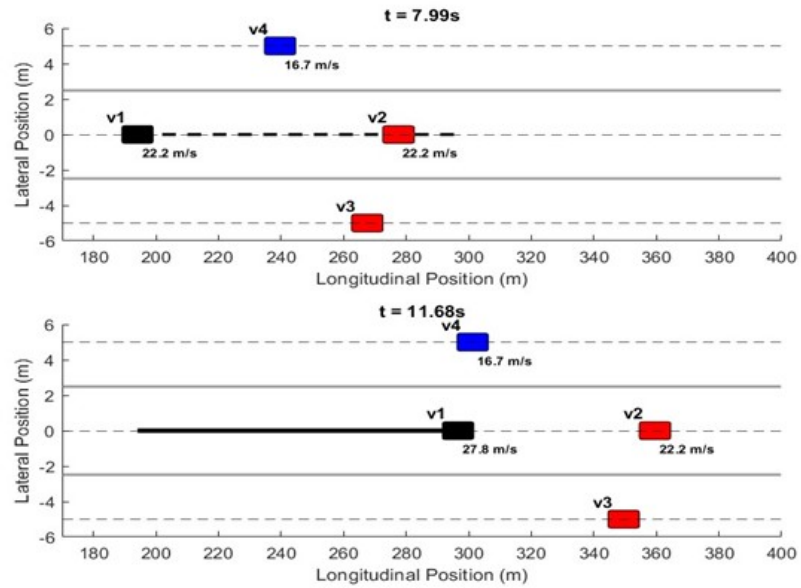


Figure 4.7: Phase 2: Gap Detection and Speeding Up ($t = 8s$ to $t = 11.68s$) and Completion ($t = 11.68s$).

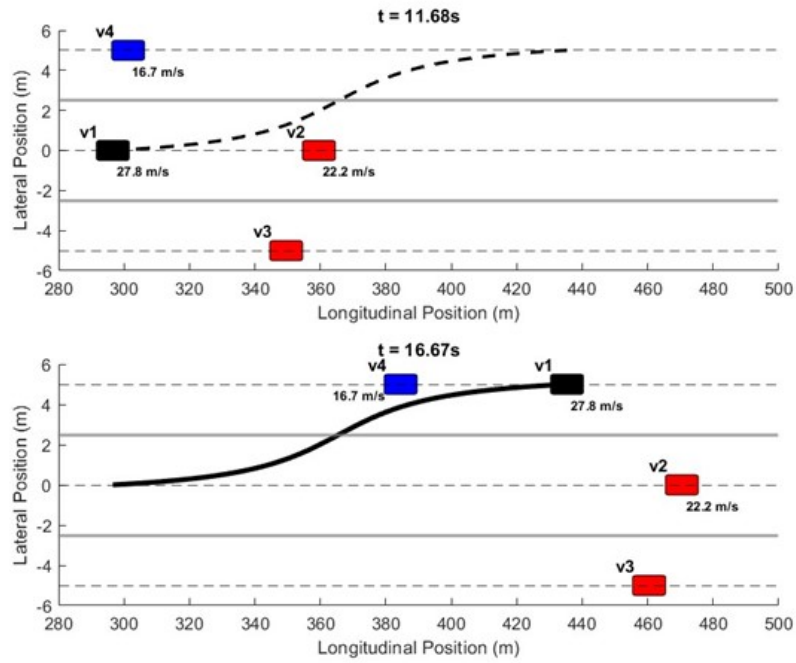


Figure 4.8: Phase 3: Performing the Lane Change ($t = 11.68\text{s}$ to $t = 16.67\text{s}$) and Final Position ($t = 16.67\text{s}$).

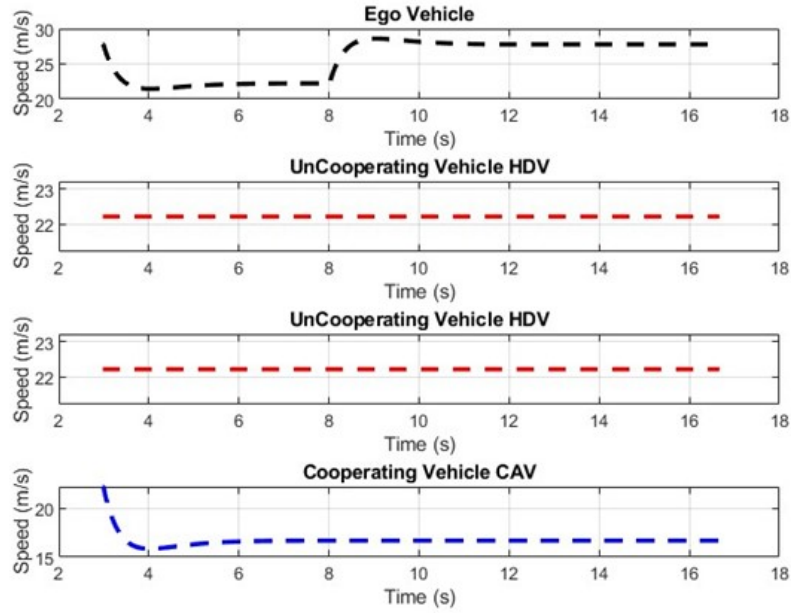


Figure 4.9: Speed Profiles of Ego Vehicle and Surrounding Vehicles Across Time.

The lane-changing process is broken down into multiple phases, as depicted in Figures 4.6, 4.7, and 4.8. This scenario involves interactions with both cooperating and non-cooperating vehicles, showcasing how the ego vehicle adjusts its behavior accordingly.

In Phase 1 (Figure 4.6), from $t = 2.98\text{s}$ to $t = 8\text{s}$, the ego vehicle (v1) detects a slower-moving vehicle ahead in its lane, prompting it to slow down. This deceleration helps maintain a safe distance and initiate the lane change smoothly. Meanwhile, the CAV v4 in the adjacent lane cooperates by decelerating, thereby creating a gap for the ego vehicle. This cooperative behavior from v4 is essential in facilitating the upcoming lane change. In contrast, HDVs v2 and v3 maintain their constant speeds, showing no cooperation.

In Phase 2 (Figure 4.7), between $t = 8\text{s}$ and $t = 11.68\text{s}$, the ego vehicle detects the gap created by v4 and begins accelerating in preparation for the lane change. The cooperative CAV v4 maintains its lower speed, keeping the gap open for a safe transition. Meanwhile, HDVs v2 and v3 continue at their constant speeds, not adjusting to accommodate the ego vehicle.

In Phase 3 (Figure 4.8), from $t = 11.68\text{s}$ to $t = 16.67\text{s}$, the ego vehicle completes the lane change by moving laterally into the adjacent lane. The cooperation from v4 enables a smooth transition, while HDVs v2 and v3 maintain their speeds without affecting the maneuver. This phase demonstrates the importance of CAV cooperation in dynamic traffic scenarios.

The speed profiles for each vehicle, as shown in Figure 4.9, illustrate the velocity adjustments during the lane change:

- **Ego Vehicle (v1):** v1 initially decelerates sharply around $t = 3\text{s}$, aligning with the start of the lane change preparation. It accelerates again at $t = 8\text{s}$ upon detecting the gap and stabilizes at its original speed after completing the maneuver.
- **Non-Cooperating HDVs (v2 and v3):** Both HDVs, represented by red dashed lines, maintain steady speeds throughout, unaffected by the lane change maneuver.
- **Cooperating CAV (v4):** v4 decelerates in response to v1's lane change signal, creating a sufficient gap in the adjacent lane to facilitate a safe lane change for v1.

