A Chrono-Based Framework for Large-Scale Traffic Simulation with Human In The Loop

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ABSTRACT

This contribution outlines a high-fidelity simulation framework for Human-in-the-loop (HIL) traffic simulation built upon Project Chrono, an open-source physics simulation engine. The framework is designed to provide the software infrastructure for human factors, traffic, and human-automation interplay research. We conclude this platform overview paper with two use cases – a human-factors study and an experiment involving a ring traffic scenario that displays the formation of phantom traffic jams.

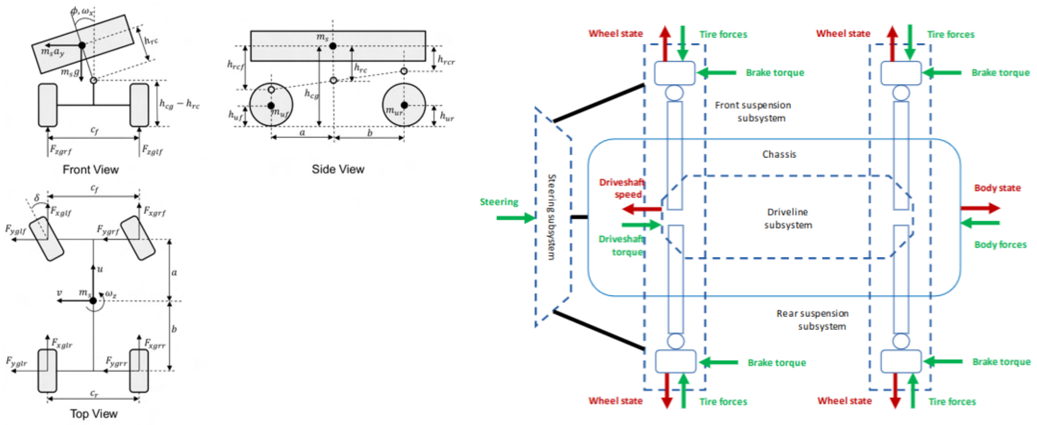
1 INTRODUCTION

Human-in-the-loop (HIL) simulation provides a safe and inexpensive testing environment for many vehicle operation scenarios that involve human intervention. To be effective, HIL simulation requires high-fidelity vehicle dynamics and a realistic virtual driving environment. HIL is important in studying human-automation interplay in the context of autonomous vehicle operation, human-machine interaction for human factors testing, traffic simulation involving one or more human drivers, driving simulation for clinical applications, etc. For HIL simulation, to accurately capture a human's reaction to a vehicle and its environment, three aspects of the simulation need to be considered and properly implemented: (i) a realistic vehicle dynamics response, such as the vehicle's pitch, roll, and yaw; (ii) the rendering of a realistic virtual driving environment; and (iii) real-time simulation performance. We report on a simulation framework built upon Chrono [1] that addresses the requirements of HIL simulation above by leveraging high-fidelity vehicle simulation, high-performance computing, high-accuracy rendering, and sensor simulation. The open-source simulation module is called Chrono::HIL and leverages the Vehicle, Sensor, and Synchrono modules in Chrono.

2 Chrono::HIL Highlights

2.1 Vehicle dynamics simulation at multiple fidelity levels

Two major vehicle dynamic models can be chosen from - Chrono::Vehicle model or a Reduced-Order Model (ROM) vehicle, see Figure 1(a). The highest fidelity model is directly defined in Chrono::Vehicle, as shown in Figure 1(b), which provides a template-based vehicle definition. The Chrono::Vehicle module provides simulation support for all mechanical components of the vehicle, including but not limited to chassis, tire models, suspensions, drive trains, engines [2]. The Chrono::Synchrono module allows vehicles to be simulated in parallel by different CPU processes via MPI or DDS [3]. Although the Chrono::Vehicle model provides high-fidelity vehicle-dynamic simulation, the computational load is heavy and the simulation does not scale very well. The initial benchmark shows that the simulation of one Chrono::Vehicle model on one CPU thread results in an real-time factor (RTF) of around 0.6 (RTF represents the amount of compute time required to



(a) Schematic of the Chassis of the ROM [4, 5] (b) Schematic of the Chrono::Vehicle Model [2]

