Utilizing High-Definition Maps and Simulation Software to Enhance Autonomous Vehicle Safety

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Abstract

The safety of autonomous vehicles (AVs) remains a major challenge, particularly within specific Operational Design Domains (ODDs). While physical testing lacks scalability, computer simulations effectively evaluate AV safety. However, most studies rely on virtual maps generated by simulation software, neglecting real-world complexities and focusing on single intersections rather than broader road networks. To fill the gap, this study lie in the development of a novel simulation workflow combining CARLA and VISSIM simulation softwares using High-definition (HD) maps while reducing data collection efforts and enabling the seamless integration of simulation results. Additionally, this study validates the effectiveness of emergency braking indicators within the AV simulation, confirming their applicability in assessing AV safety performance.

The study area conducted near Tainan-City High-Speed Railway Station, Taiwan, analyzes emergency braking events across a network of three intersections and four road segments to identify high-risk zones. HD maps of the study area data were integrated into the CARLA to generate realistic traffic scenarios, while VISSIM modeled traffic flow and signal phases.

The results indicate that emergency braking hotspots are concentrated at intersections, turns, and sharp curves near safety islands. This finding suggests that AVs make slower decisions than human drivers due to complex perception and computational models. Additionally, it highlights the importance of HD maps and traffic flow analysis in AV simulations and provides recommendations for improving AV safety, including simplifying road layouts, minimizing sharp turns, and restricting arbitrary lane changes.

1. Introduction

Numerous study have shown that autonomous vehicles (AVs) provide benefits, such as improved road safety and traffic outcomes (Mousavi et al., 2020), lower emissions, minimal driver workload (Balfe et al., 2015). and less traffic congestion (Khastgir et al., 2015). Some vehicle manufacturers claim that self-driving cars could significantly improve traffic safety since 94% of crashes are attributable to human error (Singh, 2015). However, traffic crashes tend to be a multiple causal and complex problem, so traffic safety experts must address these multifaceted components. For these reasons, ensuring AV safety remains a critical challenge, requiring rigorous assessment. The Operational Design Domain (ODD) defines the conditions under which AVs operate safely, considering factors such as weather, speed, and traffic flow (Thorn et al., 2023). To refine ODDs, extensive testing is essential, but real-world validation is costly and lacks scalability (Piazzoni et al., 2021). As a result, computer simulations have become a preferred alternative for evaluating AV performance under various conditions.

Compared to physical testing, simulations provide a controlled environment to replicate complex traffic scenarios, allowing researchers to evaluate AV behavior under diverse weather conditions, lighting, road geometry, and driving algorithms (Campanile et al., 2020). However, most existing studies rely on simplified virtual maps rather than real-world networks, limiting the authenticity of their findings (Dosovitskiy et al., 2017). For instance, Talamini et al. (2020) found that strict rule compliance in AVs could increase congestion in high-density traffic, while Wang et al. (2021) demonstrated that skewed intersections pose significant challenges for AV perception and navigation. Similarly, Tahir & Alexander (2022) developed a verification framework in CARLA to assess AV safety under various intersection scenarios and weather conditions, highlighting the role of dynamic traffic interactions. Despite these contributions, most studies focus on predefined simulation settings, failing to fully replicate real-world traffic complexities. To bridge this gap, this study integrates high-definition (HD) maps into the CARLA driving simulator, enhancing traffic realism and AV perception. HD maps provide detailed geospatial information, including road geometry, lane markings, and traffic signs, improving simulation accuracy and reducing the cost and effort of manual network creation (Liu et al., 2020).

Previous studies utilized several simulators that are available for testing autonomous vehicles, including RRADS (Baltodano et al., 2015), CarCraft, TORCS, Udacity (Wymann et al., 2000), and CAR Learning to Art (CARLA). Not all consider the dynamics of a complex environment (such as intersections, pedestrians, and traffic rules) that distinguish urban driving from track racing. An accurate simulator should clearly outline the 3D environment and have precise lower-level vehicle calculations regarding the vehicle's physics. There is a constant trade-off between 3D environment fidelity and simplified vehicular dynamics. Therefore, this study aimed to utilize a realistic simulator, CARLA, to analyze the effects of both autonomous and semi-assisted driving on vehicular traffic networks. One of clear advantages of CARLA is an open-source simulator for autonomous driving research that provides customization and control over the environment, restricted kinematic behavior, and script and sensor setting specifications (Dosovitskiy et al., 2017; Tahir & Alexander, 2021). Furthermore, this study incorporates VISSIM traffic simulation software to model dynamic traffic flow and signal phases, crucial for assessing AV decision-making in complex environments (Shin et al., 2024). Combining CARLA and VISSIM using HD maps provides a realistic and scalable approach to testing autonomous vehicles (AVs) in complex traffic environments. This integration enhances traffic realism, AV perception, and decision-making analysis, making it ideal for ODDs validation and AV safety assessments.