This scenario highlights the role of CAV cooperation in creating safe opportunities for lane changes in mixed traffic. The cooperation of v4 proves instrumental in enabling the ego vehicle’s maneuver, while non-cooperating HDVs remain unaffected, underscoring the importance of coordination in connected vehicle systems.

Table 4.3: Performance Metrics for Single Lane-Change Phase with Cooperation

Metric/Scenario	Single LCP with Cooperation
Gap Distance (m)	58.23
V1 Average Acceleration Magnitude (m/s^2), Prepare for LCP	1.50
V1 Average Acceleration Magnitude (m/s^2), During LCP	0
Long Distance Crossed (m)	111.09
Cooperation (true/false), Number of Vehicles Cooperating	True, 1
Current Distance Detected (m)	83.4
$D_{\min}$ for LCP Initiation (m)	83.4
Current Reward Value, $R(t)$	-6
Next Estimated Reward Value, $R(t + 1)$	2.2

Table 4.3 summarizes the metrics for this lane change phase. The detected gap of 58.23 meters enabled a safe maneuver, with the ego vehicle initially accelerating to prepare for the lane change. The average acceleration was 1.50 m/s^2 , allowing for smooth preparation, while acceleration dropped to zero during the actual lane change, reflecting a stable transition. The lateral distance crossed (111.09 m) indicates substantial lane shifting, facilitated by cooperation from CAV v4, which enhanced the maneuver’s safety and efficiency.

Considering the current distance detected was 83.4 meters, aligning with the required $D_{\min}$ for LCP initiation. The current reward value, $R(t)$, was -6, indicating

proximity to the safety threshold. However, the next estimated reward value, $R(t+1)$, improved to 2.2, demonstrating the positive impact of cooperation in executing a safe and efficient lane change.

4.2.2 Multi-Attempt Cooperation

Objective: The objective of this scenario is to analyze a complex multi-vehicle coordination where the ego vehicle (v1) relies on cooperation from two Connected Autonomous Vehicles (CAVs) to create a safe gap for a lane change. This scenario demonstrates the system’s adaptability when initial cooperation is insufficient, requiring further assistance from an additional vehicle. The interaction between cooperating CAVs (blue) and non-cooperating Human-Driven Vehicles (HDVs, red) is shown in Figures 4.10 to 4.14, illustrating both position dynamics and speed adjustments.

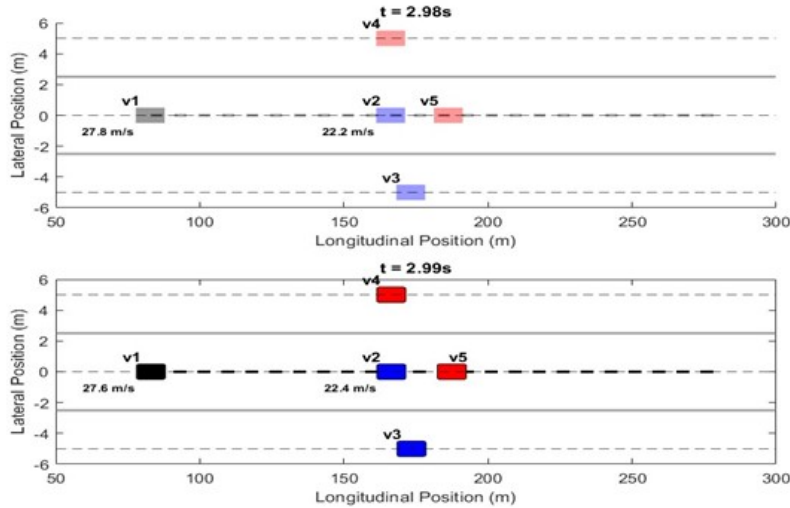


Figure 4.10: Phase 1: Initial Cooperation Attempt from First CAV and Ego Vehicle Adjustment ($t = 2.98s$ to $t = 2.99s$)

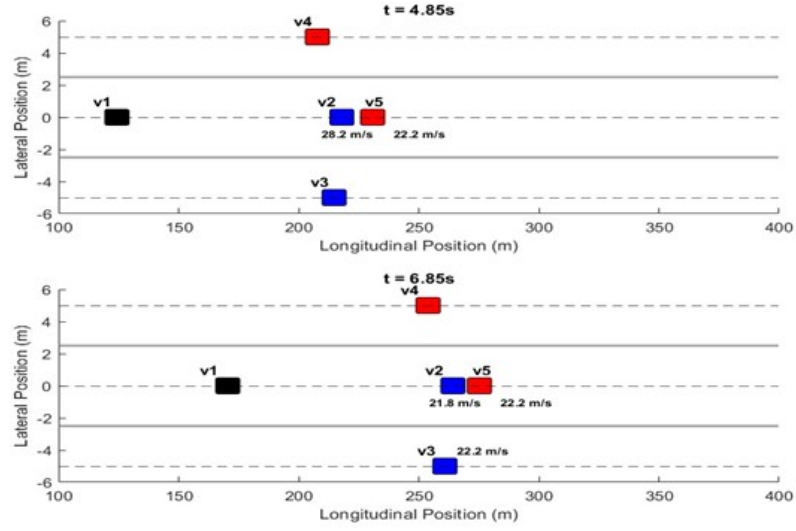


Figure 4.11: Continued Cooperation Attempt, Adjustments in Position ($t = 4.85s$ to $t = 6.85s$)

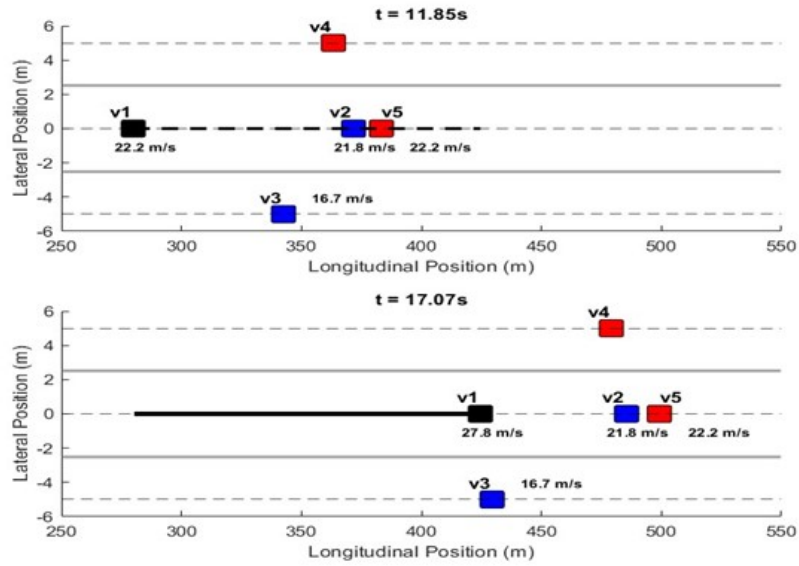


Figure 4.12: Phase 2: Additional Cooperation from Second CAV and Ego Vehicle Preparation ($t = 11.85s$ to $t = 17.07s$)

