

Effects of Driver Parameters on Traffic Flows

Introduction

Modeling traffic flows and effects is of critical importance for understanding and regulating phenomena that are encountered in many aspects of modern life. To model these phenomena several techniques are used to simulate, characterize, and understand traffic patterns. In this report a specific dynamical model called the Intelligent Driver Model was implemented in a python-based simulation to analyze the effects of driver preferences within this model on traffic flows. Specifically, two road scenarios were evaluated with different mixings of driver presets to evaluate the effect on the number of cars in a system, and therefore the throughput. This simulation is then visualized using the pygame framework.

Background

Traffic models and simulations are used to characterize and understand the flows of traffic that affect us daily. In general, the types of simulations break down into three categories. First there is macroscopic simulations, which describe the dynamics in terms of aggregate quantities like density and flow rate, which makes them more akin to fluid flow simulations. Second there are microscopic models which describe the motion of individual vehicles using some dynamical framework. Then there are mesoscopic models which attempt to unify the scale gap between microscopic and mesoscopic. These describe traffic as continuum flow, characterizing vehicles as packets that flow through the system.

This report focuses on a specific class of microscopic model called the Intelligent Driver Model. This model was developed by Treiber, Hennecke and Helbing in 2000 with the intent of developing a continuous time single lane car following model with interpretable parameters. Car following models describe the dynamics of cars in terms of the relationship between a leading car and its followers, forming a dynamically linked chain. The model parameters describe the style of driving, i.e., whether a particular driver is fast or slow, careful, or reckless, attentive, or inattentive.

Methodology

In the intelligent driver model, the car is described in terms of its relationship to the car its following shown in this diagram.

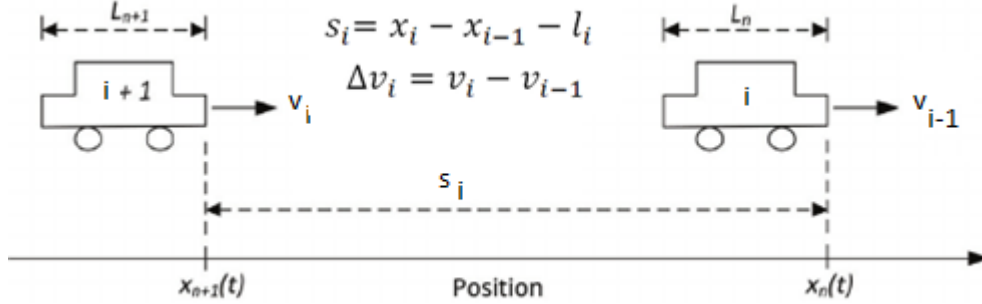


Figure 1. Defining Relationship in Follower Model

This denotes the position of two cars in a leader follower model, with their lengths L , the bumper-to-bumper distance s_i and the difference in velocity Δv .

The dynamics of the intelligent driver model are given by a set of coupled ordinary differential equations shown here. This models the acceleration of a car in terms of the relative distance and velocities of the leader and follower as well as several tunable parameters that describe the behavior of the driver.

$$\frac{dv_i}{dt} = a_i \left(1 - \left(\frac{v_i}{v_{0,i}} \right)^\delta - \left(\frac{s^*(v_i, \Delta v_i)}{s_i} \right)^2 \right), \quad s^*(v_i, \Delta v_i) = s_{0,i} + v_i T_i + \frac{v_i \Delta v_i}{\sqrt{2a_i b_i}} \quad (1)$$

$$\frac{ds}{dt} = -\Delta v \quad (2)$$

The terms in this model are as follows, where the subscript i describes the i -th vehicle. v_i is the current speed of vehicle i , a_i is the maximum acceleration for vehicle i , v_0 is the maximum desired speed, s_0 as before is minimum desired distance to vehicle $i-1$. T_i is the reaction time in seconds of i -th driver. b_i is the comfortable deceleration for vehicle i , and s^* is the actual gap between vehicle i and $i-1$. δ is the acceleration smoothness factor. These parameters use SI units.