Unlike studies limited to a single intersection, this research expands the scope by examining a more complex road network consisting of three intersections and four segments, allowing for a more comprehensive assessment of AV behavior in diverse urban settings. Different road networks create unique challenges for autonomous vehicles (AVs), affecting safety in various ways. These differences impact AV performance, making it essential to test them in diverse environments. Studying AV behavior in various road conditions helps identify risks, improve safety, and refine AV decision-making for real-world driving.

Safety metrics are quantifiable measures used to assess the performance of autonomous vehicles (AVs) in avoiding accidents and ensuring safe operation. One key safety metric is the frequency of emergency braking, which indicates how often an AV must apply sudden braking to prevent a collision. When a crash becomes unavoidable, the emergency braking system is activated to minimize impact severity. One major cause of traffic accidents is a driver's failure to brake in time or the application of insufficient braking torque during emergencies (Breuer et al., 2007). Therefore, analyzing the frequency and effectiveness of emergency braking provides valuable insights into AV safety. By studying how often and under what conditions emergency braking occurs, researchers can assess the risk of collisions with other vehicles or pedestrians and improve AV decision-making to enhance road safety (Schram et al., 2015).

2. Methodology

2.1 Study Area

The study focuses on a road network comprising three intersections and four segments near Tainan City High-Speed Railway Station, Taiwan, selected to examine safety issues where traffic converges. Specifically, the study area includes the intersections of Guiren Blvd with Guiren 7th Road and Guiren 10th Road, as well as the connection between Guiren 7th Road and Guiren 10th Road. Figure 1 provides a Google image of the location.

This intersection was selected due to its proximity to High-Speed Rail Station and outlet mall, making it a high-traffic area with significant pedestrian and vehicular activity. To analyze intersection safety under varying traffic conditions, we modified four key traffic attributes: traffic volume, traffic signal timing, the ratio of heavy vehicles to pedestrians, and the configuration of hazardous driving behaviors. By altering these real-world traffic conditions, we aimed to assess their impact on intersection safety and identify potential risk factors.In addition to intersection safety analysis, we also evaluated the safety conditions of AVs by selecting a specific test route for AV assessment. This route includes four distinct driving scenarios (Points 1–4), with a starting point (S) and an endpoint (E), as shown in Figure 1. The light blue line connects these points, representing the designated test route.

Figure 1. Google map image of the route in the study area

2.2 Framework of this study

The scenario processing is divided into three key stages to simulate scenarios for testing the ODD of AV. In the first stage, real-world data is collected and pre-processed to create a high-precision map. This involves gathering traffic flow data, signal timings, pedestrian activity, and vehicle proportions. For HD map preprocessing, Roadrunner is used to adjust the map size and set geographic coordinates. The second stage involves simulation setup and execution. The OpenDRIVE format map data is imported into VISSIM to establish traffic conditions, while the same data is imported into CARLA to define environmental conditions. In VISSIM, the simulation workflow involves reconstructing the road network based on real-world data, configuring traffic conditions by defining vehicle flow, speed, and lane settings, and running the traffic model to analyze AV performance under various scenarios. Meanwhile, CARLA is used to configure environmental parameters such as weather, road surfaces, and traffic signals. Critical traffic events, including emergency braking and pedestrian crossings, are simulated to evaluate AV responses. Data collected from CARLA, including vehicle speed, position, and acceleration, is processed to extract key insights for safety evaluation. A co-simulation between VISSIM and CARLA is performed via CARLA's Python API and a bridge assistant. During the simulation, key parameters are configured, events are triggered, relevant data is extracted, and the results are formatted into a report for analysis.