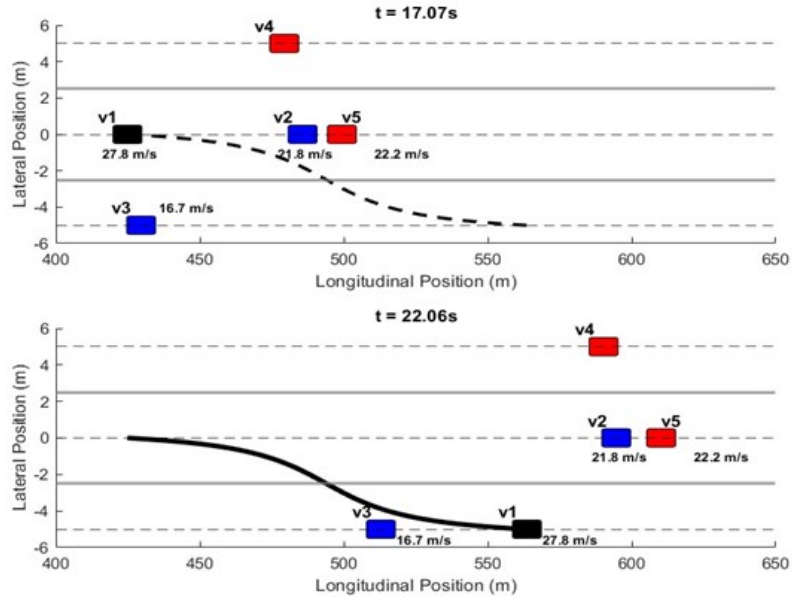


Figure 4.13: Phase 2: Ego Vehicle Completing Lane Change ($t = 17.07s$ to $t = 22.06s$)

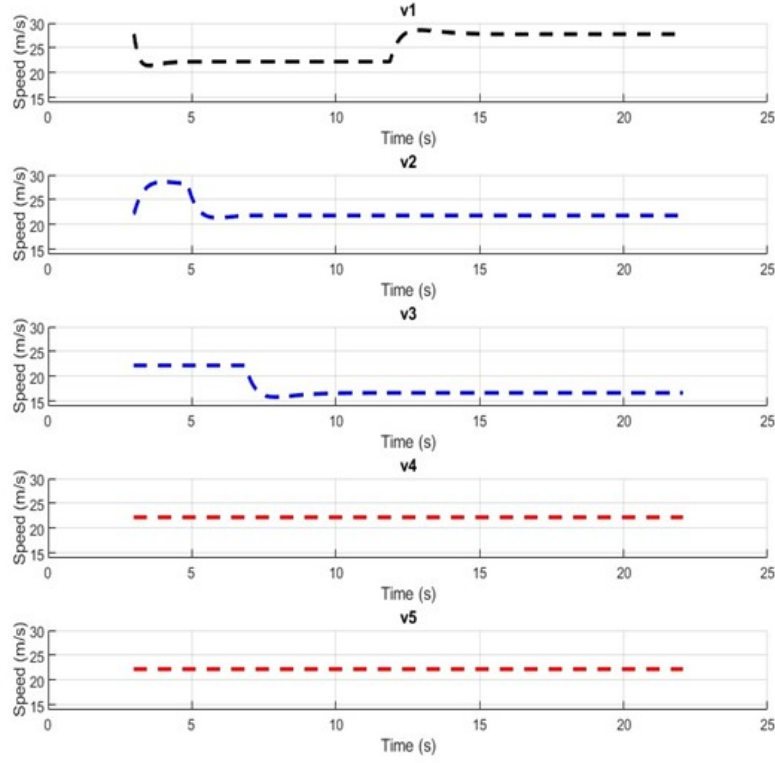


Figure 4.14: Speed Profiles of All Vehicles During Lane Change Scenario

In this scenario, the ego vehicle must rely on coordinated efforts from two CAVs (v2 and v3) to create a sufficient gap for a safe lane change. Figures 4.10 to 4.13 illustrate the phases of this maneuver:

Phase 1 (Figures 4.10 and 4.11): The ego vehicle (v1) initially detects an obstacle and decelerates from its high speed of 28 m/s to avoid a collision. At $t = 2.99$ seconds, it sends a cooperation request to the first CAV (v2), which attempts to speed up to create a gap. However, due to the presence of a non-cooperating HDV (v5), the first CAV cannot sustain the gap and has to slow down again. By $t = 6.85$ seconds, the system realizes that the first CAV cannot create enough space, prompting a request

for assistance from a second CAV (v3).

Phase 2 (Figures 4.12 and 4.13): At $t = 17.07$ seconds, after v3 decelerates to create a stable gap, the ego vehicle initiates its lane change maneuver. The ego vehicle moves laterally into the adjacent lane while maintaining its longitudinal speed, completing the lane change by $t = 22.06$ seconds. Following the maneuver, both cooperating CAVs resume normal speed, restoring traffic flow.

The speed dynamics for each vehicle are shown in Figure 4.14. Initially, the ego vehicle decelerates, waiting for a sufficient gap in the adjacent lane. Upon gap detection around $t = 11.87$ seconds, it accelerates in preparation for the lane change. Both cooperating CAVs adjust their speeds dynamically to assist, while the HDVs (v4 and v5) maintain constant speeds, unaffected by the actions of the ego vehicle and CAVs.

Table 4.4: Performance Metrics for LCP with Two Cooperating CAVs

Metric/Scenario	Single LCP with Cooperation from Two CAVs
Gap Distance (m)	58.23
V1 Average Deceleration Magnitude (m/s^2), Waiting for LCP Opportunity	2.22
V1 Average Acceleration Magnitude (m/s^2), Preparing for LCP	1.10
V1 Average Acceleration Magnitude (m/s^2), During LCP	0
Long Distance Crossed (m)	138.75
Cooperation (true/false), Number of Vehicles Cooperating	True, 2
Current Distance Detected (m)	83.4
$D_{\min}$ for LCP Initiation (m)	83.4
Current Reward Value, $R(t)$	-6
Next Estimated Reward Value, $R(t + 1)$	2.2

Table 4.4 summarizes the performance metrics for this multi-vehicle cooperation scenario. A gap of 58.23 meters was detected, allowing the ego vehicle to initiate its maneuver. The ego vehicle’s average deceleration while waiting for the gap was 2.22

m/s², ensuring it maintained a safe following distance. Once the gap was established, the ego vehicle accelerated by 1.10 m/s² in preparation for the lane change, while no further acceleration was needed during the maneuver itself, reflecting the stability of the lane change. The total lateral distance crossed was 138.75 meters, and cooperation was achieved through coordinated deceleration of two CAVs, ensuring a smooth, uninterrupted maneuver.

The current distance detected was 83.4 meters, which matches the $D_{\min}$ for LCP initiation. The current reward value, $R(t)$, was -6, indicating the urgency of the situation, but the next estimated reward value, $R(t+1)$, improved to 2.2, highlighting the effectiveness of cooperation from two CAVs in ensuring a safe and efficient lane-changing maneuver.

4.3 Multi-Vehicle Lane Change

4.3.1 Priority-Based Lane Change Coordination

Objective: The purpose of this scenario is to demonstrate the coordination mechanism for two Connected and Autonomous Vehicles (CAVs), Vehicle 1 (v1) and Vehicle 2 (v2), as they execute lane changes with priority handling. Vehicle 1, initiating its lane change first, is given priority, while Vehicle 2 defers its maneuver to avoid overlap, thus minimizing collision risks. This scenario emphasizes the importance of the priority mechanism in safely coordinating multiple lane changes.

