**The Role of Social CAVs When Lane-Changing in Mixed-Traffic Conditions**

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## 1. INTRODUCTION

Connected and autonomous vehicles (CAVs) are increasingly heralded as a transportation revolution – improving the efficiency, safety, and sustainability of transportation. CAVs are a part of the Internet of Vehicles and are developed to minimize human error and enhance decision making via automated communication (Rahmati et al., 2020). Using vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication technologies, cooperative driving plays a crucial role in this highly automated and interconnected environment. It enables cooperative functionalities like cooperative sensing and cooperative manoeuvring. (Heshami & Kattan, 2024) Nevertheless, both CAVs and human-driven vehicles (HDVs) will continue to coexist for decades (Khattak et al., 2022). Although allocating dedicated lanes for CAVs has been suggested (Wang et al., 2024; Zhao et al., 2024), real-world traffic diversity makes it impossible to adopt this approach. Since lane changing, merging, and other complicated maneuvers are involved in around 10% of traffic accidents (Deb et al., 2018), enabling safe interactions between CAVs and HDVs is critical.

CAVs have to continually prevent collisions while maximizing traffic flow. The socially adaptive CAV concept involves technological and social dynamics, as CAVs must engage with multiple human drivers. Social value orientation (SVO) is a psychological scale quantifying self-interest and concern for others (Loke, 2019), and it serves as the basis upon which a CAV can predict HDV behaviour and accordingly adjust for cooperative driving. For instance, prosocial HDVs might yield to avoid congestion, while egoistic HDVs might prioritize their efficiency above the needs of others. To capture these dynamics, CAVs require advanced mathematical models that analyze real-time data. Using existing work that characterizes cooperative decision-making and the role of vehicle-to-vehicle communication (Le et al., 2023; Schwarting et al., 2019), this study presents a novel model to emulate mixed-traffic environments for the case of multiple lane changing in a multi-lane freeway. Our approach combines shockwave damping and stability analysis, harnessing SVOs capability to quantify the precise social behaviour of HDVs. Through Model Predictive Control (MPC), the model explores the best possibilities to change lanes, maximizing the reward of vehicles involved and minimizing disturbance to the upstream flow.

In contrast to most studies, which only consider mandatory lane changes, this paper also includes discretionary lane changes based on the MOBIL (Minimizing Overall Braking Induced by Lane Changers) approach (Kesting et al., 2007). The model combines macroscopic traffic flow prediction with microscopic vehicle dynamics using trajectory replanning and cooperative control mechanisms. Additionally, it captures the stochastic behaviour of HDVs in longitudinal motion by employing the Improved 2D-IDM car-following model (Treiber & Kesting, 2013a), thereby facilitating realistic simulations of mixed-traffic scenarios. The other important contribution of this study is our approach that calculates the optimal lane-change strategy for each CAV, taking into account the different utilities of the vehicles involved (e.g. whether CAVs or HDVs). The major difficulty arises when a CAV wants to change lanes, yet the stochasticity of the human driver makes it uncertain whether yielding will occur. When the lag vehicle is a CAV, full cooperation is ensured, and if the gaps are safe, the CAV will smoothly transition to the target lane. This comprehensive approach addresses the challenge of lane changing in future mixed traffic systems, enhancing traffic flow and safety.

## 2. METHODOLOGY

As indicated, our model simulates mandatory and discretionary lane changes in a three-lane freeway scenario. Mandatory lane changing is needed for the vehicles which need to reach an off-ramp (which is in the third lane), and discretionary lane changes are designed to improve driving conditions, such as speed gain or to bypass slow vehicles. MOBIL is implemented to calculate the gains of a lane change by examining the vehicles' pre-and-post-lane change accelerations (Kesting et al., 2007). It includes a measure of politeness that considers the driver to anticipate the impact of the driver's lane change on other vehicles to simulate realistic selfish and friendly driver behaviour. The major components of this approach are represented by the flowchart illustrated in Figure 1 and are detailed below:

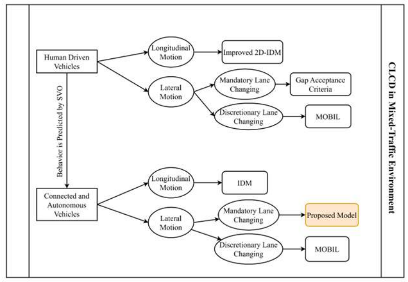


*Figure 1 Flow-chart of steps implemented in this research*

**a. Human Driven Vehicles**

The longitudinal movement of the HDVs is simulated with the Improved 2D Intelligent Driver Model (2D-IIDM), which is a modified version of the standard IDM that incorporates stochastic elements to simulate the variability of human drivers (Tian et al., 2016; Treiber & Kesting, 2013b). We especially selected this model to simulate HDVs since it has a superior capacity to replicate realistic stochastic human driving behaviors based on real-world observations. Unlike simpler, deterministic models such as Krauss—which primarily focus on collision avoidance with minimal driver variability—the Improved 2D-IDM simulates the stochasticity of the drivers' deceleration, acceleration, and response time to mimic the variability of human drivers that exist in real-world conditions of traffic. This enables complexly varied human driving behaviors to be described realistically, representing more accurately variability and randomness present in mixed-traffic scenarios. Further, its modeling adaptability harmonizes flawlessly with Gap Acceptance Criteria, allowing for realistic and uniform lane-changing simulation that adjusts dynamically to shifts in driver aggressiveness and caution. For lateral movement, HDVs make mandatory and discretionary lateral movements. Mandatory lane changing is modelled by the Gap Acceptance Criteria for HDV lane changing. If the current gap between both lead and lag vehicles in the target lane and the lead vehicle in the current lane is within the defined limits of both safety and efficiency, the HDV will implement the mandatory lane changing.