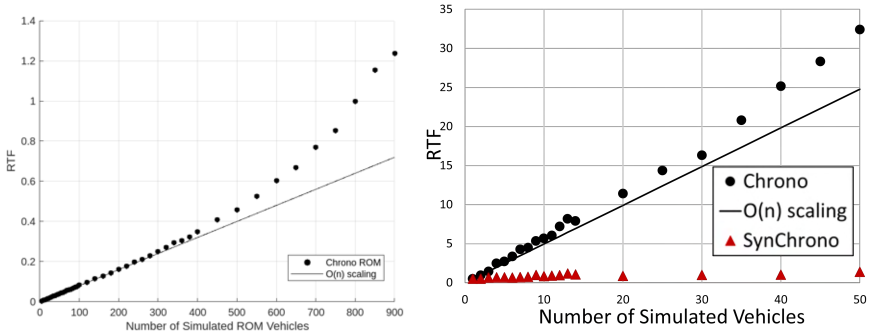
Figure 1. Two types of vehicle dynamic models are used in Chrono::HIL - A high fidelity vehicle as used in Chrono::Vehicle submodule, and a lower fidelity, but more computationally lightweight model known as Reduced-Order Model

simulate 1 second of motion of the system). While the Chrono::Synchrono does enable close-to-linear scalability, as shown in Figure 2(b), it remains difficult to achieve real-time performance when the amount of traffic vehicles exceeds 30 as synchronization cost increases significantly and such a large fleet of high-fidelity vehicles require a large amount of computing power.

As an alternative, Chrono::HIL also provides 21-DOF ROM vehicles to allow faster simulation speed with simplified vehicle dynamics. The ROM provides lower-fidelity but faster simulation speed for vehicles not in focus, "background" vehicles. The ROM ensures the influence of the vehicle dynamics in the traffic flow can be captured, and the control desired can be imposed and simulated on the traffic vehicles. The schematic of the chassis of ROM is shown in Figure 1(a). The ROM vehicle model provides fast simulation of the chassis' motion and vehicle's wheel motion, while ignoring the mechanical components of the steering mechanism and suspensions. The ROM vehicle model utilizes the TMeasy Tire model. An experiment has been conducted to examine the vehicle dynamic responses of the Chrono::Vehicle model and the ROM vehicle model. Both models use the same vehicle parameters which simulate a military HMMWV vehicle, including vehicle's weight, chassis inertia, powertrains, and tire parameters. The Chrono Vehicle is initialized at location [0,0] and the ROM model is initialized at location [0,4].The entire benchmark comparison simulation lasts for 16 seconds, and the control commands provided to the simulation includes the following: 50% throttle input and 20% left steering input between simulation time t=3s and t=8s; 30% throttle input and 40% right steering input between simulation time t=8s and t=10s; 80% braking input between simulation time t=10s and t=14s. The trajectories are shown in Figure 3(a), and the vehicle dynamic's response is shown in Figure 3(b), Figure 3(c), and Figure 3(d). Since the ROM doesn't include the vehicle's pitch, the pitch angle response of the ROM remains at 0 in Figure 3(b).

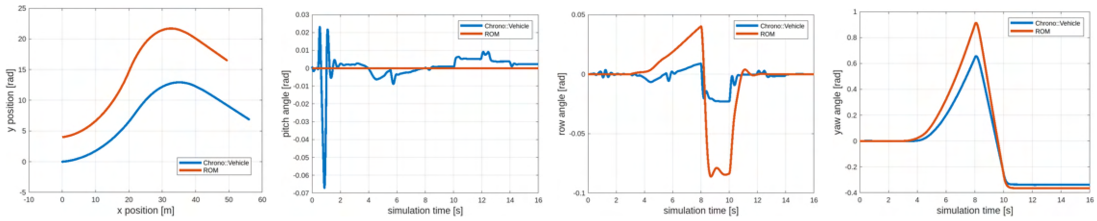
2.2 Hardware Coupling and Rendering

Chrono::HIL provides flexible controller coupling capabilities to support a range of driving simulator platforms, from a simple one-screen desktop setup to a full-cabin driving simulator. Chrono::HIL achieves this by providing two types of controller input reading methods - direct and hardware streaming. Specifically, it can be programmed to read inputs directly from a joystick connected to the same machine running Chrono::HIL. If the driving simulator is being driven by an external third-party software, Chrono::HIL is able to accept inputs from a UDP network data stream. This latter scenario is illustrated in Figure 4(d), which shows the coupling of Chrono::HIL with a



(a) Scaling of ROM on one CPU thread (b) Scaling test of single-threaded Chrono::Vehicle and parallelized multi-threaded Chorno::Syncrhono high-fidelity vehicle models