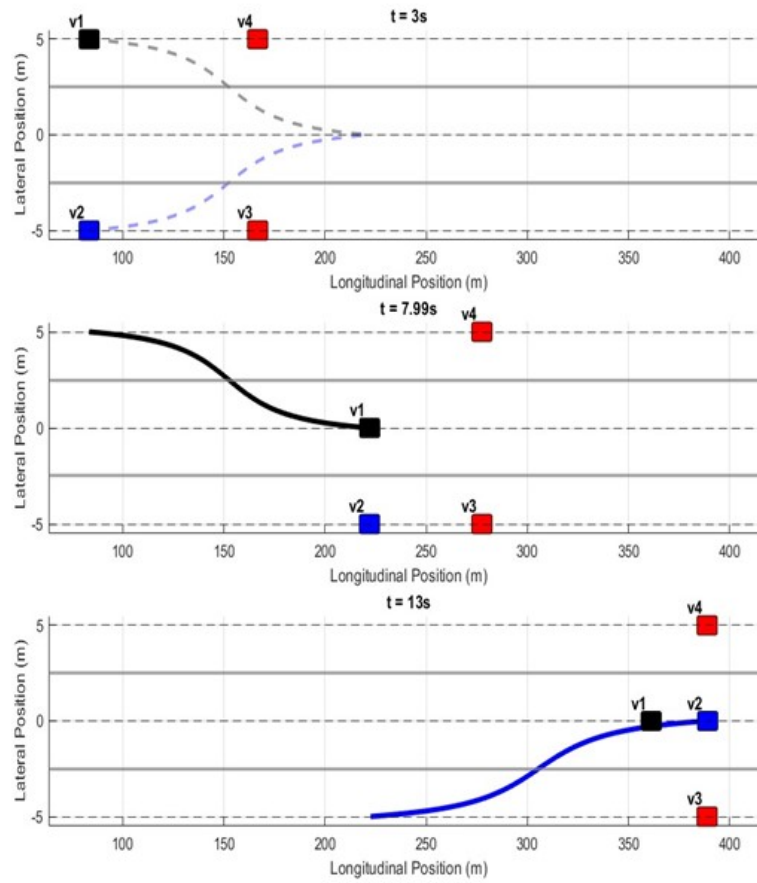


Figure 4.15: Lane Change Scenario: Vehicle 1 (v1) Initiates Lane Change with Priority
($t = 3\text{ s}$ to $t = 13\text{ s}$)

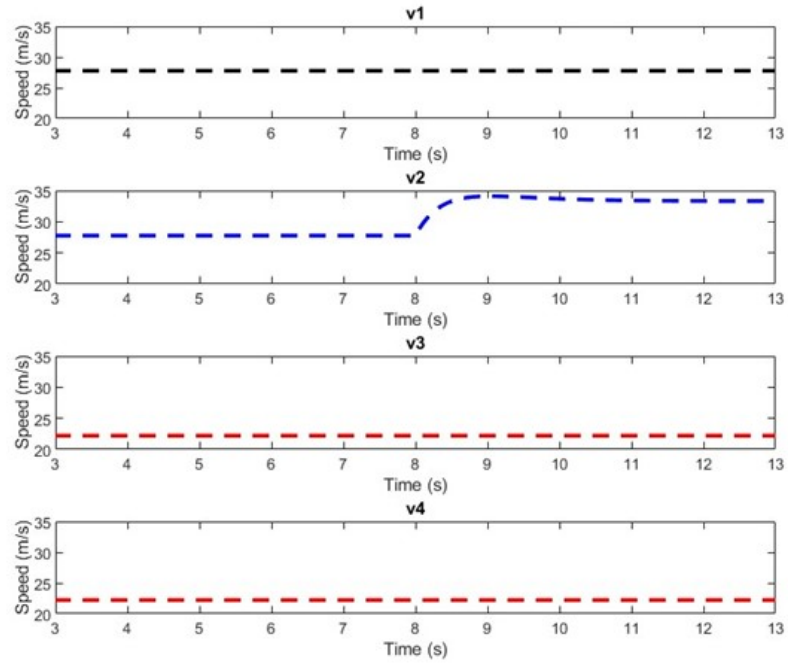


Figure 4.16: Speed Profiles for Lane Change Priority Scenario

As shown in Figures 4.15 and 4.16, the priority mechanism allows the autonomous vehicles to sequence their lane changes, effectively coordinating their maneuvers to avoid conflicts.

- **Phase 1: Vehicle 1 Lane Change Priority ($t = 3$ s to $t = 7.99$ s)**
 - Vehicle 1 (v1) initiates its lane change first, as shown in the first subplot of Figure 4.15. The priority mechanism grants it the right of way to perform the maneuver, involving a lateral shift into the middle lane.
 - During this period, Vehicle 2 (v2) maintains its position in the adjacent lane, deferring its lane change attempt to prevent potential collision, as enforced by the overlapping detection mechanism.

- Non-cooperating Human-Driven Vehicles (HDVs) (v3 and v4 in red) remain at fixed positions and are not involved in this lane change process.

- **Phase 2: Vehicle 2 Lane Change ($t = 8.01$ s to $t = 13$ s)**

- Once Vehicle 1 has completed its lane change and stabilized its position, Vehicle 2 initiates its own lane change following a similar lateral trajectory.
- This delayed maneuver is necessary due to the overlapping detection system, which ensures that Vehicle 1 completes its lane change before Vehicle 2 begins its own, preventing lateral conflicts.
- The HDVs continue unaffected by the lane changes of either Vehicle 1 or Vehicle 2.

The speed profiles for each vehicle are shown in Figure 4.16. These profiles illustrate how each vehicle adapts its speed to accommodate the priority-based lane change coordination.

- **Ego Vehicle (v1)**

- During the lane change, Vehicle 1 maintains a relatively constant speed of around 28 m/s, as seen in the top subplot of Figure 4.16.
- This stability in speed reflects that Vehicle 1 is focused on completing the lane change without needing significant deceleration or acceleration, relying on the coordination mechanism to manage space.

- **Cooperating Vehicle (v2)**

- Vehicle 2 begins its lane change later due to the priority mechanism. Between $t = 8$ s and $t = 10$ s, it slightly accelerates from 28 m/s to 34 m/s as it approaches the point where it will start its lane change.
- This acceleration is necessary to overtake Vehicle 1, which has now positioned itself in the middle lane at a high speed.
- The lane change completes successfully without further acceleration or deceleration required.

- **Non-Cooperating HDVs (v3 and v4)**

- Both HDVs (v3 and v4) maintain constant speeds of around 22 m/s throughout the scenario, unaffected by the lane change events of Vehicles 1 and 2.
- These HDVs are non-cooperative vehicles and continue their steady speeds without interacting with the CAVs involved in the lane change.

Table 4.5: Performance Metrics for Lane-Change Phase with Priority Coordination

Metric/Scenario	V1 Lane Change	V2 Lane Change
Gap Distance (m)	inf	55.49
V1 Average Acceleration (m/s^2), During LCP	0	1.11
Long Distance Crossed (m)	138.75	166.68
Cooperation (True/False)	False	False
Priority Value (s^{-1})	0.333	0.332
Current Distance Detected (m)	83.4	83.4
$D_{\min}$ for LCP Initiation (m)	83.4	83.4
Current Reward Value, $R(t)$	-6	-6
Next Estimated Reward Value, $R(t + 1)$	2.2	2.2

The table 4.5 provides a summary of the performance metrics for the lane-change phase with priority coordination. Vehicle 1 completes its lane change first due to its priority, with no cooperation needed. Vehicle 2 defers its lane change and maintains a safe distance, executing the maneuver only after Vehicle 1 has stabilized in the target lane. The priority values indicate the sequence of operations, with Vehicle 1 having a slightly higher priority value (0.333) than Vehicle 2 (0.332).

For both v_1 and v_2 , the current distance detected was 83.4 meters, aligning with the required $D_{\min}$ for LCP initiation. The current reward value, $R(t)$, was -6, indicating proximity to the safety threshold, while the next estimated reward value, $R(t + 1)$, improved to 2.2, emphasizing the algorithm's stability and robustness as they both shared similar states resulting in similar evaluations.

4.3.2 Simultaneous Lane Change Coordination

Objective:

The objective of this scenario is to evaluate complex maneuvers involving a sequence of lane changes and overtaking maneuvers by Connected Autonomous Vehicles (CAVs) and Human-Driven Vehicles (HDVs). This scenario explores the interactions, cooperative behavior, and adaptive decision-making among multiple vehicles in real-time, aiming to ensure safety, stability, and efficiency.

