Study of the Impact of Cooperative Maneuvers Among Different Types of Vehicles in Real-World Scenarios

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Abstract*—The automotive sector has seen a significant increase in autonomous mobility expenditures throughout the past decade through private-sector investments made by original equipment manufacturers and public research via universities and institutes. However, despite the significant funds invested in enabling technologies, the world is not much closer to self-driving vehicles on its main roads. One of the reasons for this is the lack of willingness to regulate this sector, as it requires taking accountability for failures. Moreover, to ensure the existence of autonomous vehicles (AV) on the road, regulation must be pushed, ensuring that both non-autonomous and AV can coexist. The lifespan of a vehicle can range from fifteen to thirty years on average. So, considering that classic vehicles still represent almost all vehicle sales, self-driving vehicles will share the roads in the next few decades. This implies that AVs must be able to adapt themselves to the behavior of human drivers and hold mechanisms to handle the higher probability of collisions and jams. Only once this adaptation is proven successful can regulation finally be implemented. This article explores how 5G, V2X, and intelligent transportation systems can make AV decisions safer by mitigating mixed-traffic vulnerabilities through V2V information exchange. Mathematical modeling and simulations such as Markov chains, Bayesian networks, and Monte Carlo simulations were used to quantify impact. Simulations modeled how non-AVs and AVs interact and estimate the probability of accidents and congestion across cooperation levels. Additionally, fleet composition dynamics were analyzed to assess accident rates and traffic flow as AV fleets grow. The results confirm that cooperation is imperative. Cooperative strategies significantly reduce crashes and optimize traffic flow at lower AV adoption. Complete autonomy is a challenging objective to obtain in the near-term future, and, under this study, cooperative integration between non-AVs and AVs must occur in a phased manner.

***Index Terms*—5G NR-U, V2X, AVs, Non-AVs, MDP, Traffic Safety**

I. Introduction

The autonomous vehicle (AV) market has attracted substantial investment, with billions of euros spent developing this technology. Some studies show that these investments are seen by their potential for improved mobility, reduced emissions, and improved public health and safety [1]. According to the SAE (Society of Automotive Engineers), the classification of vehicle automation is divided into levels 0, where there is no automation, and levels 1-4, where the vehicles are equipped with a single automated feature, meaning that they need the driver. On level 5, the vehicle is entirely autonomous, and there is no intervation from the driver [2].

Despite the advantages, the large-scale deployment in real-world environments remains limited. There are several technological obstacles, from the required systems, technologies [3] and the regulatory complexity for the transition from traditional traffic systems to the ones where coexistence must exist between different vehicles. Given the average vehicle lifespan of 15–30 years, this coexistence will persist for decades [4], requiring autonomous vehicles (AVs) to operate in diversified and often unpredictable environments [1], highlighting the uncertainty surrounding AV adoption and reinforcing the need for coexistence strategies. In mixed-traffic scenarios, human-driven vehicles introduce significant uncertainty through harsh lane changes, traffic light violations, and inconsistent interactions with vulnerable road users. Without robust mechanisms for anticipating such events, AVs are prone to sub-optimal behavior, leading to safety risks and traffic inefficiencies. To mitigate these challenges, cooperative communication technologies such as Vehicle-to-Everything (V2X), enabled by 5G New Radio Unlicensed (NR-U), have been proposed [5]. Vehicles and infrastructure can coordinate maneuvers, reduce uncertainty, and enhance situational awareness by sharing real-time information, such as position, velocity, and intent. However, quantifying the actual impact of cooperation under varying conditions (e.g., AV penetration rates, traffic density, or urban complexity) remains an open problem.

This work investigates the role of V2X-based cooperation in improving safety and efficiency in urban mixed-traffic scenarios. A probabilistic modeling approach combining Markov Chains and Bayesian Networks is proposed to capture the dynamic interactions between AVs and non-autonomous vehicles (non-AVs).

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A cooperation factor is introduced to simulate the effect of V2X in reducing transitions to critical events, such as traffic jams and collisions. In addition, Monte Carlo simulations are used for behavioral variability and uncertainty across different system configurations. Thus, the main contributions relies on a discrete parametrizable probabilistic model that captures complex interactions between AVs and non-AVs under real-world constraints that simulate the effect of V2X communication on transitions. It also aims to evaluate the influence of cooperation and AV fleet composition on accident and congestion probabilities. The conclusion of these insights will support the gradual deployment of AVs in heterogeneous traffic environments through cooperative strategies.

The remainder of the paper is organized as follows: Section II discusses relevant literature on cooperative vehicular systems. Section III presents the proposed model. Section IV introduces real-world urban scenarios that motivate the modeling choices. Section V details the simulation framework. Results are analyzed in Section VI, followed by conclusions and future directions in Section VII.

II. Related Work

The safe integration of AVs into mixed traffic environments is one of the challenges in modern Intelligent Transportation Systems (ITS). A requirement for this integration is the AVs ability to interpret and respond to the inherently unpredictable behavior of non-AVs, especially in dense urban environments.