Figure 2. Scalibilities of different vehicle dynamic models



(a) Trajectory (b) Pitch (c) Row (d) Yaw

Figure 3. Vehicle dynamic response of the Chrono::Vehicle model and ROM to the same set of control inputs

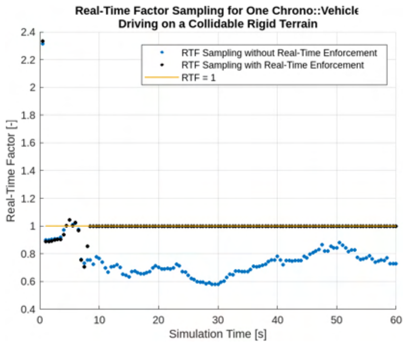
full-cabin driving simulator in the Traffic Operations and Safety Laboratory at the University of Wisconsin-Madison. Therein, the simulation is conducted by Chrono::HIL – the driver's inputs were sent through as a UDP packet and captured by proprietary third-party software. Chrono::HIL also provides native support of driving controller connected directly to the Chrono::HIL simulation machine through the usage of SDL2 interface.

Multiple rendering methods can be chosen. Chrono::Sensor uses NVIDIA's Optix ray-tracing API to provide both sensor simulation and graphics rendering [6]. Users of Chrono::HIL can directly launch the rendering window from Chrono::HIL with easy camera definition as Chrono::Sensor is well embedded to work with any simulation created within Chrono. Alternatively, other embedded rendering engines in Chrono such as Irrlicht and VulkanSceneGraph can also be used. A network interface allows users to communicate with third-party rendering pipelines, such as Unity.

2.3 Soft Real-Time Enforcing

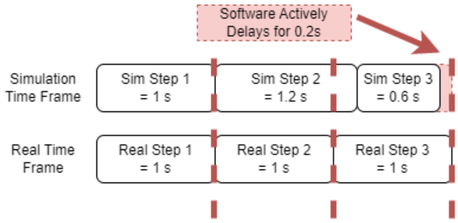
Chrono::HIL ensures that the simulation time is periodically and with high frequency synced to the real time. In other words, the RTF has to be precisely 1. Chrono::HIL employs a soft real-time synchronization method in which the program might sometimes allow simulation steps to run slower than real-time. As shown in Figure 4(c), if a simulation step runs slower than real time, it is expected that a later simulation step runs faster than real time to average out at an RTF=1. In cases when the simulation step runs faster than real time, an active synchronization delay is employed to delay the simulation via a "sleep" function call.

A benchmark experiment has been conducted to compare the RTF sampled from the simulations with real-time enforcement on and off. The benchmark experiment involves one Chrono::Vehicle running on one CPU thread on a rigid terrain, with terrain collision, as shown in Figure 4(b). The RTF sampling results can be found in Figure 4(a). The benchmark experiment lasts for 60s in

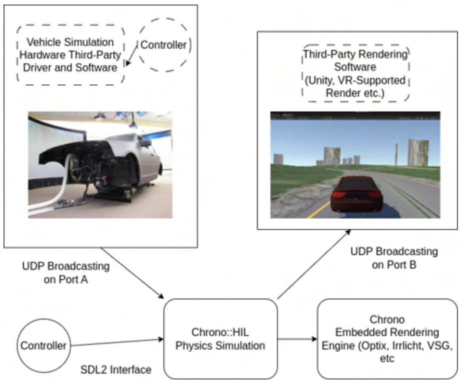


(a) Real-Time Factor of the benchmark simulation with real-time enforcement and without real-time enforcement

(b) A benchmark simulation of a rural driving scenario, involving one Chrono::Vehicle on collidable rigid terrain



(c) chrono::HIL soft-real time enforcement schematic



(d) Chrono::HIL provides flexible hardware coupling and rendering capability.

simulation time, and global RTF, the real time count-down starts at the beginning of the simulation, is sampled every 0.5 s. At the beginning of the simulation, an unusual RTF spike is noted as the initialization of the simulation is usually costly. As the simulation stabilizes, real-time enforcement in Chrono::HIL ensures the RTF sampling stabilizes at 1.

