SUMO Traffic Simulation Report

1.1. Introduction

The research question addressed in this simulation study is: "How does the existence of autonomous vehicles influence the safety of heterogeneous traffic? Do different penetration rates bring different results?" The objectives of the simulation are to assess the impact of autonomous vehicles on traffic safety, considering varying penetration rates.

1.2. Methodology

1.2.1. Data and Data Collection:

- The simulation utilized the SUMO (Simulation of Urban MObility) tool for traffic simulation.
- Various vehicle types, including human-operated cars, human-operated trucks, autonomous cars, and autonomous trucks, were defined to capture the heterogeneity of traffic.
- Traffic flow data, including vehicle type, initial speeds, lanes, and routes, were generated using a Python script.
- Parameters for vehicles, such as acceleration and deceleration and parameters for lane change models (LC2013) and car-following models (IDM), were obtained from literature research[1] and implemented to reflect real-world driving behaviors.

1.2.2. Preparation Steps in SUMO:

- The simulation employed a calibrated IDM (Intelligent Driver Model) for human-operated vehicles, equipped with a Driver State Device[2] to introduce driving errors to the car-following and lane-changing models.
- Autonomous vehicles were modeled using IDM with zero-error and without a Driver State Device to represent their precise and error-free driving behavior.
- All the vehicles are equipped with an SSM Device[3] which logs the conflicts of the vehicle with other vehicles and corresponding safety surrogate measures(SSMs).
- A 4-lane road segment resembling a German Autobahn, 420 meters in length, was chosen for simulation to encompass various traffic scenarios, including car-following, lane-changing, and potential conflicts.
- Traffic load was set to 4000 vehicles per run, with penetration rates of autonomous vehicles adjusted using the Python script.
- The SSM device was set up so as to generate an output file for every conflict encountered within a simulation run.

1.3. Execution and Results

The simulation process involved running multiple iterations for each penetration rate of autonomous vehicles. The road network was generated in SUMO's netedit tool, and vehicles were created using the "Create vehicle mode" within the "edit traffic demand" mode.

Within the extended attributes editor for the vehicle, parameters such as acceleration rate, deceleration rate, emergency deceleration rate, car-following model, and lane change model were specified for each vehicle type based on literature research[1][4]. For the vehicle types used in the simulation(i.e. cars and trucks) it was observed from literature research[1] that the drivers exhibited different driving behavior as outlined below.

1. Truck drivers tend to maintain a larger THW(Time Headway)/DHW(Distance Headway) than passenger car drivers in car-following situation.
2. Passenger car drivers tend to change lanes more often to gain speed than truck drivers.
3. The truck drivers tend to maintain a larger front gap distance than passenger car drivers when changing to the target lane.

To reflect the above behavior of human drivers within our simulation, the below parameters of the LC2013 lane changing model and IDM car following model were edited as follows:

- Set a larger tau value(the driver's desired (minimum) time headway) for trucks in IDM.
- Set a smaller lcSpeedGain(the eagerness for performing lane changing to gain speed) value for trucks in LC2013.
- Set a smaller lcAssertive(Willingness to accept lower front and rear gaps on the target lane) value for trucks in LC2013.

These values are obtained from literature research[1] and were obtained in the literature after calibrating the parameters on the highD dataset.

Then, in order to reflect the difference between autonomous vehicles and human-operated vehicles in heterogeneous traffic simulation, driving imperfection caused by human drivers needs to be added to the model. To achieve that, the model needs to be equipped with Driver State Device, which is a generic mechanism provided by SUMO to introduce driving errors to the car-following and lane-changing models. The human operated vehicles are equipped with this Driver State Device and its parameters are set based on the values obtained from the literature research[1].

Finally, the traffic safety is evaluated using the number of conflicts. A traffic conflict is an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remain unchanged. In this project, Time-to-Collision(TTC) and Deceleration Rate of Approaching Collision(DRAC) are the criteria used to identify potential conflicts. The threshold for TTC is set to 3.0 seconds, and for DRAC 3.4 $m/s2$. These values were obtained from literature research[1]. Since all the vehicles are equipped with an SSM Device which logs the conflicts of the vehicle, every time the actual value exceeds the threshold, a record is written in the SSMs file. Then from this output file we are able get the number of conflicts.