The final stage focuses on analyzing the collected simulation data. GIS analysis tools are used for hotspot analysis, and key safety metrics such as emergency braking are calculated. These analyses allow for a comprehensive evaluation of AV safety performance under different traffic conditions. Through this structured process, we can systematically simulate, analyze, and assess AV behavior across varying traffic scenarios, ensuring a thorough evaluation of their safety and operational reliability. The procedure from the first step to the third step is illustrated in the diagram in Figure 2.

The Route Setting Framework established in this study (Figure 3) outlines the process of path setup and data analysis, including waypoint generation, vehicle generation and path planning, and final data analysis. Waypoints are generated and plotted on a HD map, with road segments and nodes exported as images, while node positions are saved in a CSV file. The start and end points of the route are selected, and the generated route points are exported as Route_point.csv. Next, Co-Simulation is conducted using the exported route points for vehicle generation and path planning. Finally, Data Analysis is performed by processing the emergency braking event report, calculating braking incidents within 5 meters of the path, and analyzing the navigation data of the AV.

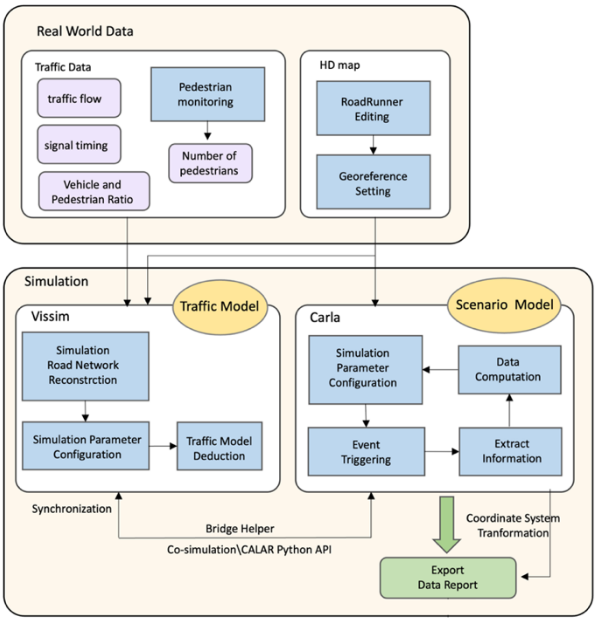

Figure 2. Framework of this study

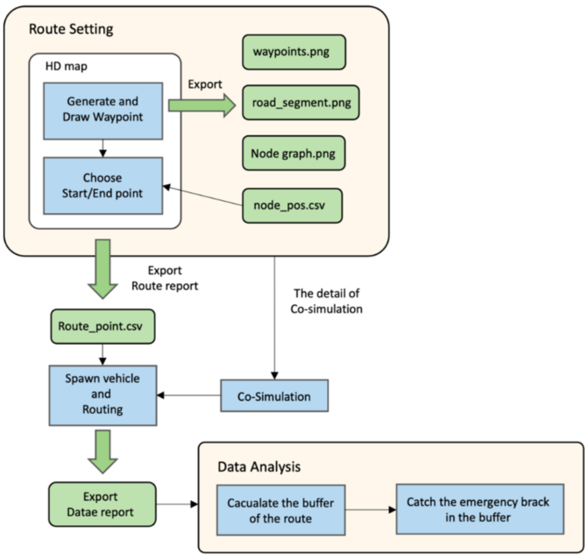

Figure 3. Route setting framework

In HD maps, waypoints are predefined points used to define critical positions in a path, route, or navigation system. In autonomous vehicles (AVs), waypoints determine the driving trajectory, guiding the vehicle through turns, stops, and accelerations, while also serving as navigation reference points. They help the system localize and plan optimal routes. To designate a route for an AV in CARLA, waypoints must first be integrated into the simulation environment. The process of creating navigation nodes on HD maps in CARLA consists of four key steps.

Step 1: Waypoint Creation
Waypoints are generated at one-meter intervals across the entire HD map in CARLA, as shown in Figure 4, to define precise vehicle paths. These green points capture lane geometry, road curvature, and intersections, ensuring smooth navigation in the simulation.