2.4 Vehicle Following Behavior Definition

The path and lane data need to be defined as a Bezier curve in the simulation. A PID steering controller is used to output steering data to ensure the vehicle stays on the path. Speed control can be defined by customized driving control algorithms to provide different driving behaviors. In Chrono::HIL, two types of control can be used - a PID controller for autonomous cruising vehicles and an Intelligent Driver Model (IDM) used to simulate the human driver's control of the vehicle.

IDM is a deterministic and collision-free car-following model [7]. IDM has been widely used in the industry as its parameters can be interpreted and matched with values with physical meanings. The IDM computes the desired acceleration for the vehicle at a certain state and time. The acceleration is then translated to throttle and braking commands using a PID speed controller to control the vehicle.

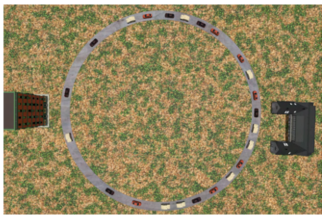
The equations used for the IDM model are

$$\frac{dv}{dt} = a[1 - (\frac{v}{v_0})^{\delta} - (\frac{s^*(v,\Delta_v)}{s})^2] \tag{1}$$

$$s^*(v,\Delta_v) = s_0 + max[0, (vT + \frac{v\Delta_v}{2\sqrt{ab}})] \ , \tag{2}$$

(e) Chrono::HIL used for studying human-automation interplay.

(f) Photo of Test Case 2 Human-in-the-loop experiment in progress



(g) Birdeye view of the experiment of Test Case 2

Figure 4. Chrono::HIL provides a cost-effective and controllable environment for traffic flow ring experiment

where

1. s_0, in m, is the standstill distance between the lead vehicle and the following vehicle when both two vehicles brake to a stop
2. v_0 is the desired cruising speed for the following vehicle in $\frac{m}{s}$
3. a is the maximum acceleration of the following vehicle in $\frac{m}{s^2}$
4. b is the maximum deceleration of the following vehicle in $\frac{m}{s^2}$
5. T is the time gap in second
6. v is the current speed of the following vehicle
7. Δ_v is the speed difference between the following vehicle and the lead vehicle.

3 Demonstration of technology

The open-source nature of the software allows customization and freedom to define a spectrum of driving scenarios by controlling the environment, ego car dynamics, lead vehicle behaviors, etc. Chrono::HIL has been recently used in human-factor research. Two data collection scenarios have been conducted – a human factor distraction experiment, which showcases the capabilities of simulation to reproduce dangerous edge cases [8] and a classic ring experiment [9] involving one human driver in the loop, which showcases the ability to simulate real life traffic behaviors and provide useful data for researchers in traffic dynamics.

3.1 Human Factor Research for Human-Automation Interplay

Chrono::HIL is being used to conduct research that examines human-automated vehicle interaction. These interactions often determine whether or not the expected benefits of automated vehicles materialize. In the future, highly automated vehicles will allow drivers to switch between manual and automated control [10]. In cases where the automation is fully capable of navigating the driving environment, driver-initiated transitions to manual control (i.e., disuse of vehicle automation) eliminate the potential benefit of the automation. This disuse of vehicle automation can degrade traffic flow, which might be smoother and more efficient when drivers use vehicle automation [11]. Understanding the factors that provoke disuse of the vehicle automation can improve automation acceptance and trust and reduce disuse [12].

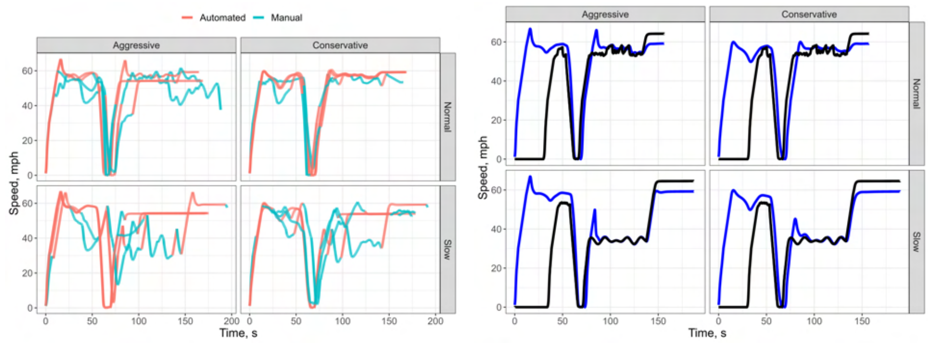
One such factor in human factors research is the concept of driving style similarity [13]. The hypothesis guiding driving style similarity research is that vehicle automation that drives in a manner similar to how the driver may drive manually may increase drivers' trust and acceptance of the automation [14]. Chrono::HIL makes it possible to examine these factors empirically by exposing drivers to different driving styles of automation and observing how drivers interact with the automation. For instance, drivers that tend to drive conservatively with longer headways may distrust vehicle automation that drives aggressively with shorter headway. Such interactions may undermine trust, leading drivers to disengage the automation. An ongoing driving simulator experiment with human subjects leverages Chrono::HIL to examine the effect of driving style similarity on trust in automation.