This acceleration term can be divided into two terms. Firstly, a desired acceleration, or free road acceleration, given by parameters of current and desired velocity and the acceleration factor.

$$a_{free\ road} = \frac{dv_i}{dt} = a_i \left(1 - \left(\frac{v_i}{v_{0,i}} \right)^\delta \right) \quad (3)$$

And the interaction acceleration governed by the relative velocity and positions of the leader and follower.

$$a_{interaction} = -a_i \left(\frac{s^*(v_i, \Delta v_i)}{s_i} \right)^2 = -a_i \left(\frac{s_{0,i} + v_i T_i}{s_i} + \frac{v_i \Delta v_i}{2s_i \sqrt{a_i b_i}} \right)^2 \quad (4)$$

The interaction acceleration is a braking term which is based on the ratio of desired gap s^* and actual gap s . The interaction acceleration itself breaks in two terms. The first term governed by, s_0 , v_i , T_i and s_i takes over when Δv is near zero, meaning that the leader and follower are at the same velocity. This term then acts as a mediating term for follow distance, acting as braking to keep the car tracking its leader. The second term is built so that when Δv is large and the bumper-to-bumper distance s_i is small, i.e., when the follower is approaching the leader quickly, that a larger breaking force is applied, proportional to the parameters of the driver, a_i , the maximum acceleration, and b_i the comfortable deceleration.

The values for all these parameters can be adjusted on a car-by-car basis, some realistic bounds are given for each parameter in the table below

Parameter	Symbol	Realistic Bounds	A Realistic Value
Desired Velocity	v_0	[0, 11]	3.33 (m/s)
Safe Time Headway	T	[1, 3]	1.6 (s)
Maximum Acceleration	a	[.5, 2]	.73 (m/s ²)
Comfortable Deceleration*	b	[.5, 2]	1.67 (m/s ²)
Acceleration Exponent	δ	—	4
Length of car	l	4, 5	4 (m)
Linear Jam Distance	s_0	[0, 5]	2 (m)
Non-linear Jam Distance	s_1	[0, 5]	3 (m)

Table 1: IDM Realistic Driver Parameters

We will be examining how drivers of different parameter presets interact and effect bulk flow through traffic systems. In general, careful drivers have a high safety time headway T , aggressive or pushy drivers have low T and high values for v , a , and b . Trucks are characterized by low values of v , a , and b . Mixing different distributions of these drivers in particular road scenarios can have a large effect on the number of cars in system and the throughput of a system.

For traffic lights we use a method that defines a slow down and stop distance when approaching a light. The slow down zone is characterized by a distance and factor which controls how fast the maximum speed of a driver changes. Shown as

$$v_{0,i} = \gamma v_{0,i} \quad \text{for } \gamma < 1 \quad (5)$$

For stopping at a traffic light, we update the equation for acceleration using a damping force proportional to velocity given as.

$$\frac{dv_i}{dt} = -b_i \frac{v_i}{v_{0,i}} \quad (6)$$

Simulation

To update our velocities and accelerations we will numerically integrate these equations. This is a standard approximate solution for coupled differential equations and uses a finite numerical update time Δt and integrates over this time step assuming constant acceleration. This method is called the ballistic method, and for its application to IDM any time steps below around 0.5 seconds lead to the same result. The update is given in the following equations.

$$\begin{aligned} v(t + \Delta t) &= v(t) + \frac{dv}{dt} \Delta t \\ x(t + \Delta t) &= x(t) + v(t) \Delta t + \frac{1}{2} \frac{dv}{dt} (\Delta t)^2 \\ s(t + \Delta t) &= x_l(t + \Delta t) - x(t + \Delta t) - L_l \end{aligned} \quad (7)$$

These are the updates for velocity, position, and gap for a given time step. The $\frac{dv}{dt}$ term in these equations is the IDM acceleration calculated the time t .