Cooperative communication technologies, such as V2X, have been studied as situational awareness and decision-making enablers. Recent surveys [5], [6] highlight the potential of NR-U in delivering low-latency, high-reliability communication to support real-time data exchange between vehicles and infrastructure. This continuous sharing of positional, kinetic, and intention-based data improves the AV 's perception horizon and compensates for sensor limitations such as obstructions or reduced Field of View (FoV) [7]–[9].

The importance of cooperative sensing and positioning becomes even more evident in visually complex or obstructed environments, where onboard perception alone may be insufficient. For instance, [8] introduces CoDrive, a collaborative positioning framework that augments Global Navigation Satellite Systems (GNSS) accuracy by fusing information from neighboring vehicles. Similarly, [10] examines how vertical road geometry affects sight distances and consequently limits the decision-making capabilities of AVs. Complementary work [11] models longitudinal behavior of human drivers using probabilistic trajectories, highlighting that AVs must contend with in shared traffic. These insights reinforce the value of cooperation in mitigating errors introduced by humans.

Datasets capturing interactions between automated and manually controlled vehicles are also emerging to support modeling and validation. [12] presents a comprehensive collection of real-world scenarios involving both AVs and non-AVs, capturing behaviors such as lane incursions, sudden braking, and misaligned signaling. While these datasets are valuable for training and benchmarking, they have yet to be explored for probabilistic modeling of cooperative mechanisms in mixed fleets.

Probabilistic modeling techniques have been used to analyze mobility patterns and risk propagation in traffic systems. For instance, approaches based on Markov Chains are commonly used to represent sequential transitions between discrete driving states [13]. On the other hand, Bayesian Networks can encode dependencies and causal relations between contextual variables in dynamic scenes [14], [15]. However, most existing works apply these models in simplified simulation settings or assume homogeneous fleets with full cooperation, often overlooking the degraded reliability introduced by communication failures or partial adoption.

At the decision-making level, multi-agent coordination frameworks using Vehicle-to-Vehicle (V2V) messaging have been proposed to support maneuver planning, platooning, and gap negotiation [16], [17]. These works demonstrate promising results under controlled assumptions but often lack mechanisms to handle the presence of non-cooperative entities explicitly. In such cases, model predictions tend to split from actual outcomes, particularly in the presence of aggressive or distracted human drivers.

Some recent studies have addressed this limitation by introducing behavioral modeling of non-AVs using stochastic methods. For example, [13] incorporates randomness into Markovian transitions to emulate unexpected deceleration or intersection blocking but does not integrate cooperative mechanisms. The authors focus on specific failure types, such as obstructed object misdetection or delayed signal interpretation, rather than evaluating systemic outcomes, such as accident rates or traffic congestion.

In contrast to these approaches, the work presents a probabilistic framework custom-made for urban cities and mixed-traffic conditions. By integrating Markov Chains and Bayesian dependencies, the work models both the evolution of vehicle states and the influence of contextual factors such as pedestrian interference or rule violation by non-AVs. Furthermore, the work introduces a parametrizable cooperation factor to simulate the impact of V2X-enabled communication on transition probabilities toward essential events. Through Monte Carlo simulations, the work accounts for behavioral variability and quantifies how different levels of cooperation and AV fleet composition affect accident and congestion risks. Taken together, these works highlight the need for models that can operate under partial cooperation, account for environmental uncertainty, and remain interpretable. The proposed framework directly addresses these gaps by integrating context-aware probabilistic modeling with support for non-cooperative agents, offering a scalable alternative to more rigid or data-intensive approaches previously proposed.

III. An Approach with Collaborative Systems

Based on the gaps identified in previous literature, this work proposes a probabilistic simulation framework to model cooperative behavior between AVs and non-AVs in mixed urban environments. The core idea is to quantify how real-time communication enabled by V2X, particularly through Cooperative Awareness Messages (CAM) and Distributed Environment Notification Messages (DENM) messages, can reduce the likelihood of traffic incidents such as collisions and congestion under partial automation conditions. The proposed system architecture leverages V2X over NR-U, specifically in the n47 band, to support direct and network-assisted message dissemination across heterogeneous vehicles. This includes both AVs equipped with cooperative perception capabilities and legacy non-AVs that lack automation or connectivity. Road Side Units (RSU)s serve as infrastructure-supported coordination intermediates, especially in urban intersections where vehicle density and obstacle obstruction are critical.

This approach integrates cooperative localization and maneuver prediction. Vehicles continuously broadcast their state using CAM, including position, heading, and velocity, while emergency or abnormal behavior is reported via DENM. These messages enable vehicles and roadside infrastructure to build a shared representation of the environment and anticipate potential conflicts. The work introduced a simulation of the effect of cooperation, a cooperation factor, into the probabilistic model (detailed in Section V). This parameter controls how access to shared information influences the probability of transitioning into critical states such as accidents or blockages. High cooperation implies a timely and accurate perception of surrounding entities, while low cooperation reflects uncertainty and a lack of communication. This work then adopts a hybrid modeling approach based on Markov Chains, Bayesian Networks, and Monte Carlo simulations. Markov Chains are chosen for their ability to model discrete, sequential state transitions typical of traffic systems in a computationally and interpretable manner. Bayesian Networks are integrated to address contextual dependencies influencing transitions (such as pedestrian density or visibility loss), feeding the basic Markovian assumptions with environment-aware modulations. Monte Carlo methods simulate behavioral uncertainty and capture the probabilistic variability inherent in real-world interactions. This combination provides a light framework capable of representing stochastic evolution and context-aware deviations without the complexity or data requirements associated with deep learning or reinforcement learning techniques, which are less suited to scenarios where interpretability and explicit risk quantification are critical.

