A multi-agent reinforcement learning-based longitudinal and lateral control of CAVs to improve traffic efficiency in a mandatory lane change scenario

TEAM 6

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CLOUD COMPUTING

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Introduction

Why Bottleneck Traffic is a Problem:

- Vehicles slow down significantly at bottlenecks, causing **traffic jams**.
- Sudden lane changes and braking increase **collision risk**.
- Inefficient traffic flow leads to **long delays** and higher fuel consumption.

Real-World Relevance:

- Common in **highways, construction zones, and lane closures**.
- Impacts **commuter time, logistics, and road safety**.

What the Paper Aims to Solve:

- Reduce congestion and improve traffic flow in **mandatory lane-change scenarios**.
- Ensure **safety** while vehicles merge in bottleneck areas.
- Enable **autonomous vehicles (CAVs) to coordinate** for smoother traffic.

Gaps in Existing Research

Papers	Simulation Scenario		RL algorithm		collision avoidance strategy		Action			
	SS	RS	SA	MA	1D	2D	LO	LA	CO	DI
Bouton et al. (2019)	√	–	√	–	√	–	√	–	–	√
Nishi et al. (2019)	–	√	√	–	√	–	√	–	–	√
Wu et al. (2020)	–	√	√	–	√	–	√	–	–	√
Ren et al. (2020)	√	–	√	–	√	–	√	–	√	–
Chen et al. (2021)	√	–	–	√	√	–	–	√	–	√
Guo et al. (2021)	–	√	√	–	√	–	√	√	√	√
Wang et al. (2021)	√	–	–	√	√	–	–	√	–	√
Han et al., (2022a)	–	√	√	–	√	–	√	–	–	√
Han et al., (2022b)	√	–	√	–	√	–	√	–	–	√
Jiang et al. (2022)	–	√	√	–	√	–	√	–	√	–
Wang et al. (2022)	–	√	√	–	√	–	–	√	–	√
Li et al. (2022)	√	–	√	–	–	√	–	√	–	√
Proposed	–	√	–	√	–	√	√	√	√	–

SS - Simulations based on simulated scenarios; RS - Simulations based on real-world scenarios; SA - Single-agent; MA - Multi-agent;
1D - One-dimensional; 2D - Two-dimensional; LO - longitudinal; LA - lateral; CO - continuous; DI - discrete;

Lack of real driving data: Most studies rely on simulations and cannot compare results with actual human driving behavior.

Oversimplified lane-change modeling: Fixed lateral speeds or durations fail to capture realistic interactions between vehicles during merges.

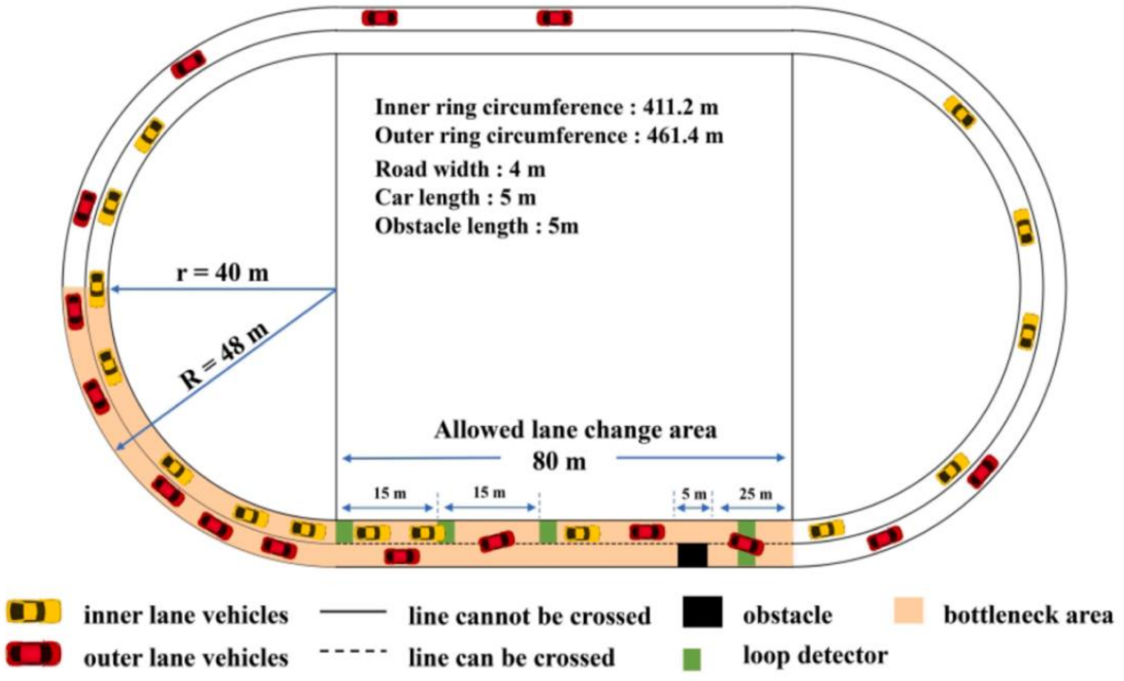
Why these gaps matter:
- Makes it hard to evaluate how well new methods work in real-world conditions.
- Motivates the use of **real-world data collection** and **more realistic lane-change modeling** in the proposed MARL approach.