The effect of driving style similarity on trust in automation is examined using a driving simulator experiment that exposes drivers to a simple car-following scenario. During the experiment, participants are situated in the following vehicle and can switch between driving in manual and automated mode. When drivers switch to the automated mode, vehicle automation is programmed to drive conservatively in some drives and aggressively in others. Conservative and aggressive car-following driving styles are dictated by the car-following model parameters that are implemented in Chrono::HIL. These parameters modify automated vehicle driving style based on time headway, standstill distance, desired velocity, desired acceleration, and desired deceleration. In addition to modifying the behavior of the following vehicle, Chrono::HIL also makes it possible to modify the lead vehicle's behavior. The lead vehicle that participants encounter in the experiment scenario follows a preset path and speed profile that simulation generates based on parameters defined by the researcher. In this study, participants are exposed to two types of lead vehicle behavior. In some scenarios, the lead vehicle drives below the posted speed limit, and in others, it drives smoothly at the posted speed limit. Thus, Chrono::HIL simulation makes it possible to vary two general behaviors in the driving simulator experiment: (1) the driving style of the following vehicle (conservative versus aggressive), and (2) the behavior of the lead vehicle (slow driving versus normal speed).

A combination of these variables allows testing four conditions of human-automated vehicle interactions in which driver-initiated transitions to manual control can be studied. Table 3.1 shows the average values of the parameters differentiating the driving behavior across the four conditions. Figure 5(a) shows the speed profiles of the automated vehicle following a lead vehicle across the four conditions. Data from a pilot study in Chrono::HIL conducted with four drivers (3 female, and 1 male; aged between 25 and 55) is shown in Figure 5(b). During the study, drivers were instructed to use the automated vehicle to reach a destination located 2.3 miles away from the starting point in less than 3 minutes while staying at or below the posted speed limit (55 mph). They were also informed that they may choose to drive in automated or manual mode to achieve this goal. A countdown timer and the estimated time of arrival based on the following vehicle's speed were shown on the dashboard to help guide decisions to transition between automated and manual control. Figure 5(b) shows the transitions of drivers between automated and manual control. The amount of time drivers spend in automated mode and the number of transitions to manual control can serve as indicators of trust in the vehicle automation. More time spent in automated mode and fewer transitions to manual control may indicate high trust in the automated vehicle. Table 3.1 shows the mean percent of time spent in automated mode and the mean number of driver-initiated transitions to manual control across all the conditions tested in Chrono::HIL. These data provide the foundation for estimating parameters of driver models, which can be incorporated into the simulation for parametric testing of automated vehicle control algorithms. These tests can reveal the effect of algorithm parameters on vehicle behavior, but more importantly, on traffic behavior.

3.2 Ring Experiment for Traffic Flow Research

Capturing the dynamics and the response of the traffic flow when instabilities are introduced is crucial for traffic flow research and human-factor research. The simulation of the traffic flow needs to capture the instabilities and the propagation of the traffic wave when perturbations are introduced, amplified, and grown in the traffic wave, also known as a phantom traffic jam. The instabilities can be generated in many ways, such as human drivers' response time, lane-changing behavior, or the in-homogeneity of the dynamics of the vehicle involved in the traffic flow. The



(a) Speed profiles of the automated vehicle following a lead vehicle across the four conditions.

(b) Data from pilot study with Chrono showing four drivers transitioning between automated and manual driving model across four combinations of experimental conditions.

Figure 5. The speed profile of all 23 vehicles involved in each experiment during the first 200s of experiment, the Ego Vehicle's (ID 13) speed profile is shown in blue.

	Aggressive AV		Conservative AV	
	Slow LV	Normal LV	Slow LV	Normal LV
Mean speed (m/s)	13.39	22.17	14.15	21.49
Mean acceleration (m/s2)	0.52	0.56	0.50	0.52
Mean deceleration (m/s2)	0.47	0.43	0.49	0.47
Mean headway (m)	10.44	32.51	24.99	70.10
Standstill distance (m)	3.1	3.1	10.1	10.1

Table 1. Parameters differentiating the aggressive and conservative automated vehicle while interacting with a lead vehicle.