Unlike centralized coordination frameworks, this approach supports decentralized decision-making based on shared context. This design choice reflects the reality of near-term deployment, where not all vehicles or nodes can rely on persistent connectivity or cloud-based control.

By combining V2X-driven collaboration with probabilistic modeling, the proposed system serves as a testbed for evaluating the role of communication in urban mobility efficiency.

IV. Real Use Case Study

As mentioned above, one problem facing modern automobile driving is deploying autonomous vehicles in urban areas. Urban intersections are among the most complex and unpredictable environments for AVs. These areas often involve dynamic interactions with multiple road users, including pedestrians, human-driven vehicles, delivery vans, and buses. This work considers a real-world intersection in New York City (the convergence of Broadway and Amsterdam Avenue, (40.77799013534391, -73.98213920032559)) as a representative scenario to extract behavioral patterns and model critical transitions in mixed-traffic settings, represented on Figure 1.

Fig. 1. New York City complex intersection

This intersection presents several challenges: high pedestrian density, frequent obstruction due to parked or stopped vehicles, and multiple overlapping traffic rules and signals, all represented in Figure 2. From this scenario, the following representative situations were identified that showcase common causes of traffic disruptions and safety risks:

- **Red Light Violation by a Non-AV (1)**: A human-driven vehicle ignores a red light, obstructing the intended path of another vehicle — typically an AV attempting a protected turn. This behavior can trigger last-moment evasive maneuvers or collisions without prior communication or detection.
- **Stopped Vehicle Blocking the Intersection or Sidewalk (2,5)**: A delivery van stops abruptly in the middle of the intersection, obstructing the view and path of approaching AVs. The lack of visibility forces cautious behavior, which may lead to congestion if other vehicles are not informed of the blockage.
- **Pedestrians Crossing Outside Crosswalks (3)**: Pedestrian behavior in dense urban centers is often non-compliant with signals. AVs must be able to infer intent and react conservatively, which leads to abrupt stops and potential rear-end incidents if not shared with the following vehicles.
- **Merging Across Opposing Lanes for Divergent Turns (6)**: Vehicles approaching the intersection from opposite directions may need to perform intersecting turning maneuvers, for example, a vehicle in the rightmost lane turning left and another in the leftmost lane turning right. This requires precise coordination to avoid trajectory overlaps, especially in the presence of pedestrians and cyclists. While AVs can theoretically resolve these interactions with high precision, the presence of non-AVs introduces significant uncertainty. Without real-time communication,

the probability of collision or traffic blockage increases substantially.

Fig. 2. Showcase of the complex situation on the New York City complex intersection

These real-world situations directly inform the definition of the states in the work probabilistic model (Section V). Transitions such as "Violation" $\rightarrow$ "Blocked" $\rightarrow$ "Accident" or "Blocked" $\rightarrow$ "Traffic Jam" are abstracted from the dynamics observed in these urban configurations, where the unpredictability of non-AVs introduces risk to different maneuvers. Each scenario encapsulates interactions that, depending on the level of communication, may be effectively mitigated. In this context, cooperative maneuvers play a crucial role. Vehicles equipped with V2X can proactively coordinate their behavior by continuously broadcasting CAM containing location, speed, and heading information. They can disseminate DENM messages to warn nearby entities when abnormal events occur.

The presence or absence of cooperation directly influences the system's development through the modeled state space. Without cooperation, vehicles rely on onboard perception, increasing the probability of incorrect intent estimation or delayed response. This simulation reflects this by higher transition probabilities toward accident and congestion states. In contrast, higher levels of cooperation flatten the transition pathways toward critical events, allowing the system to remain in stable operational states even under high-density conditions.

By modeling cooperative behavior parametrically, the created framework evaluates the static benefits of communication and its dynamic influence across diverse configurations of vehicle autonomy, infrastructure support, and environmental complexity. This lays the basis for the methodology presented in the next section.

V. Methodology

This work will extend and quantify the interaction between AVs and non-AVs in different scenarios, taking into account a complex setting such as shown in Figure 2. The different interactions between vehicles can lead to different situations that can lead to critical situations. So, the principal objective of this study is to evaluate the probability of achieving these situations considering the interactions between the vehicles. The focus will be on accidents and traffic congestion in critical environments. The study of critical situations, such as overtaking, lane merging, and blocking at intersections, to understand how these interactions can trigger critical events. All information that is possible to get from these situations can help quantify the risk reduction (accidents and congestion) provided by cooperation compared to scenarios without cooperation.