1.4. Discussion and Conclusion

1.4.1. Summary of Main Findings:

The simulation study aimed to investigate the influence of autonomous vehicles on traffic safety in heterogeneous traffic conditions, considering varying penetration rates.

The introduction of autonomous vehicles led to improvements in traffic safety metrics, as reflected by a reduction in the number of conflicts. As the penetration rate of autonomous vehicles increased, there was an overall decrease in the number of traffic conflict occurrences. Vehicles equipped with autonomous technology tend to demonstrate more predictable and consistent driving behavior, which could have resulted in fewer instances of potential collisions.

The simulation captured the behaviors of different vehicle types, including human-operated cars and trucks, as well as autonomous vehicles. Parameters such as lane change dynamics and car-following behaviors were adjusted to reflect real-world driving tendencies, enhancing the realism of the simulation.

1.4.2. Evaluation of Results:

The findings of the simulation hold relevance for understanding the implications of autonomous vehicle integration into existing traffic environments. By evaluating the safety performance of heterogeneous traffic scenarios, policymakers and transportation stakeholders can make informed decisions regarding the deployment and regulation of autonomous vehicles.

The applicability of the results extends to various domains, including urban planning, traffic management, and autonomous vehicle development. Insights gained from the simulation can inform the design of future transportation systems, emphasizing the need for comprehensive safety measures and integration strategies for autonomous technologies.

It's important to note that the simulation did not incorporate the Vehicle-to-Everything (V2X) communication aspect of autonomous vehicles. V2X technologies enable vehicles to communicate with each other and with infrastructure, allowing for enhanced safety and efficiency on the road.

In conclusion, while the current simulation offers valuable insights into the safety effects of autonomous vehicles in heterogeneous traffic, future research should consider the integration of V2X communication and explore additional aspects of autonomous vehicle interaction for a more comprehensive understanding of their impact on transportation systems.

1.5. Appendix

1.5.1. Images:

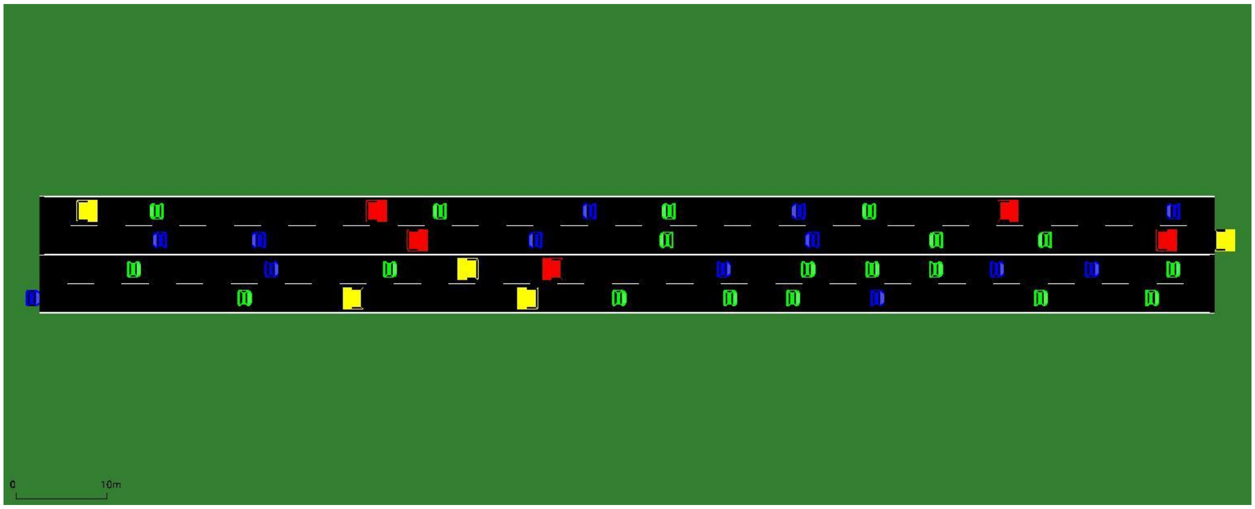

Figure 1: SUMO Simulation Scenario with 50% AV Penetration (Blue: Human Operated Car, Red: Human Operated Truck, Green: Autonomous Car, Yellow: Autonomous Truck)