	Aggressive AV		Conservative AV	
	Slow LV	Normal LV	Slow LV	Normal LV
Mean percent of time spent in automated mode	75.03	63.59	59.51	73.82
Mean number of driver-initiated transitions to manual control	2.00	2.25	2.75	1.75

Table 2. Mean percentage of time spent in automated mode and the number of driver-initiated transitions to manual control across all four experimental conditions

experiment attempted to capture such traffic flow phenomena through a ring experiment.

Although such phenomena and experiments can be conducted in a field experiment [9], they are costly and difficult to set up. Chrono::HIL provides a controllable and cost-effective way for researchers to investigate traffic flow without the hassle to set up the field experiment. In the experiment we have conducted, we have run five different test cases, which involved different experiment setups, to examine the overall traffic flow dynamic response and total pass-thru performance. Three types of IDM drivers, as shown in Table 4, and three types of vehicle dynamics have been modeled. The details about the experiment test cases are shown in Table 3.

Each experiment lasts for 20 minutes, and the speed profiles are shown in Figure 3.2 for all 23 vehicles involved in the traffic ring experiments.

Table 3. Experiment Scenarios

Test Case No.	Description	Ego Vehicle Average Speed [m/s]	Ego Vehicle Total Wait Time [s]
Test Case 1	Mixed vehicle types and mixed IDM drivers	1.8488	691
Test Case 2	The ego vehicle is driven by human, mixed vehicle types for other traffics and mixed IDM drivers[15]	1.8259	777.2
Test Case 3	Same vehicle type vehicles are driven by different IDM drivers	1.7708	812.4
Test Case 4	All vehicle has the same dynamics and are driven by the same IDM driver	7.6605	0.4
Test Case 5	Mixed vehicle dynamics, the same IDM driver parameter	2.6064	603

Table 4. IDM Parameters Used in the Experiment

	Aggressive	Neutral	Conservative
Desired Speed, v_0 $[m/s]$,	8.9408	8.9408	8.9408
time gap, T, $[s]$	0.1	0.2	0.7
Standstill bumper-to-bumper spacing, s_0, $[m]$	5.0	6.0	8.0
Max acceleration rate, a, $[m/s^2]$	3.5	3.0	2.5
Max deceleration rate, b, $[m/s^2]$	2.5	2.1	1.5
Acceleration exponent, δ, [-]	4.0	4.0	4.0

4 Conclusion and Future Work

Video gaming usually focuses on the excitement of the experience and pays limited attention to the fidelity of the simulation itself. At the other end of the spectrum, commercial driving simulation solutions are often expensive, closed source, and lack the ability to easily customize/adapt simulation scenarios and data collection. The Chrono::HIL framework aims to democratize the use of simulation as a tool for traffic and human factors research. Owing to its open-source nature, the proposed Chrono::HIL framework leverages high-fidelity vehicle dynamics simulation and high-performance parallel computing to allow broad customization of the experimental environment. Looking ahead, we plan to provide a more user-friendly software interface to allow researchers to control scenario parameters and deploy simulation quickly. A second development thrust is tied to improving Chrono::HIL's execution speed, which gets compromised on slow hardware or when used for complex scenarios.

Table 5. Vehicle types and IDM driver parameters used in Test Case 1 and Test Case 2

Vehicle ID	Vehicle Types	IDM Driver Type
0	Sedan 1 - Nissan Sentra	Aggressive
1	Sedan 2 - Audi A3	Neutral
2	Heavy Utility - HMMWV	Aggressive
3	Heavy Utility - HMMWV	Conservative
4	Sedan 1 - Nissan Sentra	Aggressive
5	Heavy Utility - HMMWV	Neutral
6	Sedan 2 - Audi A3	Neutral
7	Sedan 2 - Audi A3	Aggressive
8	Heavy Utility - HMMWV	Conservative
9	Sedan 2 - Audi A3	Aggressive
10	Sedan 1 - Nissan Sentra	Conservative
11	Heavy Utility - HMMWV	Aggressive
12	Heavy Utility - HMMWV	Aggressive
13 [Ego Vehicle]	Sedan 2 - Audi A3	Neutral
14	Sedan 1 - Nissan Sentra	Conservative
15	Heavy Utility - HMMWV	Aggressive
16	Sedan 1 - Nissan Sentra	Conservative
17	Heavy Utility - HMMWV	Neutral
18	Heavy Utility - HMMWV	Aggressive
19	Sedan 2 - Audi A3	Neutral
20	Sedan 1 - Nissan Sentra	Conservative
21	Heavy Utility - HMMWV	Aggressive
22	Sedan 1 - Nissan Sentra	Conservative