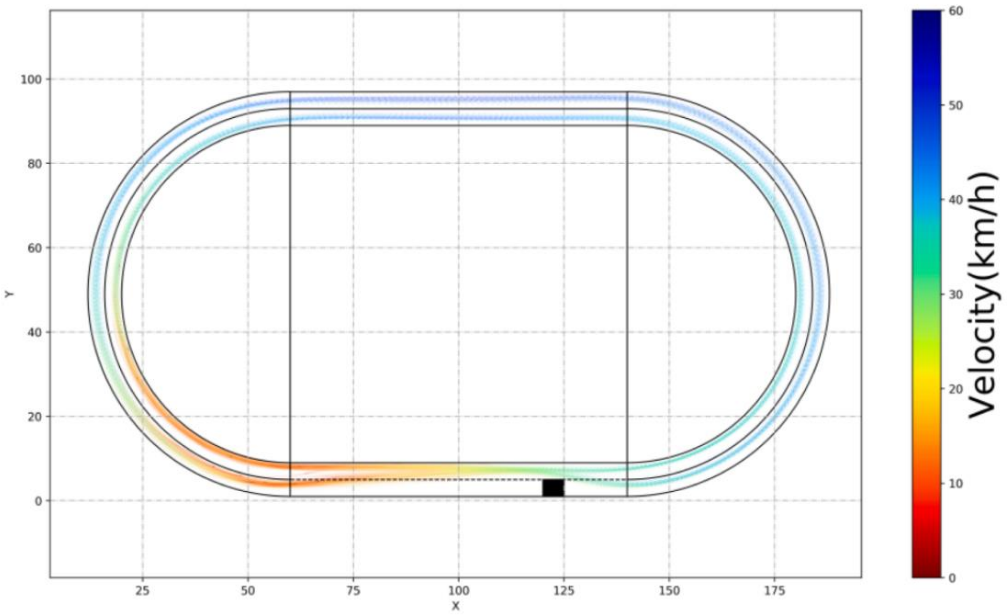
Problem Statement

Congestion at bottlenecks: Vehicles slow down significantly, causing traffic jams and delays.