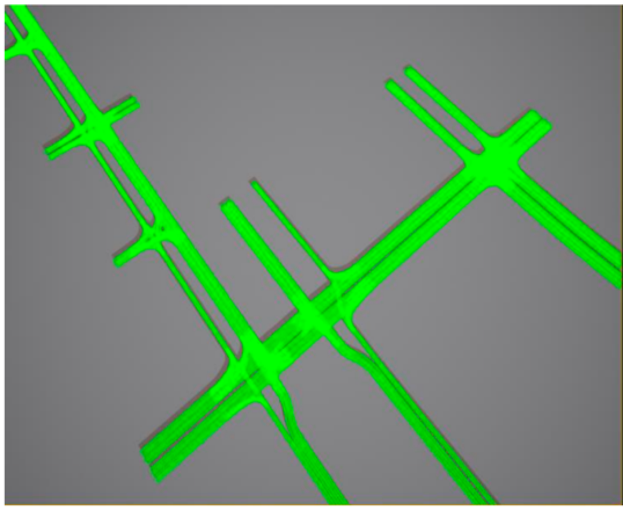

Figure 4. Waypoints

Step 2: Waypoint ID Assignment
If two waypoints are within 0.2 meters on the same road, they are assigned the same ID to group closely spaced points. This process helps simplify the representation of the road network by reducing redundant waypoints. After assigning IDs, the waypoints (blue points) are exported, as shown in Figure 5.

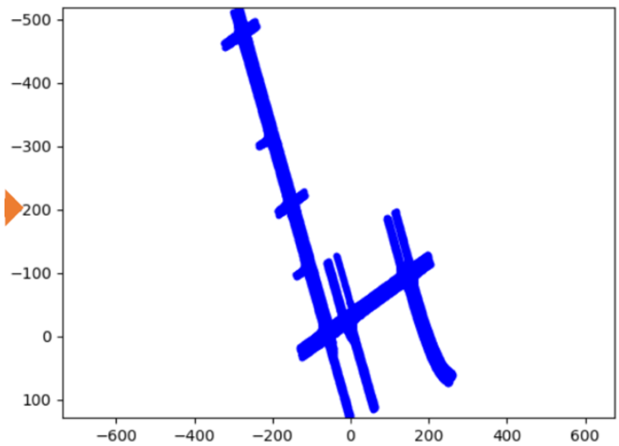

Figure 5. Waypoints ID

Step 3: Road Segment Coloring
Road segment coloring, as shown in Figure 6, is used to visually distinguish different sections of the road network. Each color indicates a distinct road segment, including intersections with turns and lane changes, facilitating the creation of navigation nodes.

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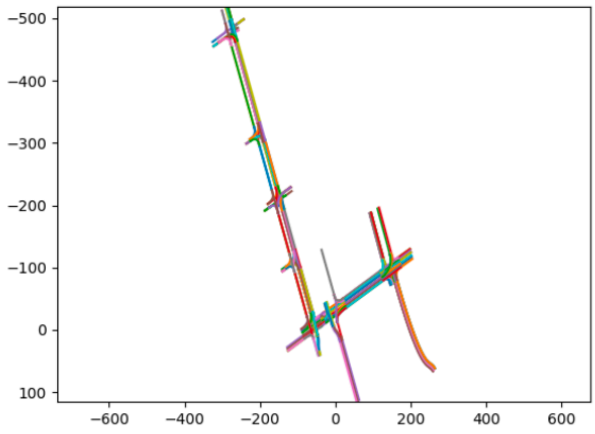


Figure 6. Road segment colors

Step 4: Navigation Node Marking:
Navigation nodes were marked with blue dots, with the start and end points of each road segment numbered, as shown in Figure 7. Arrows were used to indicate the direction of travel. This step simplifies the selection of starting and ending positions, ensuring efficient navigation path generation for AV simulations.