**b. Connected and Autonomous Vehicles**

CAVs follow classical IDM, the longitudinal controller that adjusts speed and following distance to the relative speed and spacing of vehicles (Treiber & Kesting, 2013a). In addition, CAVs leverage the potential of vehicle-to-vehicle (V2V) communication to access real-time information about the state of the current traffic to aid anticipatory and adaptive maneuvers that enhance the quality of the traffic stream and overall safety (Dubey et al., 2025). Like HDVs, CAVs can also perform mandatory and discretionary lane changes. However, their decision-making is aided by anticipatory algorithms that predict the behaviour of nearby vehicles using Social Value Orientation (SVO). This psychological scale measures the trade-off between personal gain and other-oriented considerations, informing CAVs of the likely behaviour of a proximal HDV - namely whether it might yield during a lane-change maneuver (Loke, 2019). SVOs are assigned to the HDVs as per Schwarting et al., (2019). When two CAVs interact, they always yield to each other due to their inherent cooperative behaviour. In contrast, when a CAV interacts with an HDV, it evaluates several opportunities to change lanes, ensuring the optimal timing and location of the maneuver. The decision-making process is further enhanced by an MPC approach that explores a range of potential lane change scenarios within a pre-determined prediction time (Zhao et al., 2021).

A change in the longitudinal car-following model (e.g., utilizing an Adaptive Cruise Control (ACC) model as an alternative to IDM) would have a primary impact on vehicle speed profiles and gap management. However, since our novel contribution is specifically designed for the lateral lane-changing behavior, the performance and validity of our proposed lateral decision-making model would still remain robust and unaffected. The objective of the optimization model aims to maximize the system utility while minimizing the disruption caused by lane changes, the system includes the lane-changing vehicle, the lag vehicle in the target lane, and all other upstream vehicles affected due to lane changes downstream. Utility of ego vehicle includes longitudinal movement while completing lane changing, comfort, and efficiency. Utility of lag vehicle includes disruption made by lane changing and comfort and efficiency of the lag HDV in the target lane. Constraints ensure that lane changes are performed within safe gaps and that CAVs maintain appropriate following distances before and after the maneuver.

## 3. RESULTS AND DISCUSSION

We run the model on a 500 m three-lane freeway; the freeway length and the simulation time of 1800 s (0.5 h) were specifically selected to match the characteristics in the published benchmark research, guaranteeing a constant baseline for comparison. We also run the model on a longer horizon (3km) to find deeper insights into long-term traffic dynamics and shockwave behaviors. The vehicle simulations were conducted using MATLAB on an Asus

Zenbook UX3404VC (2023). Our simulation incorporates both CAVs and HDVs at various CAV penetration rates to assess how traffic dynamics are affected by growing autonomous vehicle use. Here, the validation results show that the suggested model faithfully captures the required lane-changing behaviour shown in the benchmark situation with mixed traffic. To control flow level, we simulate vehicle headways by lognormal distribution (Luttinen, 1996), which offers a realistic depiction of the distances between cars, particularly in mixed traffic. for the following results, we had an input of 3000 vehicles per hour. Ten percent of the cars in this model are marked as exiting the highway from the off-ramp. Comparing our strategy to other cooperative lane-changing techniques is crucial. In order to achieve this, we decided to use the approach described in (Monteiro & Ioannou, 2023). Their research considers autonomous safe lane change maneuvers within a mixed-traffic environment by employing a control-agnostic, distributed approach built upon vehicle-to-vehicle (V2V) communication. Safety is guaranteed by a worst-case braking approach while allowing CAVs to create safe gaps by modulating longitudinal behaviour. Under the usage of the VISSIM simulator, they compare various types of vehicles—HDVs, ACC vehicles, AVs, and CAVs—in both congested and uncongested conditions. To validate our proposed mandatory lane change model for CAVs, we tried to compare our results with this paper in Figure 2 in terms of safety, and traffic efficiency.