To evaluate the impact of cooperative communication in mixed-traffic urban environments, a probabilistic framework based on Markov Chains enhanced with Bayesian dependencies was proposed. The framework simulates transitions between traffic states influenced by environmental factors and vehicle behavior while capturing the effect of varying levels of cooperation among road users.

A. Probabilistic State Model

A set of nine discrete traffic states representing key situations encountered in urban scenarios was defined . These states are derived from the real-world use cases described in Section IV and are listed below:

- S1: Normal Operation
- S2: Traffic Rule Violation (e.g., red light)
- S3: Pedestrian Conflict
- S4: Obstruction / Visibility Loss
- S5: Complex Maneuver (e.g., merging turns)
- S6: Unexpected Stop
- S7: Vehicle Reaction / Evasive Action
- S8: Congestion / Blockage
- S9: Accident

Transitions between these states are modeled using a discrete-time Markov Chain governed by a 9x9 transition probability matrix P, where each element $P[i, j]$ denotes the probability of moving from state S_i to state S_j. Formally:

$$P[i, j] = \text{Probability of change from state } i \text{ to state } j. \quad (1)$$

The values in P were constructed heuristically, informed by the qualitative severity and likelihood observed in the case study scenarios, and supported by empirical literature. For example, violations (S2) have a higher probability of transitioning to accidents (S9) or evasive actions (S7), while visibility losses (S4) often lead to congestion (S8) or delays in response (S6). Figure 3 illustrates a contextual Bayesian network that conceptually represents how environmental and behavioral variables can influence transition probabilities, particularly those leading to states such as S9 (Accident). This representation complements the transition matrix and shows the dependencies considered in the simulation logic.

The transition matrix P used in the simulation is shown in Table I. Each row corresponds to a current state, and each column indicates the probability of transitioning to another state. The values were defined heuristically based on behavior from the real-world case studies presented in Section II, studies like [18] and refined to reflect the risk profile of each situation.

The matrix reflects involuntary risk propagation patterns. For instance, state S2 (violation) has a relatively high probability of leading to S9 (accident), while S3 (pedestrian conflict) also

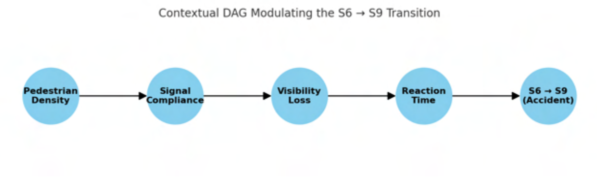

Fig. 3. Contextual Bayesian network showing how environmental and behavioral variables influence the probability of transitioning from S6 to S9.

TABLE I
TRANSITION PROBABILITY MATRIX P

	S1	S2	S3	S4	S5	S6	S7	S8	S9
S1	0.10	0.10	0.20	0.10	0.10	0.20	0.10	0.05	0.05
S2	0.05	0.20	0.10	0.15	0.10	0.10	0.10	0.10	0.10
S3	0.05	0.05	0.10	0.10	0.10	0.05	0.05	0.10	0.40
S4	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.20	0.20
S5	0.10	0.10	0.05	0.10	0.10	0.10	0.05	0.20	0.20
S6	0.20	0.10	0.05	0.10	0.10	0.20	0.10	0.10	0.05
S7	0.10	0.10	0.05	0.10	0.05	0.10	0.20	0.20	0.10
S8	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.20	0.20
S9	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.20

shows a strong linkage to both S8 (congestion) and S9. In contrast, transitions from S1 (regular operation) are more evenly distributed, with higher probabilities toward harmless states. These contextual dependencies are reflected in conditional probabilities used to modulate the Markov transitions. For instance, high pedestrian density combined with low signal compliance significantly increases the likelihood of visibility loss (estimated at 0.80). If visibility is lost and the AV's reaction time is slow, the probability of transitioning from a stopped vehicle (S6) to an accident (S9) increases to approximately 0.30. In contrast, when visibility is clear and reaction time is fast, this probability drops to 0.10. Additionally, scenarios with compliant signals and low pedestrian density are associated with reduced visibility risk (approximately 0.20). These values are dynamically adjusted at runtime, as described in the following subsection.

B. Incorporating Cooperation

To model the impact of cooperative systems, was introduced a cooperation factor $f_{\text{coop}} \in [0,1]$ that scales the transition probabilities leading to critical states. Specifically, for a given transition P_{ij}, if $j \in \{\text{S8}, \text{S9}\}$, the modified probability becomes:

$$P_{ij}^{\text{coop}} = \begin{cases} P[i,j] \cdot (1 - f_{\text{coop}}), & \text{if } j \in \{S8, S9\} \\ P[i,j], & \text{otherwise} \end{cases} \tag{2}$$

This model shows the effect of V2X-enabled communication on reducing accident and congestion risks. The released probability mass is redistributed among non-critical transitions to preserve the matrix's row stochasticity. The cooperation factor can be tuned to simulate various levels of V2X adoption and message reliability.