Table 6. IDM driver type specified in Test Case 3, while all vehicles are Sedan 1 - Nissan Sentra Type

Vehicle ID	IDM Driver Type
0	Aggressive
1	Conservative
2	Neutral
3	Conservative
4	Aggressive
5	Neutral
6	Conservative
7	Aggressive
8	Conservative
9	Aggressive
10	Conservative
11	Aggressive
12	Conservative
13 [Ego Vehicle]	Neutral
14	Conservative
15	Aggressive
16	Conservative
17	Neutral
18	Aggressive
19	Neutral
20	Conservative
21	Aggressive
22	Conservative

Table 7. Vehicle type specified in Test Case 5, while all vehicles use the aggressive type of IDM driver

Vehicle ID	Vehicle Type
0	Sedan 1 - Nissan Sentra
1	Sedan 2 - Audi A3
2	Heavy Utility - HMMWV
3	Sedan 1 - Nissan Sentra
4	Sedan 2 - Audi A3
5	Sedan 2 - Audi A3
6	Sedan 1 - Nissan Sentra
7	Heavy Utility - HMMWV
8	Sedan 1 - Nissan Sentra
9	Sedan 2 - Audi A3
10	Sedan 2 - Audi A3
11	Heavy Utility - HMMWV
12	Heavy Utility - HMMWV
13 [Ego Vehicle]	Sedan 1 - Nissan Sentra
14	Heavy Utility - HMMWV
15	Sedan 2 - Audi A3
16	Sedan 1 - Nissan Sentra
17	Heavy Utility - HMMWV
18	Sedan 1 - Nissan Sentra
19	Sedan 1 - Nissan Sentra
20	Sedan 2 - Audi A3
21	Heavy Utility - HMMWV
22	Sedan 1 - Nissan Sentra

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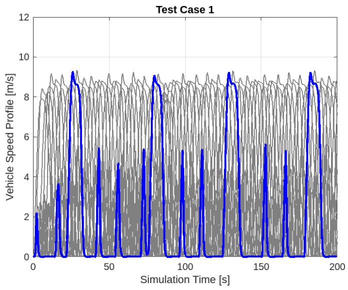
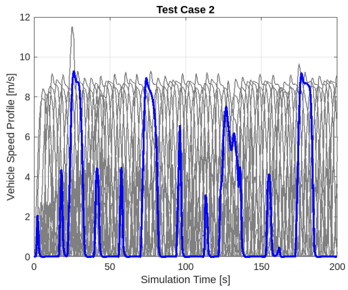
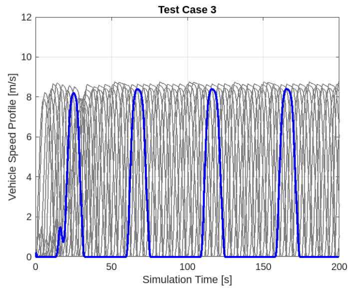


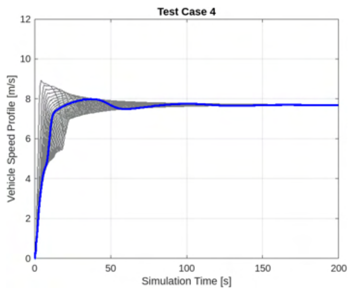
(a) Test Case 1



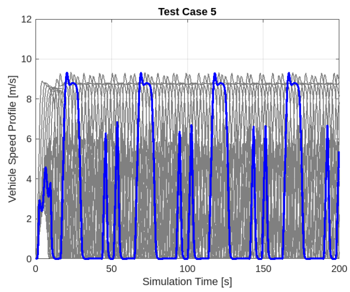
(b) Test Case 2



(c) Test Case 3



(d) Test Case 4



(e) Test Case 5

Figure 6. The speed profile of all 23 vehicles involved in each experiment during the first 200s of experiment, the Ego Vehicle's (ID 13) speed profile is shown in blue.

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