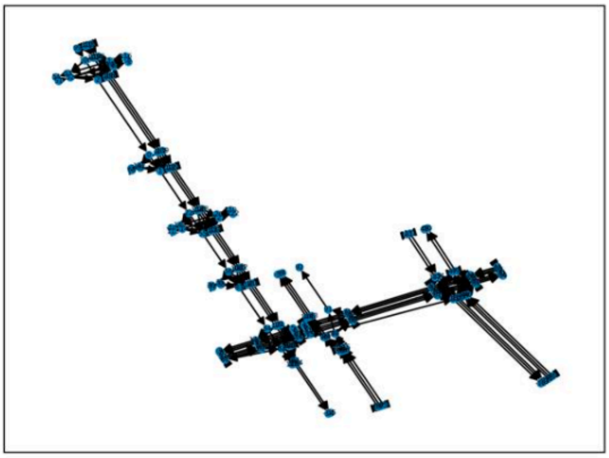


Figure 7. Navigation node marking

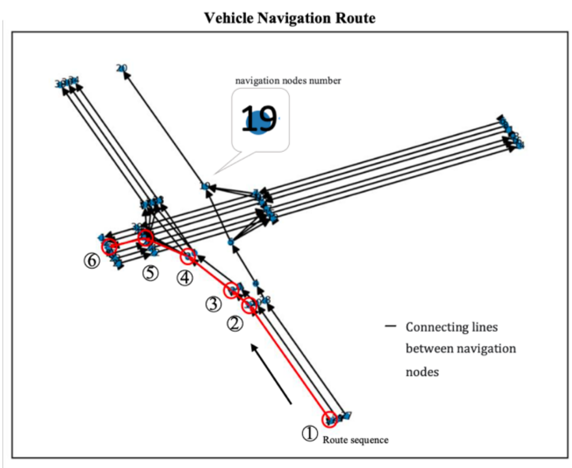


Figure 8. Navigation node marking

After marking the navigation nodes, we generate node numbers and their coordinates. To design a test route, we select waypoints based on these node numbers along the route. The selected waypoints, shown in the Figure 8, are then stored in a CSV file. If the route only specifies the start and end points without following a predefined waypoint sequence, the A-star algorithm is used to determine the shortest path automatically.

2.3 Co-simulation

The primary objective of co-simulation is to integrate the strengths of both platforms for a more realistic simulation environment. VISSIM accurately simulates macro-level traffic flow, while CARLA provides detailed micro-level vehicle dynamics and environmental perception. Co-simulation requires real-time data transmission between CARLA and VISSIM, achieved through TCP (Transmission Control Protocol) connections, with clients and servers set up in both platforms. Simulation data, such as vehicle positions and speeds, is synchronized using ROS (Robot Operating System) topics and services to ensure consistency between the two simulators. For example, vehicle positions in CARLA must align with traffic flow in VISSIM.

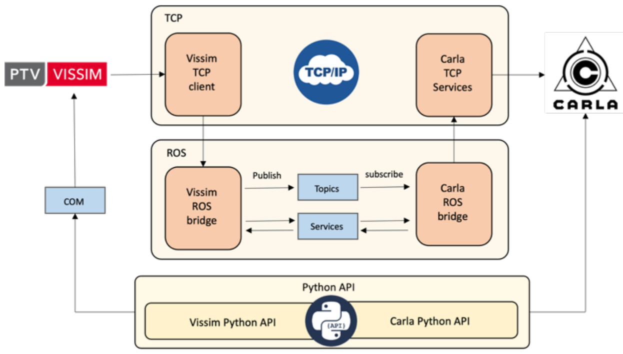


Figure 9. Co-simulation framework between CARLA and VISSIM

As shown in Figure 3, we employed the Python API to establish co-simulation via TCP/IP, enabling coordinated control and data exchange between CARLA and VISSIM. The CARLA Python API manages environment and sensor setup, including configuring maps, vehicles, pedestrians, and onboard sensors (cameras, radar, and LiDAR) for data collection and perception. The VISSIM Python API interfaces with VISSIM via COM (Component Object Model) to handle traffic network modeling and vehicle behavior modeling, defining traffic parameters (signals, lanes, traffic flow) and behavioral models (car-following, lane-changing).

3. Result and Discussion

3.1 Simulation present

The simulation route begins at point S, located at the intersection of Guiren Blvd and Guiren 7th Road, and proceeds through Scenarios 1 to 4 before reaching the endpoint E on Gaofa 1st Road (Figure 1). The simulation covers various signalized intersection scenarios, including left turns at a green light, lane positioning for left turns onto the outer lane of Guiren 7th Road’s two-lane section, straight driving in the outer lane, and right turns at a green light. A detailed explanation of the route, including its street view and representation in the CARLA simulation, can be found in Table 1.