C. Bayesian Dependencies

While Markov Chains effectively capture the sequential nature of vehicle interactions, they assume that transitions depend only on the current state and not the external context. In real-world traffic, however, environmental and behavioral factors can significantly influence the likelihood of state transitions. To incorporate these influences, a Bayesian layer modulated the transition matrix P dynamically.

The Bayesian component models contextual dependencies as a directed acyclic graph (DAG), where each node represents a latent variable that affects transition likelihoods. For instance, the presence of obstruction (visibility_loss) increases the probability of a transition from "Stopped Vehicle" (S6) to "Accident" (S9), while high pedestrian density (ped_density) raises the probability of entering "Congestion" (S8) from any maneuvering state (e.g., S5 or S7).

Each variable is treated as a random variable with its probability distribution derived from empirical traffic studies or assumed uniform without data. These are then used to calculate conditional probabilities for specific transitions via Bayes' theorem. The updated transition probabilities are defined as follows:

$$P'_{ij} = P_{ij} \cdot \mathbb{E}[C_{ij}]$$

Where $\mathbb{E}[C_{ij}]$ represents the expected value of contextual influence for transition $i \to j$, computed over the Bayesian network. This factor adjusts P_{ij} based on environmental signals (such as RSU alerts or sensor-based inference), making the model more realistic under urban scenarios. An example structure could include nodes such as weather, visibility_loss, ped_density, reaction_time, and signal_compliance; and edges such as visibility_loss $\to$ higher S6 $\to$ S9 and ped_density $\to$ S3 $\to$ S8.

This structure does not replace the Markov Chain but enriches it by incorporating contextual realism. During simulation, sampled values from the Bayesian network are used to update selected transition paths in the matrix P, simulating dynamic risk factors. By doing so, the model captures short-term sequence logic (Markovian) and context-aware deviations from expected behavior (Bayesian), offering a more complete probabilistic understanding of traffic evolution under partial cooperation.

A Bayesian inference step was implemented before each episode simulation to operationalize this contextual modulation. The pseudocode below illustrates this process:

D. Monte Carlo Simulation

To assess the impact of cooperative behavior across differing levels of system adoption, a Monte Carlo simulation framework was implemented in Python, entirely independent of external simulators such as SUMO or CARLA. This choice ensures full control over state modeling and the ability to inject controlled perturbations into the simulation environment.

Each simulation run consists of a discrete sequence of state transitions based on the Markov Chain model defined in the previous subsection. A total of 1000 episodes are generated per configuration. Each episode starts from the baseline state S_1 (Normal Operation) and evolves over a fixed number of

Algorithm 1 Bayesian Adjustment of Transition Matrix

Input: Base transition matrix P, Bayesian context model $\mathcal{B}$
Sample context variables from $\mathcal{B}$:
$v \leftarrow \texttt{visibility\_loss} \sim \mathcal{B}$
$p \leftarrow \texttt{ped\_density} \sim \mathcal{B}$
$r \leftarrow \texttt{reaction\_time} \sim \mathcal{B}$
for all transition $P[i, j]$ **do**
  if transition depends on context **then**
    Compute context weight $C_{ij} = f(v, p, r)$
    Adjust transition: $P[i, j] \leftarrow P[i, j] \cdot C_{ij}$
  end if
end for
Normalize all rows of P
return modulated matrix P

Algorithm 2 Monte Carlo Simulation for Traffic State Evolution

Input: Base transition matrix P, cooperation factor range $\{f_{\text{coop}}\}$, number of episodes N
for all $f \in \{f_{\text{coop}}\}$ **do**
  for $e = 1$ to N **do**
    Perturb $P \to P'$ with noise $\delta \sim \mathcal{U}(-0.05, 0.05)$
    Apply cooperation factor f to reduce P'_{ij} for $j \in \{S_8, S_9\}$
    Normalize rows of P'
    Initialize state $s = S_1$
    for $t = 1$ to T **do**
      Sample next state $s' \sim P'[s, :]$
      $s \leftarrow s'$
      if $s \in \{S_8, S_9\}$ **then**
        Record event
      end if
    end for
  end for
  Compute average and std. dev. of visits to critical states
end for

discrete steps (e.g., 20 steps). At each step, the next state is sampled from the current row of the transition matrix P using a categorical distribution.

The base transition matrix is perturbed at the start of each episode to account for behavioral uncertainty and environmental variability. Noise is introduced by applying a uniform random deviation $\delta \in [-\epsilon, +\epsilon]$ to each row:

$$P'_{ij} = \max(0, P_{ij} + \delta), \quad \delta \sim \mathcal{U}(-0.05, 0.05) \tag{3}$$

The resulting row is re-normalized to preserve the matrix's stochastic property (i.e., each row sums to 1). This mechanism simulates slight variations in driver behavior or sensor/perception inconsistencies.

The cooperation factor f_{coop} is also applied to each perturbed matrix, reducing the transition probabilities toward critical states (e.g., S8, S9) proportionally to the assumed level of V2X adoption and message reliability. Configurations are tested for multiple values of $f_{\text{coop}} \in [0.0, 1.0]$, representing the full spectrum from no cooperation to fully coordinated environments.