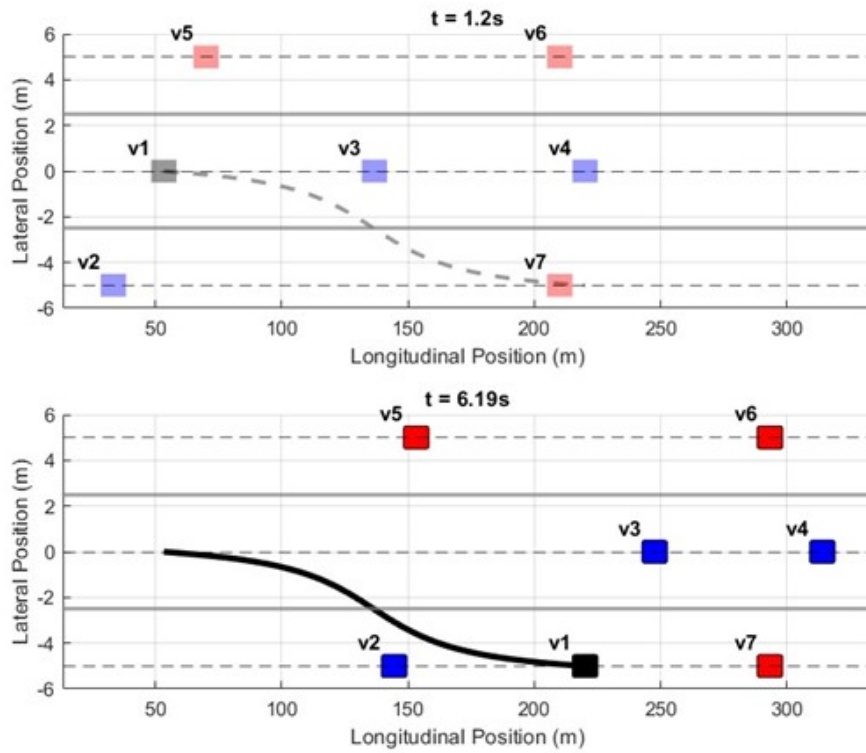


Figure 4.17: Phase of Single Overtaking: Position of Vehicles at $t = 1.2s$.

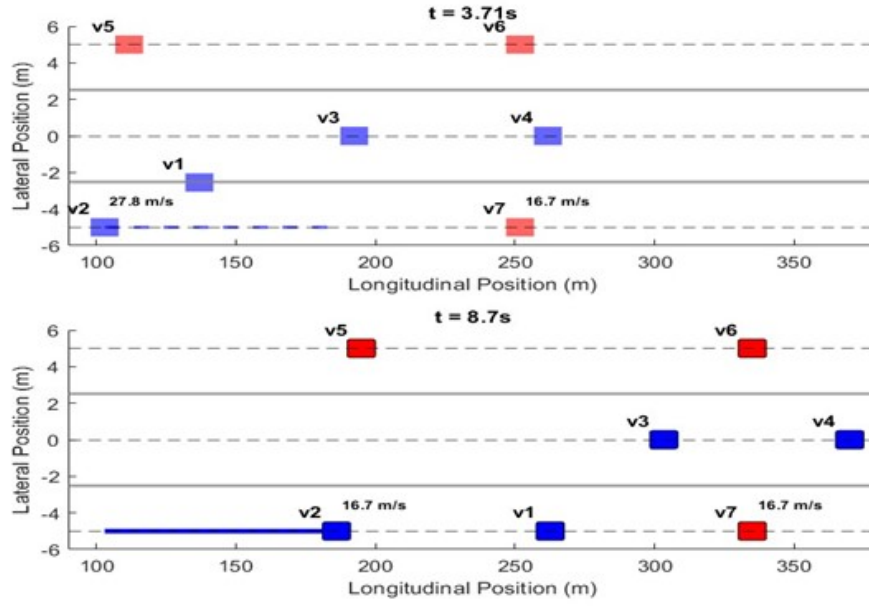


Figure 4.18: Phase of Necessary Speed Control and Stability at $t = 3.71s$.

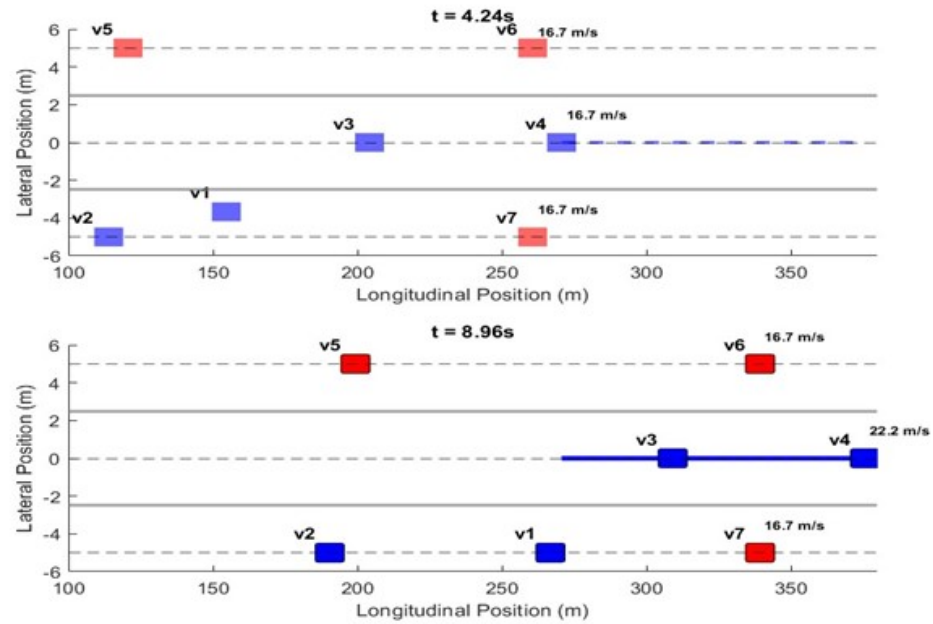


Figure 4.19: Phase of Necessary Speed Control and Stability at $t = 4.24s$.

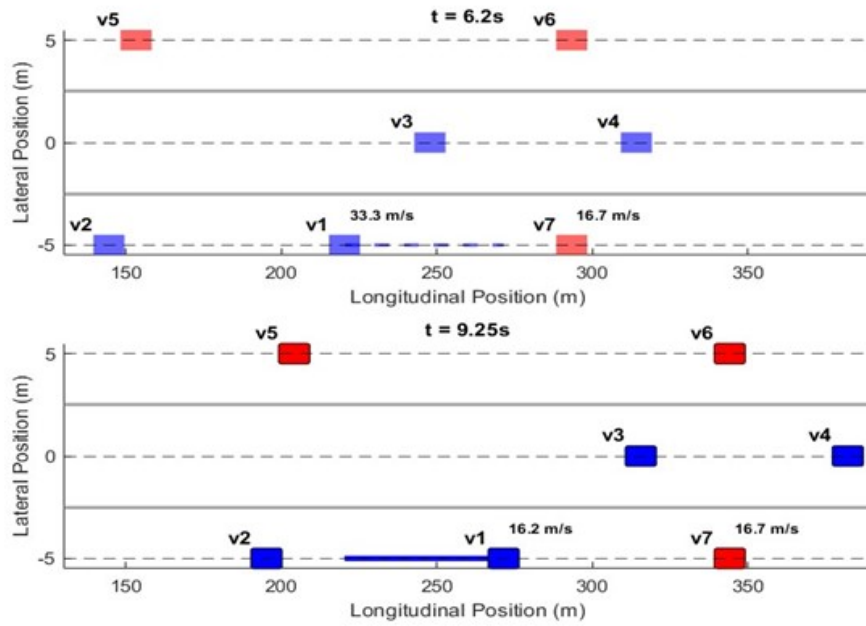


Figure 4.20: Phase of Necessary Speed Control and Stability at $t = 6.2s$.