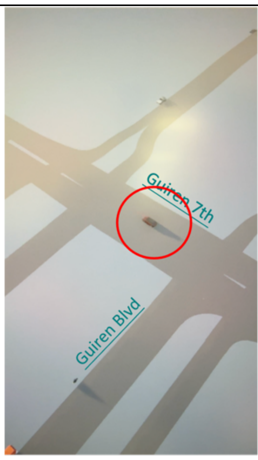
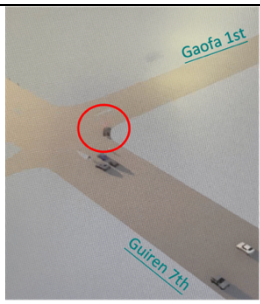
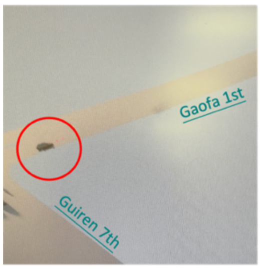
Real world	Simulation
Signalized intersection left turn – At the intersection of Guiren 10th Road and Guiren Blvd, the vehicle makes a left turn at a green light, continues straight, and prepares to turn left onto the two-lane section of Guiren 7th Road. 	
Signalized intersection straight driving – At the intersection of Guiren 7th Road and Guiren Blvd, the vehicle continues straight in the outer lane of the two-lane section 	
Signalized intersection right turn – At the intersection of Guiren 7th Road and Gaofa 1st Road, the vehicle makes a right turn at a green light, continues straight in the outer lane of the two-lane section, and prepares to merge into the outer lane of Gaofa 1st Road's three-lane section. 	 

Table 1. A detailed explanation of the selected route

3.2 Simulation present

In this study, we also evaluate the impact of crash risk on an AV navigating a specified road network. Using predefined nodes along road segments on the map, we define a start point, intermediate waypoints, and an endpoint to establish the AV's trajectory. To analyze the AV's safety performance, we utilize a emergency braking hotspots as a key safety indicator. The emergency braking occurrences of AVs during each simulation were recorded automatically by CARLA. These data points were subsequently processed using GIS tools to visualize hotspot distributions. Figure 10 illustrates the spatial distribution of emergency braking hotspots on the AV's route as well as on other vehicle paths. The blue trajectory represents the AV's intended driving path, while red points indicate locations where emergency braking was triggered. According to Figure 10, emergency braking events are notably concentrated at intersections and lane-changing areas, particularly around point ③, suggesting potential hazards related to road design or external traffic interactions. The high density of emergency braking hotspots at the intersection near point ③ indicates a zone of increased conflict, possibly due to unexpected vehicle movements or insufficient reaction time. Additional red markers along the AV's path, particularly near the starting section (①) and lane-changing area (②), imply that AV stability might be affected during these transitions.

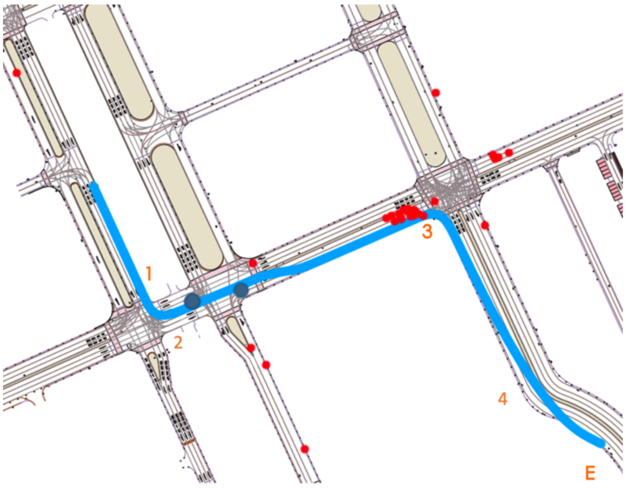


Figure 10. The spatial distribution of emergency braking hotspots

To quantify the impact of emergency braking at this intersection, we defined 14 key intersection reference points, including road corners, merging areas, and a sharp traffic island, to better capture critical braking locations. By computing the Euclidean distance between each braking event and its nearest reference point, we found that the majority of incidents occurred within 50 meters of these critical points as shown in Figure 11. The highest concentration of emergency braking was observed at sharp turns and merging lanes, where sudden stops are likely due to abrupt lane changes, congestion, and reduced maneuvering space. The map visualization further highlights clusters of braking events, particularly at locations requiring significant speed reduction. To enhance traffic safety, we recommend optimized signal timing, clearer lane markings, and speed control measures to mitigate sudden braking at high-risk zones.