For each episode, the frequency with which terminal or critical states (especially S8: Congestion and S9: Accident) are reached was tracked. These frequencies were averaged across 1000 simulations, and the standard deviation was computed to quantify robustness. This allows us to empirically estimate how cooperation influences traffic safety and fluidity under controlled, repeatable experimental conditions.

The following pseudocode outlines the simulation workflow for evaluating system behavior under different cooperation levels.

The simulation setup described above allows us to empirically explore how different levels of cooperation influence the system's resilience to critical events. The following section presents the results of these simulations, focusing on the probabilities of reaching accident and congestion states across various configurations. Both mean occurrence and standard deviation are reported to capture the average risk and its volatility under uncertainty.

VI. Results

This section presents the results obtained from the Monte Carlo simulations described in Section V. The objective is to quantify the impact of cooperative behavior (modeled through the cooperation factor f_{coop}) on the occurrence of critical events, particularly accidents (S9) and congestion (S8), under mixed-traffic scenarios. The values calculated where the average (μ) values, representing the average probability of accidents or congestion occurring, the standard deviation (σ) value that measures the variability between iterations, the maximum and minimum values obtained to capture the extremes of the simulated probabilities and with a confidence interval of 95% using equation 4.

$$IC = \mu \pm 1.96 \cdot \frac{\sigma}{\sqrt{1000}} \tag{4}$$

A. Impact of Cooperation on Accident Probability

Figure 4 shows the average probability of transitioning to the Accident state (S9) across all source states, comparing scenarios with and without cooperation. Results are presented with error bars representing one standard deviation across 1000 simulations with the ($f_{\text{coop}} = 0.5$).

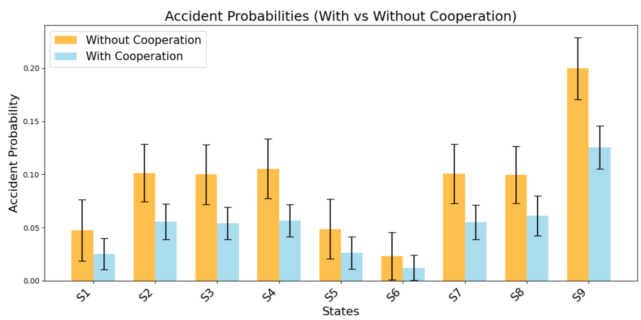

Fig. 4. Accident probability per state with and without cooperation.

The results clearly show that cooperative communication reduces the probability of accidents in all states. The most significant impact is observed in transitions from S2 (Violation) and S5 (Complex Maneuver), where V2X-enabled information sharing helps preemptively mitigate conflicts. Variability is also reduced under cooperative scenarios, indicating greater stability across episodes.

B. Impact of Cooperation on Congestion Probability

Figure 5 presents similar results for the Congestion state (S8). While reductions are generally less pronounced than in the accident case, cooperation still leads to measurable improvements in most high-risk states, particularly those involving obstruction (S4) and evasive behavior (S7).

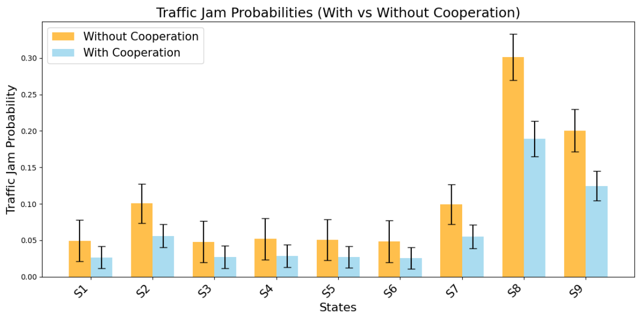

Fig. 5. Congestion probability per state with and without cooperation.

These results confirm that introducing V2X mechanisms for cooperation facilitates smoother traffic flow by enabling early reaction and adaptation to unexpected behaviors or road conditions.

C. Effect of Fleet Composition on System Behavior

Beyond fixed cooperation levels, the work evaluated how the system evolves with varying percentages of AVs in the traffic composition. Figure 6 shows the average accident and congestion probabilities as the AV ratio increases from 10% to 90%.

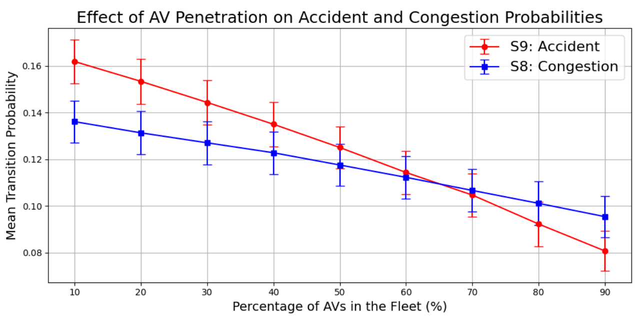

Fig. 6. Impact of AV fleet penetration on accident and congestion probability.