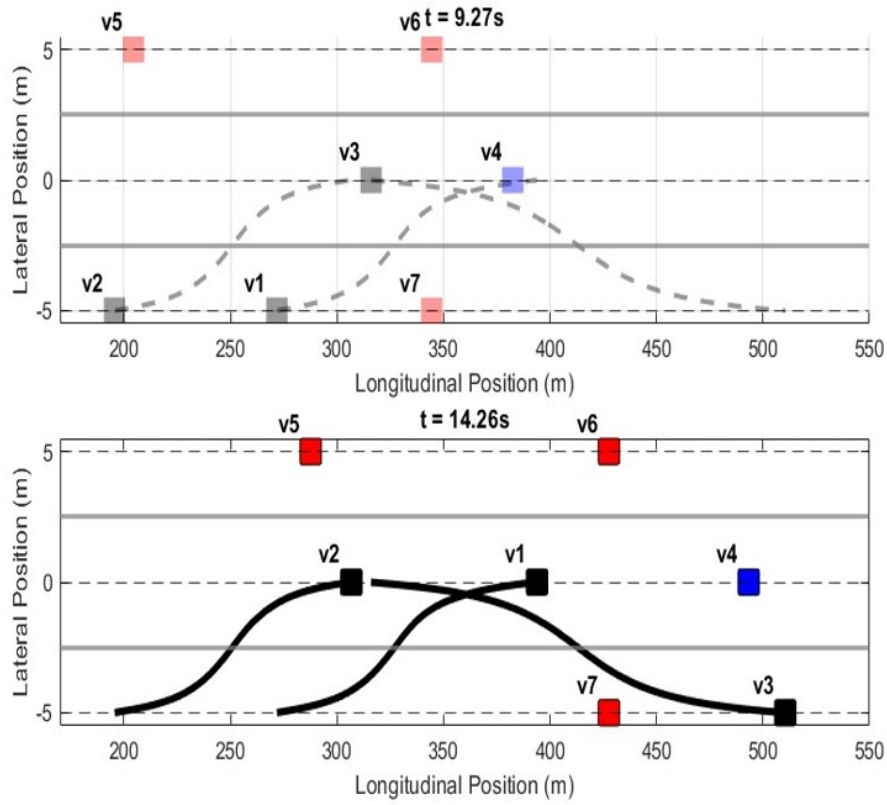


Figure 4.21: Multi-Simultaneous Lane Change Initiation at $t = 9.27s$.

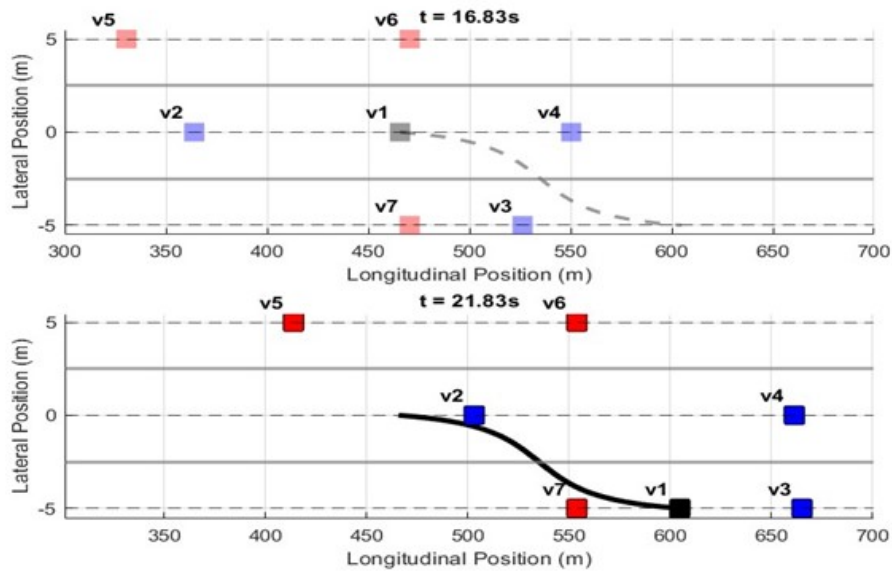


Figure 4.22: v1 Sequential Overtaking Maneuver at $t = 16.83s$

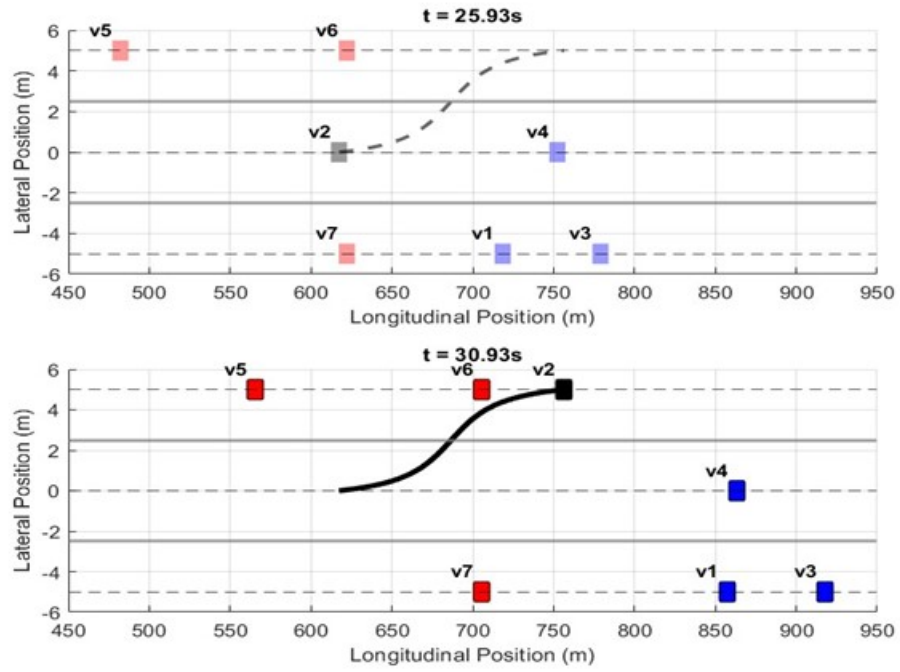


Figure 4.23: v2 Sequential Overtaking Maneuver at $t = 25.93s$.

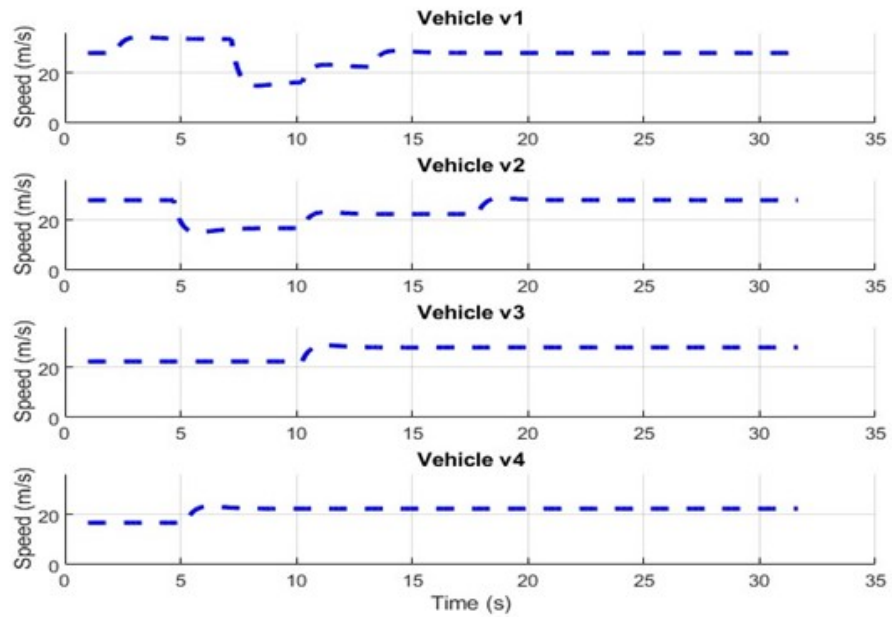


Figure 4.24: CAVs Speed Profiles.