In Figure 2, model (1) provides the values from the benchmark paper by (Monteiro & Ioannou, 2023). Model (2) is the result from the model that we customized to closely resemble the benchmark study, which doesn't include MOBIL and MPC, and mandatory lane changing for all vehicles is based on the paper's model. Model (3) provides the result from our contribution model for mandatory lane changing of CAVs with MPC and discretionary lane changing with MOBIL, under the same spatial and temporal parameters as (2) and (1) to offer a proper comparison. The key performance indicators used are based on the same definitions and methodology employed in the comparative study to ensure consistency and comparison. Comparing the three scenarios, we can understand that there are safety improvements by utilizing the proposed model. Compared to the benchmark (1), the proposed model (3) minimizes the number of risky intervals by -50.7% at 75% CAV penetration, indicating the efficacy of the use of the proposed model. Total simulation risk decreases by -82.9% in the proposed model, indicating better overall handling in the event of lane changes. Risky lane-changing is minimized by -58.7% to demonstrate the efficiency in shockwave reduction and leaving proper gaps to HDVs through cooperative driving between the CAVs.

Moreover, traffic flow is more efficient. Median flow improves at all the penetration rates by +1.4% at 75% CAV penetration in the current model, compared to +1% in the comparison study. This indicates the proposed model provides not just greater safety, but also efficient and smooth traffic movement. The average discomfort in the proposed model (+197.7% increase from the baseline) is less in comparison to the discomfort in the benchmark model (+321% increase). It suggests less sudden deceleration and smooth lane changes, which is because of stability analysis, whereby upstream CAVs adapt gaps dynamically to avoid disturbances from lane-changing maneuvers.

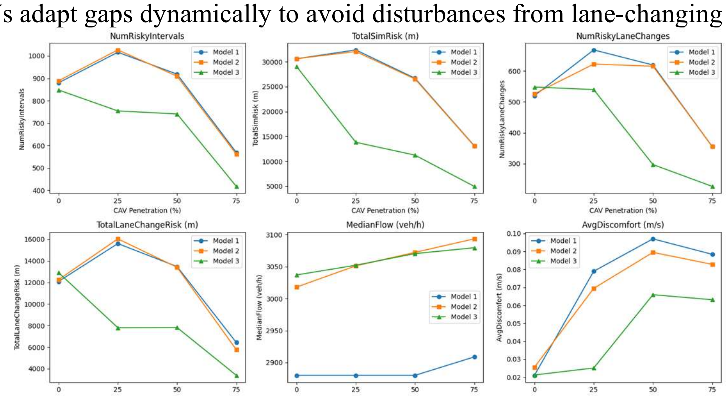


*Figure 2 Validation results for different CAV penetration rates*

The close match between the benchmark study and the customized model ((1) and (2)) shows that we could model their job correctly. Variations in stochastic components and simulated randomness lead to minor variances because of longitudinal motion. Regarding safety and comfort, the suggested model performs better than the reference study and the customized model, highlighting the advantages of cooperative lane change and proactive shockwave damping. When compared to the reference research, the suggested model offers notable gains in comfort, safety, and traffic flow overall. The results clearly show that Model (3) performs noticeably better than Models (1) and (2), especially when it comes to improving traffic safety. Even with no CAVs on the road (0% penetration), Model (3) reduces the number of risky intervals by 4.6% compared to Model (2) and 3.6% compared to Model (1) because we implemented MOBIL for discretionary lane changing in Model (3). The total simulation risk also drops by 5%

compared to both models, while the number of risky lane changes is lower by 4.2% and 5.4%, respectively. Lane-changing risks are also minimized, with a 5.3% reduction compared to Model (2) and 5.7% compared to Model (1). On top of that, traffic flow improves slightly—up by 0.6% compared to Model (2) and a more notable 5.4% compared to Model (1).

As more CAVs exist on the road, the benefits of Model (3) become even more pronounced. With 75% CAV penetration, the total simulation risk is reduced by a remarkable 82.9%, far outperforming the 57.3% and 57.1% reductions seen in Models (2) and (1). Risky lane changes drop by 58.7%, compared to 32.4% in Model (2) and 31.7% in Model (1), and the total lane-changing risk falls by 73.7%, significantly better than the 52.9% and 46.8% reductions of Models (2) and (1). These results highlight how our model helps vehicles make smarter lane-change decisions prioritizing individual and collective safety, resulting in safer, smoother, and more efficient traffic flow—especially when CAVs are more prevalent. CAVs successfully collaborate to reduce shockwaves and establish safe gaps, which lowers the hazards involved in both mandatory and discretionary lane changes. The outcomes confirm that the suggested strategy works well in mixed-traffic situations, opening the door for safer and more effective autonomous driving technologies.

## 4. CONCLUSION

This paper proposes a new model to improve lane-changing behaviour in mixed-traffic situations. The suggested method considerably lowers dangerous lane changes (-58.7%), overall simulation risk (-82.9%), and risky intervals (-50.7%) when compared to the benchmark model. At the same time, it improves traffic flow (+1.4%) and driving comfort. The simulation setup is validated by the tight correspondence between the customized model and the benchmark research. Future research will apply other performance measurement framework to include comprehensive safety indicators (e.g., near-crash scenarios, conflict analysis) and environmental impacts (fuel consumption, emissions), further ensuring model validity. Future autonomous transportation systems might benefit from the model's ability to improve safety and efficiency by allowing CAVs to collaborate proactively, reduce shockwaves, and establish safe gaps.

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