The results indicate a non-linear improvement in safety and instability as the proportion of AVs grows. However, the benefits flatten beyond 60–70% AV penetration if cooperation is not present. Notably, accident probability shows a sharp decline between 30–60% AV penetration, followed by a stagnation effect. Congestion, however, exhibits more gradual improvements. This highlights that cooperation amplifies the benefit of automation and is not a mere side feature but an essential element in bridging the performance gap in mixed-traffic environments. Importantly, in scenarios without V2X cooperation, the stagnation phase is reached earlier and at a higher residual risk level. This suggests that cooperation mechanisms are a multiplier of AV benefits, reducing mean risk and variance. The difference in standard deviation between cooperative and non-cooperative cases increases with AV penetration, indicating that cooperation improves average outcomes and stabilizes the system's behavior under uncertainty.

D. Probability of Returning to S1 (Normal State)

The probability of returning to the Normal Operation state (S1) from each source state was analyzed to assess the modeled system's resilience. This metric offers insight into the system's recovery ability after encountering a potentially risky or uncertain situation. Figure 7 presents the transition probability to S1 across all states. As expected, transitions from high-risk or critical states such as S8 (Congestion) and S9 (Accident) exhibit low probabilities of returning to a stable condition. Conversely, transitions originating from less severe states, such as S2 (Violation) or S5 (Complex Maneuver), show moderate return probabilities, reflecting intermediate recovery potential. The error bars in Figure 7 show the variability in recovery likelihood due to simulation perturbations. A higher deviation in transitions from critical states indicates reduced stability and shows the importance of proactive cooperation to recover.

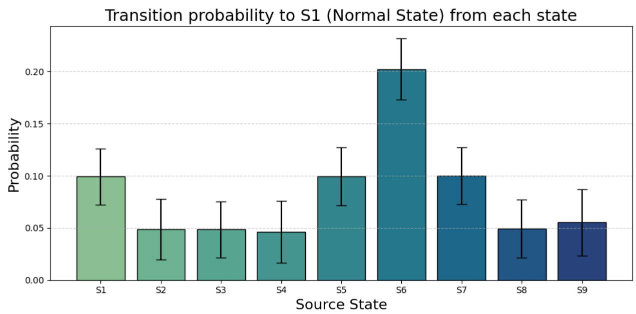

Fig. 7. Transition probability to S1 (Normal State) from each state.

These results provide a complementary view of system dynamics, indicating the risk of escalation to critical states and the probability of spontaneous recovery. This reinforces the need for cooperative strategies that facilitate transitions back to regular operation, particularly in states where autonomous decision-making may be limited by perception or obstruction.

E. Effect of Cooperation Factor on Critical State Transitions

In addition to binary comparisons (with vs. without cooperation), this work examined how incremental increases in the cooperation factor, denoted as f_{coop}, affect the system's exposure to critical transitions. Figure 8 shows the mean probability of transitioning to S8 (Congestion) and S9 (Accident) as a function of $f_{coop} \in [0.0, 1.0]$. Both curves consistently decrease critical transition probabilities, with the most significant reductions observed between $f_{coop} = 0.0$ and $f_{coop} = 0.5$, suggesting diminishing marginal returns at higher cooperation levels. These results validate cooperative behavior's role as a system risk modulator. Even partial adoption of V2X communication yields measurable safety benefits, and full cooperation reacts to limit the propagation of errors and delays in complex environments.

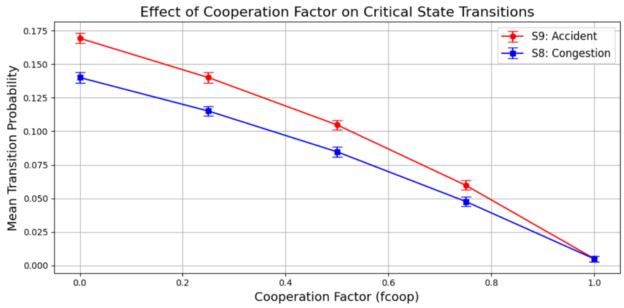

Fig. 8. Mean transition probabilities to critical states as a function of the cooperation factor f_{coop}.

The simulation shows that cooperative communication mechanisms are important in mitigating risk and enhancing systems in mixed-traffic scenarios. Beyond reducing the frequency of critical events, cooperation demonstrably stabilizes system behavior under uncertainty. These findings support the premise that the benefits of autonomy are not linearly correlated with AV penetration alone but are significantly amplified through structured cooperation. The following section demonstrates these insights and delineates the implications for future research and deployment strategies.

VII. Conclusion

This study proposed a probabilistic framework to assess the role of cooperation in mixed urban traffic scenarios, where autonomous and non-autonomous vehicles must coexist. By combining Markov Chains with Bayesian context modeling and simulating different levels of V2X-based cooperation, the work could quantify how communication between vehicles affects the evolution of critical events such as accidents and congestion. The results show that cooperation significantly improves safety and stability in heterogeneous traffic. Even partial adoption of communication strategies leads to measurable reductions in risk and system variability, particularly in situations involving obstruction, unpredictable behavior, or complex interactions. These findings highlight that the benefits of autonomous driving are not strictly tied to fleet penetration levels but rather to the presence of mechanisms that enable timely and informed coordination. The analysis reinforces the idea that vehicle cooperation is not just a desirable feature but a necessary condition for scalable and resilient deployment of autonomy in real-world environments. In this context, cooperative communication acts as an enable, bridging the gap between today's fragmented mobility and future, more integrated traffic ecosystems. In the future, efforts will focus on designing a collaborative protocol adapted to real-world urban scenarios. This includes defining message structures, decision rules, and timing constraints that account for infrastructure variability, behavioral uncertainty, and network reliability.