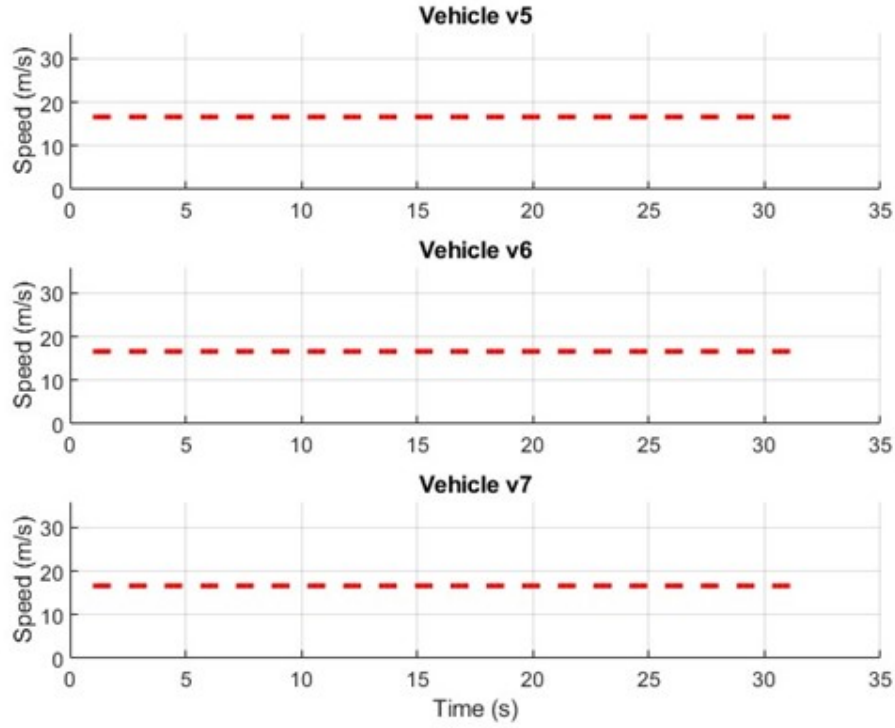


Figure 4.25: HDVs Speed Profiles.

Analysis: The lane-changing and overtaking scenario involves multiple phases of complex interactions among Connected Autonomous Vehicles (CAVs) and Human-Driven Vehicles (HDVs).

- **Phase of Single Overtaking (Figures 4.17):**

- *Ego Vehicle (v1):* At $t = 1.2s$, v1 begins a lane change, adjusting its trajectory and completing the maneuver by $t = 6.19s$. The planned path is indicated by a dashed line, which transitions to a solid line upon maneuver completion.
- *Surrounding Vehicles:* CAVs (v2, v3, and v4) maintain their speeds and

positions around v1, with HDVs (v5, v6, and v7) continuing at constant speeds without adjustments, as shown in the top plot.

- **Phase of Necessary Speed Control and Stability (Figures 4.18, 4.19, and 4.20):**

- At t=3.71s, vehicle v2 slows down to avoid a rear-end collision with v1.
- At t=4.24s, vehicle v4 speeds up in response to v3's request, indicating another CAV's lane change preparation.
- At t=6.20s, v1 decelerates right after completing its lane change, as a response to reduced spacing with v7. By t=8.7s, 8.96s, and 9.25s, all vehicles stabilize at their new speeds, indicating successful cooperation in speed adjustment.

- **Simultaneous Multi-Vehicle Lane Change Initiation (Figure 4.21):**

- At t=9.27s, v1, v2, and v3 initiate lane changes simultaneously. The priority mechanism does not trigger any delays, as no trajectory overlaps are detected.
- By t=14.26s, v1, v2 and v3 complete their lane change maneuvers issues simultaneously without .

- **Sequential Overtaking Maneuver (Figures 4.22 and 4.23):**

- At t=16.83s, v1 begins a lane change to the left to overtake v4. Vehicle v2 holds its position behind, while v7 and v6 maintain their lanes.

- At $t=25.93s$, $v2$ initiates an overtaking lane change, choosing the right lane since $v1$ is occupying the left.
- At $t=30.93s$, both $v1$ and $v2$ complete their overtakes. The sequential lane changes and adaptive decisions demonstrate effective coordination, enabling both vehicles to overtake smoothly.

Additionally, the speed profiles (Figures 4.24, 4.25) indicate strategic acceleration and deceleration phases, managed automatically by the system. This coordination allowed CAVs to handle overtakes, lane changes, and potential hazards smoothly, demonstrating effective speed regulation and cooperation between vehicles. Even so, throughout the sequence of maneuvers, the automated system, driven by a Markov Decision Process (MDP) and supporting algorithms, showcased precise and adaptive control among the Connected Autonomous Vehicles (CAVs). The scenarios involved various phases including initial lane changes, necessary speed adjustments, and coordinated multi-vehicle overtaking. The MDP effectively managed complex traffic interactions by facilitating safe and efficient maneuvers. Vehicles like $v1$, $v2$, and $v3$ demonstrated seamless lane changes, while cooperating CAVs adjusted speeds to create necessary gaps. Even in situations where multiple lane changes occurred simultaneously, the system ensured no trajectory conflicts, maintaining smooth transitions.

Table 4.6: Performance Metrics for Vehicle v1 across LCP Phases

Metric/Scenario	V1 First LCP	V1 Second LCP	V1 Third LCP
Gap Distance (m)	inf	inf	79.84
V1 Avg Deceleration Magnitude (m/s^2) (waiting)	N/A	5.60	N/A
V1 Avg Acceleration Magnitude (m/s^2) (preparation)	0	0	1.21
V1 Avg Acceleration Magnitude (m/s^2) (during LCP)	1.07	1.95	0
Long Distance Crossed (m)	166.68	66.58	139.03
Cooperation (true/false), number of vehicles cooperating	False	False	True, 1
Synchronization (true/false)	False	True	False
Current Distance Detected (m)	83.4	73	84.6
$D_{\min}$ for LCP Initiation (m)	83.4	83.4	66.7
Current Reward Value, $R(t)$	-7	-9.5	-8
Next Estimated Reward Value, $R(t+1)$	1.1	-1.53	0.015

Table 4.7: Performance Metrics for Vehicle v2 across LCP Phases

Metric/Scenario	V2 First LCP	V2 Second LCP
Gap Distance (m)	inf	130.14
Avg Deceleration Magnitude (m/s^2) (waiting)	3.51	0
Avg Acceleration Magnitude (m/s^2) (preparation)	0	1.85
Avg Acceleration Magnitude (m/s^2) (during LCP)	1.80	0
Long Distance Crossed (m)	66.56	139.03
Cooperation (true/false)	False	False
Synchronization (true/false)	True	False
Current Distance Detected (m)	33.9	135
$D_{\min}$ for LCP Initiation (m)	66.7	83.4
Current Reward Value, $R(t)$	-3	4
Next Estimated Reward Value, $R(t+1)$	5.56	4.44