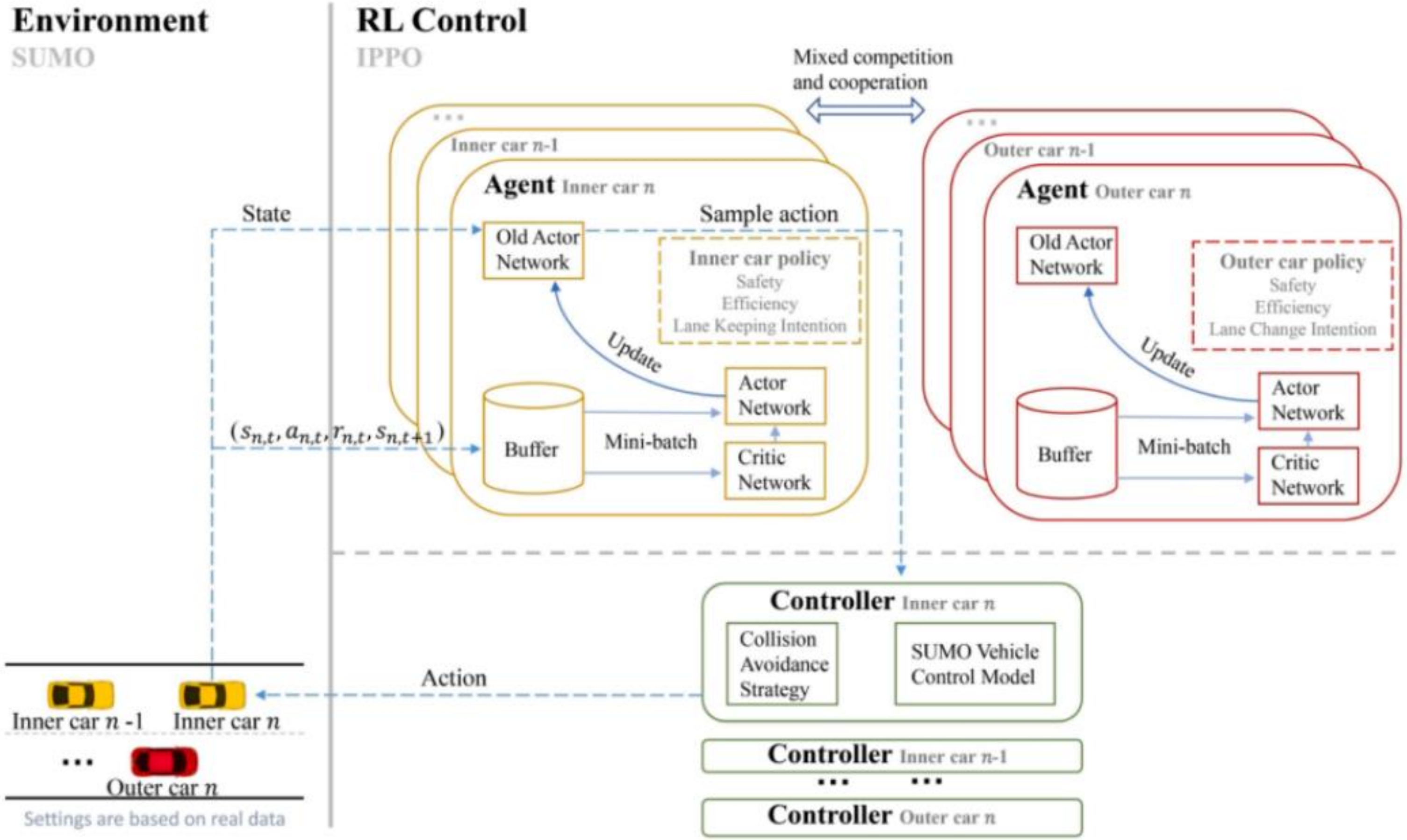
Suboptimal human driving: Lane changes often unsafe or inefficient, increasing collision risk.

Limitations of prior studies: Many assume **fixed lateral speeds or durations**, oversimplifying real-world lane-change behavior.





Proposed Solution



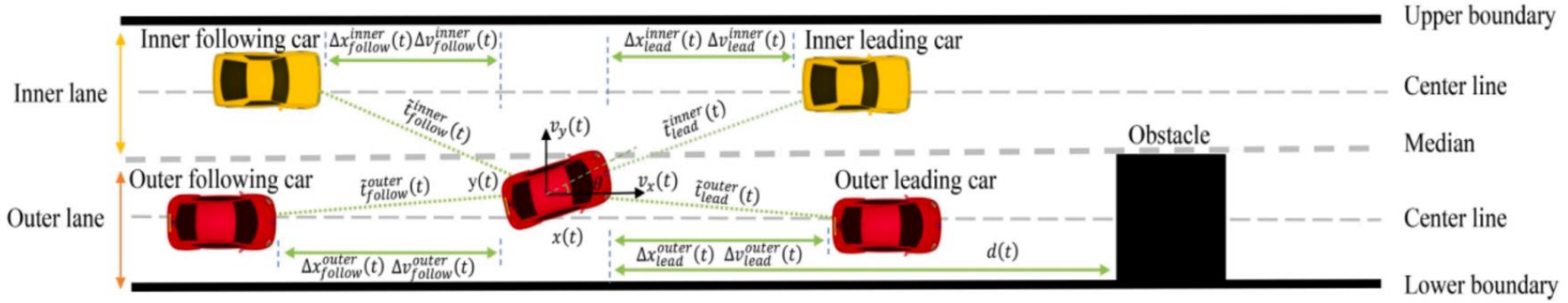
Multi-Agent RL Framework: Each autonomous vehicle (CAV) learns to control acceleration, braking, and steering while coordinating with other vehicles.