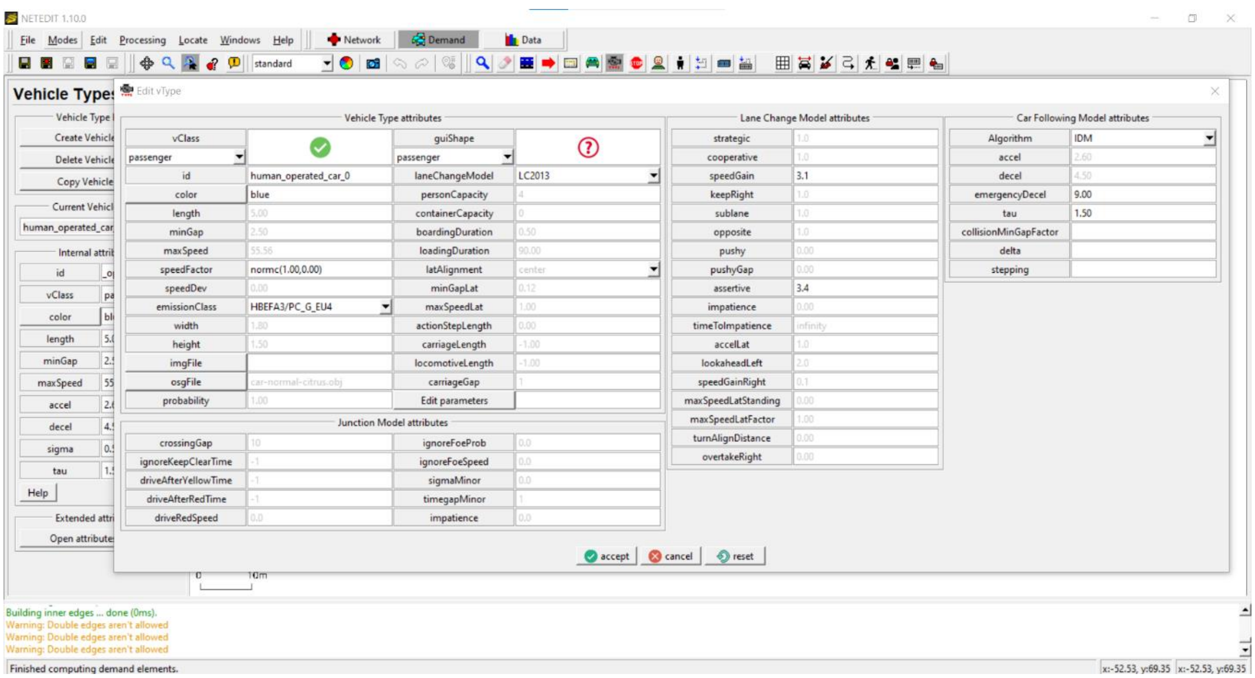

Figure 2: Parameters for Human Operated Car

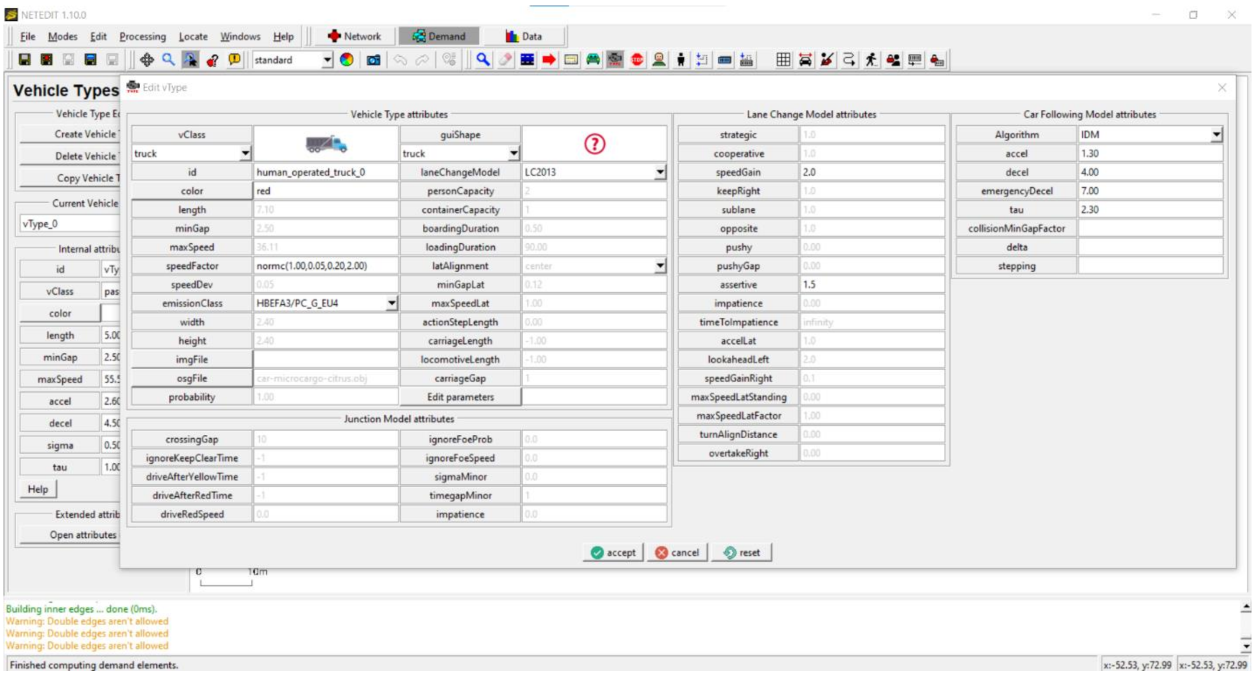

Figure 3: Parameters for human operated truck

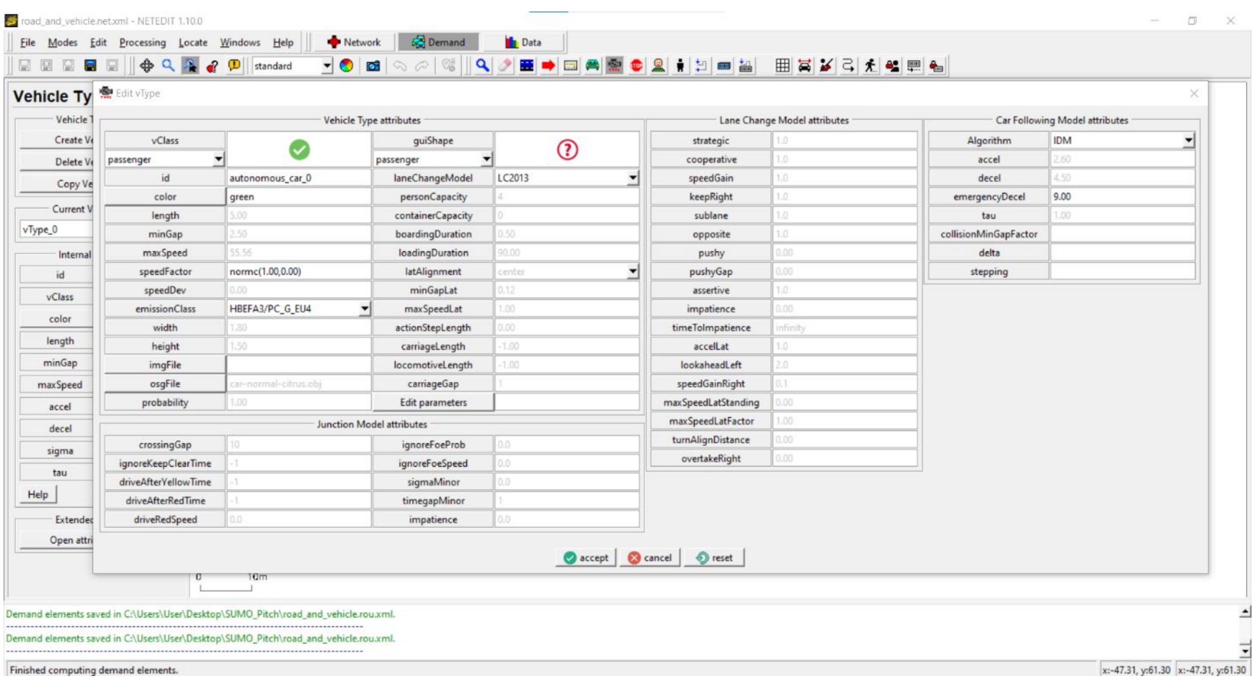

Figure 4: Parameters for autonomous vehicle

S. No	AV Penetration Level	Number of Conflicts - Run1	Number of Conflicts - Run2	Number of Conflicts - Run 3	Average Number of Conflicts
1	10%	10	17	9	12
2	20%	10	13	10	11
3	30%	16	11	6	11
4	40%	15	10	15	13.33
5	50%	5	8	10	7.67
6	60%	9	4	5	6
7	70%	10	7	5	7.33
8	80%	6	4	4	4.67
9	90%	3	4	1	2.67
10	100%	0	0	0	0