Table 4.8: Performance Metrics for Vehicle v3 during LCP

Metric/Scenario	V3 LCP
Gap Distance (m)	38.04
Avg Deceleration Magnitude (m/s^2) (waiting)	0
Avg Acceleration Magnitude (m/s^2) (preparation)	0
Avg Acceleration Magnitude (m/s^2) (during LCP)	1.07
Long Distance Crossed (m)	138.66
Cooperation (true/false), number of vehicles cooperating	True, 1
Synchronization (true/false)	False
Current Distance Detected (m)	66.5
$D_{\min}$ for LCP Initiation (m)	66.7
Current Reward Value, $R(t)$	-9
Next Estimated Reward Value, $R(t + 1)$	-0.98

Table Analysis: The tables summarize the performance metrics for each vehicle involved in the multi-phase lane changes and overtaking maneuvers:

- Vehicle v1 performs three lane change phases, with a synchronization requirement only during the second phase (Table 4.6). It completes maneuvers with minimal deceleration.
- Vehicle v2 undergoes two lane changes, showing adaptive speed adjustments with

minimal deceleration and high synchronization in the first phase (Table 4.7).

- Vehicle v3 performs a single lane change, demonstrating cooperation with other CAVs to maintain safety and avoid conflicts (Table 4.8).

Overall, the vehicles adapt dynamically to traffic conditions and coordinate their actions for safe and efficient maneuvers, underscoring the role of CAVs in modern traffic management.

CHAPTER 5

CONCLUSION

5.1 Summary of Findings and Implications

The integration of Connected and Automated Vehicles (CAVs) into mainstream traffic systems represents a significant leap towards improving road safety, traffic efficiency, and the overall dynamics of transportation. This research has focused on developing and implementing a robust MATLAB-based simulation that facilitates coordinated multi-vehicle lane-changing maneuvers in decentralized manner, particularly within a mixed traffic of CAVs and Human-Driven Vehicles (HDVs). By addressing the complexities of multi-lane changes and cooperation strategies, this study contributes to the evolving landscape of intelligent transportation systems.

The core objective of this research was to design a system that enhances the synchronization of lane changes among multiple vehicles, thus optimizing road space usage, minimizing traffic disruptions, and reducing the likelihood of collisions. To achieve this, the study employed several advanced techniques, including Markov Decision Processes (MDPs) for decision-making, smooth trajectory planning and priority

mechanisms for collision avoidance. Each of these components played a crucial role in enabling the system to make real-time, adaptive decisions that maintain safety and efficiency across various traffic scenarios.

The simulation results indicated that coordinated maneuvers among CAVs could significantly improve traffic flow and safety. The MDP-based decision algorithm enabled vehicles to make intelligent, context-aware decisions by evaluating real-time data about surrounding vehicles, gaps, and potential trajectory collisions. The study also demonstrated the benefits of cooperative strategies, where CAVs could communicate and adjust their speeds to create safe gaps, allowing for smoother lane transitions. This cooperative approach proved to be particularly effective when dealing with scenarios involving multiple vehicles, highlighting the system's ability to manage complex traffic interactions.

Furthermore, the use of trajectory planning ensured that lane changes were not only safe but also smooth and predictable, enhancing the comfort of passengers and reducing the likelihood of abrupt maneuvers that could lead to accidents. The integration of speed control through PID (Proportional-Integral-Derivative) mechanisms also allowed for precise adjustments, further contributing to the overall stability of the system.

The study's emphasis on the interaction between CAVs and HDVs added a realistic dimension to the simulation, as it accounted for the unpredictable behavior of human drivers. The results confirmed that while CAVs could effectively communicate and cooperate, the presence of HDVs posed additional challenges, particularly when these vehicles exhibited aggressive or erratic behavior. Nonetheless, the proposed sys-

tem’s ability to predict and adapt to these behaviors underscored its robustness and applicability in real-world scenarios.

In conclusion, this research has made substantial contributions to the field of autonomous vehicle technology by demonstrating how coordinated lane-changing processes can be efficiently managed in mixed traffic environments. The findings lay a foundation for future advancements, offering insights into how CAVs can be integrated seamlessly into existing traffic systems. Through intelligent decision-making, adaptive cooperation, and advanced trajectory planning, this study has paved the way for further developments in automated driving systems, making roads safer and more efficient. The success of the simulations provides optimism for real-world applications, where such systems could significantly alleviate congestion, reduce accidents, and improve the overall driving experience for all road users.

5.2 Future Work

While this study has successfully established a framework for coordinated lane-changing among CAVs in a mixed traffic environment, there are several areas where future research could build upon and refine the current findings. The suggestions for future work aim to address limitations observed during the study and explore new avenues that could enhance the performance and applicability of the system.

- **Incorporation of Environmental Factors:** The current model assumes ideal weather and road conditions, which may not always be the case in real-world scenarios. Future research should consider integrating environmental factors

such as rain, fog, snow, and varying road surfaces, which can affect sensor accuracy, vehicle traction, and overall vehicle dynamics. By simulating adverse conditions, the system can be further refined to handle diverse weather scenarios, ensuring reliability and safety in all conditions. Additionally, factors like road curvature and gradient can be incorporated to make the simulation more representative of real-world driving environments.

- **Enhanced Communication Protocols:** While the current system demonstrates effective cooperation among CAVs through Vehicle-to-Vehicle (V2V) communication, future studies could explore more sophisticated communication protocols, including Vehicle-to-Infrastructure (V2I) and Vehicle-to-Everything (V2X). These protocols would allow vehicles to receive real-time data from traffic lights, road sensors, and even pedestrians, enabling more informed and context-aware decisions. Future work could also focus on developing fail-safe mechanisms to handle communication disruptions, ensuring that CAVs can still make safe decisions in the event of data transmission issues.
- **Machine Learning and Artificial Intelligence Integration:** The integration of advanced machine learning algorithms, such as deep reinforcement learning (DRL), could significantly enhance the decision-making capabilities of CAVs. Unlike rule-based systems, machine learning models can learn from a vast array of traffic scenarios, including rare and unpredictable events, which improves the system's ability to adapt to new situations. Future research could explore the use of neural networks to predict the behavior of nearby vehicles, both CAVs and

HDVs, enabling more proactive and precise lane-change maneuvers. Moreover, combining DRL with real-time data processing could lead to the development of CAVs that continuously improve their performance through experience.

- **Incorporation of Human Behavioral Models:** To better anticipate the actions of HDVs, future studies could incorporate models that simulate human driving behavior under various conditions. These models could be based on real-world data collected from HDVs, which would allow the system to predict and adapt to aggressive, hesitant, or erratic driving patterns more effectively. By understanding common human responses, such as sudden lane changes or abrupt braking, CAVs can plan more defensive maneuvers that enhance overall safety.

In summary, the development of coordinated lane-changing systems for CAVs represents a significant step towards realizing fully autonomous traffic networks. While the research presented in this study has established a robust foundation, the field remains ripe for exploration and innovation. Future studies that address environmental factors, enhance communication protocols, and incorporate advanced machine learning techniques will play a critical role in advancing the capabilities of CAVs.

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VITAE

- Name: Abdullah Ali Alshakhs
- Nationality: Saudi
- Date of Birth: 10/02/1998
- Email: *alshakhs.work@gmail.com*
- Permenant Address: Al-Qarah Town, Al-Hasa, Eastern Province, Saudi Arabia
P.O. 36351
- Academic Background: B.Sc. Control and Instrumentation System Engineering, 2015-2020, KFUPM, Dhahran, Saudi Arabia.