2D-iTTC Safety Metric: Measures potential collisions considering both forward and lateral movements during lane changes.

2D Gipps Collision Avoidance: Extends classic Gipps model to handle both longitudinal and lateral safety proactively.

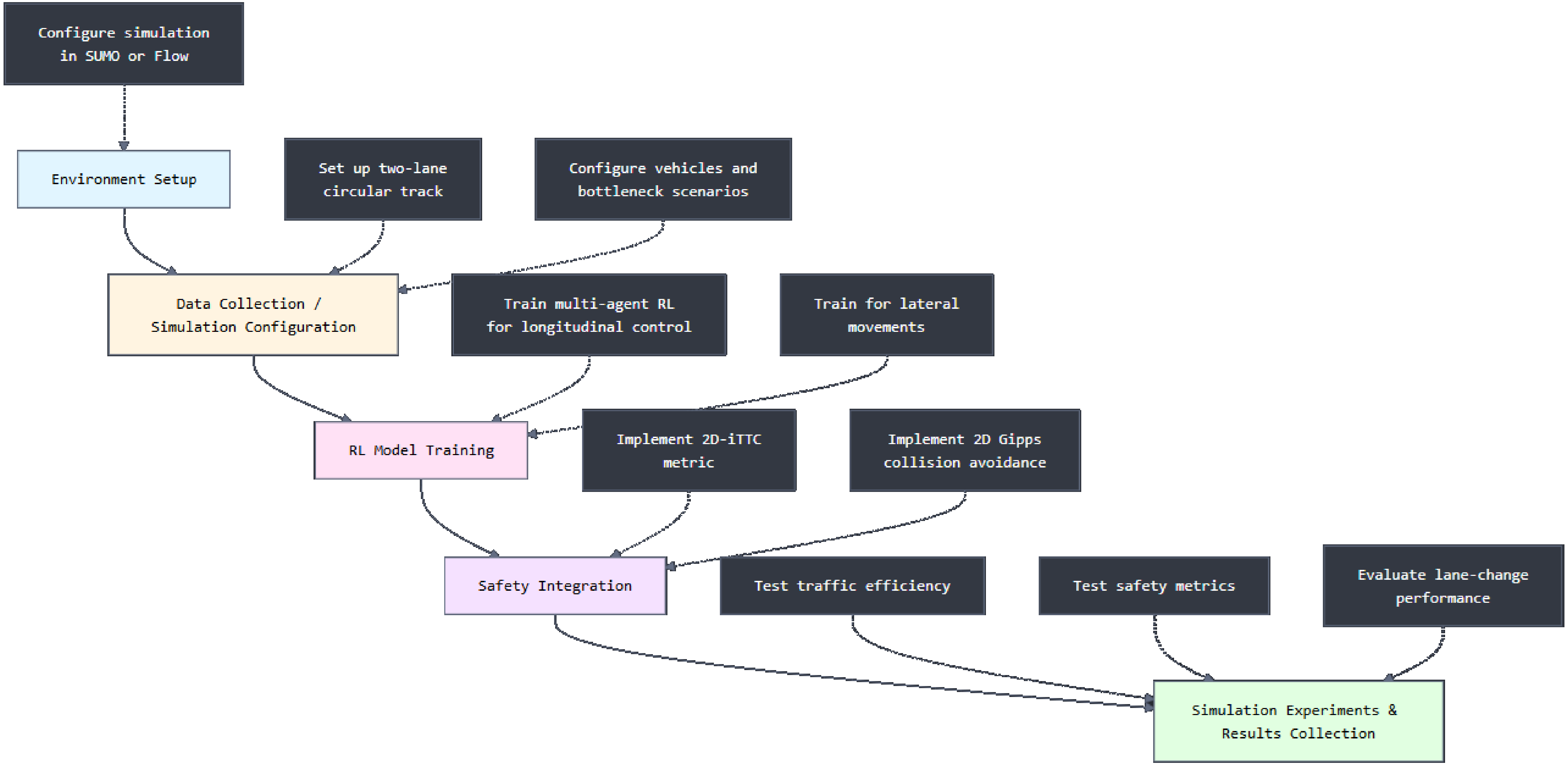
Buffer Zone Strategy: Maintains safe spacing before bottlenecks to reduce congestion and allow smoother lane changes.