References

[1] K. Othman, "Exploring the implications of autonomous vehicles: a comprehensive review," *Innovative Infrastructure Solutions*, vol. 7, no. 2, p. 165, Mar. 2022. [Online]. Available: https://doi.org/10.1007/s41062-022-00763-6

[2] e. Cao, "L3pilot-code of practice for the development of automated driving functions," 2022.

[3] L. Andrei, M. Negulescu, and O. Luca, "Premises for the future deployment of automated and connected transport in romania considering citizens' perceptions and attitudes towards automated vehicles," *Energies*, vol. 15, p. 1698, 02 2022.

[4] N. Saha and D. Motuba, "Estimating the Impacts of AV and CAV and Technologies Transportation Systems for Medium, Long, and Buildout Transportation Planning Horizons," *Future Transportation*, vol. 3, no. 2, pp. 457–478, Jun. 2023, number: 2 Publisher: Multidisciplinary Digital Publishing Institute. [Online]. Available: https://www.mdpi.com/2673-7590/3/2/27

[5] B. Mendes and et al, "Exploring v2x in 5g networks: A comprehensive survey of location-based services in hybrid scenarios," *Vehicular Communications*, vol. 52, p. 100878, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214209625000051

[6] S. An, "Resource management for collaborative 5g-nr-v2x rsus to enhance v2i/n link reliability," *Sensors*, vol. 23, no. 8, p. 3989, 2023.

[7] S. Ren, S. Chen, and W. Zhang, "Collaborative perception for autonomous driving: Current status and future trend," *arXiv*, 2022. [Online]. Available: http://arxiv.org/abs/2208.10371

[8] D. et.al., "CoDrive: Improving Automobile Positioning via Collaborative Driving," in *IEEE INFOCOM 2018 - IEEE Conference on Computer Communications*, Apr. 2018, pp. 72–80. [Online]. Available: https://ieeexplore.ieee.org/document/8486281/?arnumber=8486281

[9] C. et.al., "Proactive effects of c-v2x-based vehicle-infrastructure cooperation on the stability of heterogeneous traffic flow," *IEEE Internet of Things Journal*, vol. 11, no. 5, pp. 9184–9197, 2024.

[10] S. Wang and e. Ma, "Sight Distance of Automated Vehicles Considering Highway Vertical Alignments and Its Implications for Speed Limits," *IEEE Intelligent Transportation Systems Magazine*, vol. 16, no. 4, pp. 45–61, Jul. 2024, conference Name: IEEE Intelligent Transportation Systems Magazine. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10349109

[11] e. Wang, "Probabilistic Prediction of Longitudinal Trajectory Considering Driving Heterogeneity With Interpretability," *IEEE Intelligent Transportation Systems Magazine*, pp. 2–18, 2024, conference Name: IEEE Intelligent Transportation Systems Magazine. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10542992

[12] e. Certad, "Interaction of Autonomous and Manually Controlled Vehicles Multiscenario Vehicle Interaction Dataset," *IEEE Intelligent Transportation Systems Magazine*, vol. 16, no. 4, pp. 6–20, Jul. 2024, conference Name: IEEE Intelligent Transportation Systems Magazine. [Online]. Available: https://ieeexplore.ieee.org/document/10488477

[13] G. et.al., "Arow: V2x-based automated right-of-way algorithm for cooperative intersection management," 2024. [Online]. Available: https://arxiv.org/abs/2304.04958

[14] D. Maksimovski and C. Facchi, "Decentralized v2x maneuver sharing and coordination message for cooperative driving: Analysis in mixed traffic," in *2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC)*, 2023, pp. 5182–5189.

[15] Z. Mu and Chen, "Cooperative platooning with mixed traffic on urban arterial roads," in *2022 IEEE Intelligent Vehicles Symposium (IV)*, 2022, pp. 1578–1583.

[16] M. R. Hidayatullah, J.-C. Juang, Z.-S. Zheng, and W.-H. Chang, "Cooperative perception using cellular v2x in mixed traffic scenario," in *2021 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, 2021, pp. 1–6.

[17] S. Rong and Meng, "Multi-vehicle collaborative planning technology under automatic driving," *Sustainability*, vol. 16, no. 11, p. 4578, 2024.

[18] Ghorai, "A Causation Analysis of Autonomous Vehicle Crashes," *IEEE Intelligent Transportation Systems Magazine*, pp. 2–15, 2024, conference Name: IEEE Intelligent Transportation Systems Magazine. [Online]. Available: https://ieeexplore.ieee.org/document/10522880