Figure 5: Number of Conflicts for different AV Penetration Level

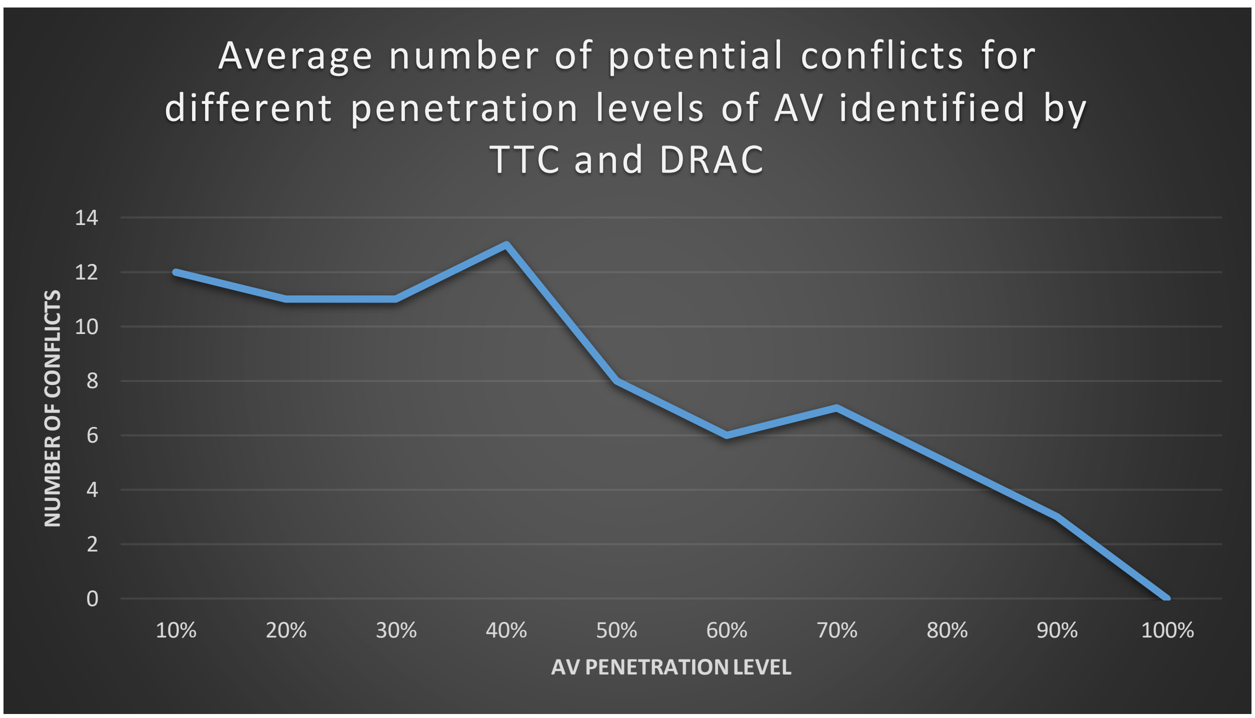

Figure 6: Line Chart for Number of Conflicts for different AV Penetration Level

1.5.2. References:

[1] Weicheng, X.(2020). Safety evaluation of heterogeneous traffic [Master's thesis, Chalmers University of Technology]. https://odr.chalmers.se/bitstreams/683cbb7a-f62e-4667-8f19-5437f5fe72d3/download

[2] "Driver State - SUMO Documentation," *sumo.dlr.de*. https://sumo.dlr.de/docs/Driver_State.html (accessed Apr. 23, 2024).

[3] "SSM Device - SUMO Documentation," sumo.dlr.de. https://sumo.dlr.de/docs/Simulation/Output/SSM_Device.html (accessed Apr. 23, 2024).

[4] "Vehicle Type Parameter Defaults - SUMO Documentation," *sumo.dlr.de*. https://sumo.dlr.de/docs/Vehicle_Type_Parameter_Defaults.html (accessed Apr. 23, 2024).