Input & Output



Symbol	Description	Unit
$v_x(t)$	longitudinal speed of the current vehicle at time t	m/s
$v_y(t)$	lateral speed of the current vehicle at time t	m/s
$\theta(t)$	steering angle of the current vehicle	$\circ$
$x(t)$	horizontal axis coordinates of the current vehicle at time t	–
$y(t)$	vertical axis coordinates of the current vehicle at time t	–
$d(t)$	distance to obstacle	m
$\Delta v^{inner}_{lead}(t)$	relative speed between the current vehicle and the leading vehicle in the inner ring	m/s
$\Delta v^{inner}_{follow}(t)$	relative speed between the current vehicle and the following vehicle in the inner ring	m/s
$\Delta v^{outer}_{lead}(t)$	relative speed between the current vehicle and the leading vehicle in the outer ring	m/s
$\Delta v^{outer}_{follow}(t)$	relative speed between the current vehicle and the following vehicle in the outer ring	m/s
$\Delta x^{inner}_{lead}(t)$	clearance distance between the current vehicle and the leading vehicle in the inner ring	m
$\Delta x^{inner}_{follow}(t)$	clearance distance between the current vehicle and the following vehicle in the inner ring	m
$\Delta x^{outer}_{lead}(t)$	clearance distance between the current vehicle and the leading vehicle in the outer ring	m
$\Delta x^{outer}_{follow}(t)$	clearance distance between the current vehicle and the following vehicle in the outer ring	m
$\tilde{t}^{inner}_{lead}(t)$	2-dimensional inverse time-to-collision between the current vehicle and the leading vehicle in the inner ring	s^{-1}
$\tilde{t}^{inner}_{follow}(t)$	2-dimensional inverse time-to-collision between the current vehicle and the following vehicle in the inner ring	s^{-1}
$\tilde{t}^{outer}_{lead}(t)$	2-dimensional inverse time-to-collision between the current vehicle and the leading vehicle in the outer ring	s^{-1}
$\tilde{t}^{outer}_{follow}(t)$	2-dimensional inverse time-to-collision between the current vehicle and the following vehicle in the outer ring	s^{-1}

Expected Workflow for Phase-2



Technology & Tools

Traffic Simulation: SUMO or Flow for modeling vehicle interactions and bottlenecks.

Programming & RL Implementation: Python with libraries like **Stable Baselines**, **RLlib**, **PyTorch**, or **TensorFlow**.

Safety & Collision Modeling: Custom scripts for 2D-iTTC and 2D Gipps implementation.

Cloud Resources (Optional): AWS, GCP, or Azure for running parallel simulations and RL training efficiently.

Visualization & Analysis: Matplotlib or other Python plotting tools to track traffic flow, speed, and safety metrics.

Expected Outcomes

Reward design	Average speed (**km/h**)	Difference (%)	Average travel time (s)	Difference (%)
real data	18.4	–	29.3	–
$r_{2DiTTC} + r_{collision} + r_{speed}$	19.8	+7.6 %	27.3	−6.8 %
$r_{2DiTTC} + r_{collision} + r_{speed} + r_{distance}$	22.4	+21.7 %	24.1	−17.7 %
proposed	31.9	+73.4 %	16.9	−42.3 %

- **Improved Traffic Throughput:** Vehicles move more efficiently through bottleneck areas.
- **Higher Average Speed:** Reduced slowdowns at lane-change zones.
- **Enhanced Safety Metrics:** Fewer collisions or near-misses due to 2D-iTTC and 2D Gipps integration.
- **Realistic Lane-Change Behavior:** Closer to natural human driving than traditional rule-based models.