Overall, the GIS-based spatial analysis highlights key risk-prone zones in AV navigation. The concentration of emergency braking events at intersections and lane-changing regions suggests that AV decision-making algorithms may require further calibration to improve responsiveness in complex urban traffic conditions. This insight can inform future improvements in AV control algorithms to enhance safety and adaptability in real-world environments.

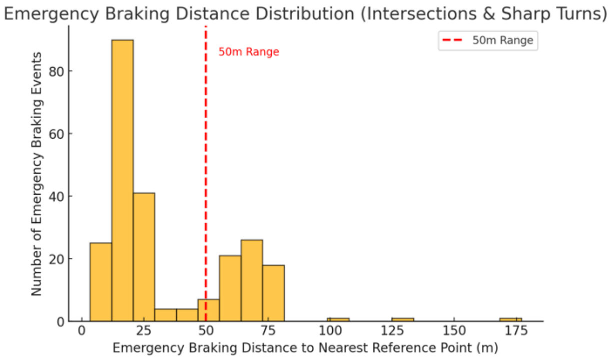


Figure 11. The emergency braking distance distribution

4. Conclusions

This study aims to enhance AV safety by integrating high-precision maps with simulation-based testing in CARLA. By incorporating real-world data and conducting co-simulations with VISSIM, we create realistic traffic scenarios, improving the reliability and accuracy of safety assessments. The study focuses on a single AV route across a network of three intersections and four road segments to evaluate its ODD and safety performance.

The hotspots for AV emergency brakings are primarily concentrated at intersections, turns, and V-sharp areas near safety islands. These locations present unique challenges for AV decision-making, highlighting the complexities of AV navigation in dynamic traffic environments. Our results were compared with existing studies and found to be consistent with current research findings. Zhang et al. (2023) indicate that AVs typically make decisions more slowly than human drivers in complex traffic scenarios. This discrepancy arises because AVs rely on sophisticated perception and computation models to ensure driving safety. Unlike human drivers, AVs require additional time and data processing to manage interactions and make decisions effectively.

The increased decision-making time for AVs underscores the challenges posed by dynamic traffic conditions and intricate road layouts. While human drivers leverage intuition and experience to react swiftly, AVs must process vast amounts of sensory input to navigate safely. Consequently, the computational complexity involved in AV decision-making necessitates further advancements in real-time processing algorithms and predictive modeling. Future research should focus on optimizing AV response times and enhancing their adaptability in highly dynamic and complex traffic environments.

Our study also found that high traffic flow significantly impacts the ODD, especially at intersections, where unpredictable road-user behaviors (e.g., red-light violations, failure to stop) pose risks (Morris et al., 2021). Additionally, lane-splitting by motorcycles affects AV safety, highlighting the need for traffic flow management. To mitigate risks, we recommend limiting mixed traffic flow to reduce unpredictable interactions between vehicles. Additionally, controlling the overall traffic volume can improve the efficiency of autonomous vehicle (AV) decision-making. Furthermore, enhancing AV perception systems is essential for better detection of road users, ensuring safer navigation in various traffic conditions.

To improve AV safety, we recommend that local governments consider the following when opening routes to AVs. First, road layouts should be simplified by reducing sharp turns and complex intersections. Additionally, avoiding sharp traffic island designs to minimize emergency braking occurrences. Lastly, restricting arbitrary lane changes to enhance AV driving stability, ensuring smoother and safer operations on the road.

Despite its contributions, this study has three key limitations. First, the study area was limited, as only one intersection was analyzed due to time constraints. Future research should explore various road types and more complex intersections, such as roundabouts. Second, there was a lack of real-world validation, as video recordings to verify whether the simulation data accurately reflected actual traffic conditions. Future research should deploy dashcams on AVs and install intersection cameras to compare real-world near-collision incidents with simulation-based emergency braking reports for virtual-real integration. Lastly, the study covered only a partial subset of possible scenarios. Future studies should expand scenario testing to develop more comprehensive safety assessment strategies for AVs. By addressing these limitations, future research can further refine AV safety evaluations and support the real-world deployment of AVs.

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