For our simulation environment, we used python and an object-oriented approach. As IDM is a follower based single lane model, we represent our roads as directed graphs made of nodes and edges. Every vehicle has a path defined as a list with the ID of the roads it is going to travel on. Each straight road will have a double ended queue that allows vehicles to be added to the end of the queue when you join a road. When a vehicle reaches the end of a road it is removed from that road's queue and appended to the queue of the next road. It is through this road hopping that we can examine scenarios like on ramps to highways. We have a road class that maintains the properties of a road, like it positions and angle. The road also maintains its queue of cars, and contains an update for vehicles place in queue, and whether they should stop at a stop light. The vehicle class maintains the parameters for a given vehicle, and the methods to update the velocities and accelerations.

For viewing this simulation in pygame, the window class is created, with several functions to draw to the screen that come standard with pygame. Most of this class is standard helper functions to draw rectangular boxes and lines to the screen, as well as keeping track of user inputs on the mouse or keyboard.

The cars are added to the simulation at the start of the first road on their path. The interarrival times can be specified, and when the simulation reaches an arrival time, it draws a car from the list of potential drivers presets and chooses one randomly as a function of the weights of each driver preset.

Results

We look at two specific road scenarios, first the case of an onramp to a highway shown in the top figure. Second a traffic light intersection of 2 lanes shown in the bottom figure. In both cases the distance between where the cars start and interact with each other or the light is large, to accurately capture wave phenomena.

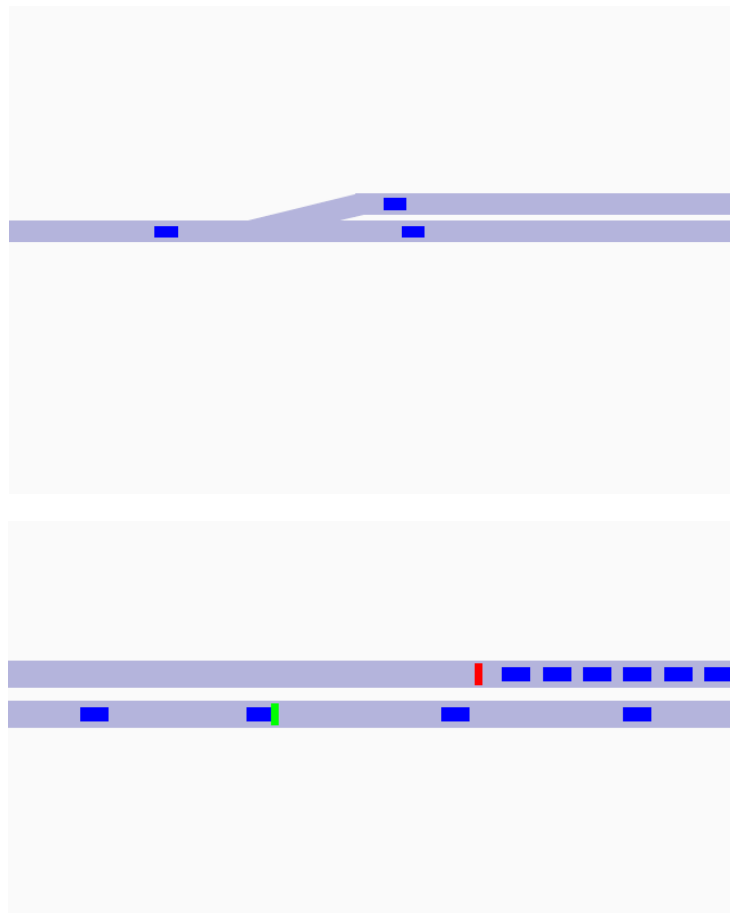


Figure 2: Experimental Cases

In these experiments three driver presets are evaluated, a cautious driver, an aggressive driver, and a truck. One preset is chosen randomly at every arrival time for the simulation. Cautious drivers are displayed in blue, aggressive drivers in red and trucks as magenta.

	Length L (m)	Desired Velocity V (m/s)	Max Acceleration a (m/s/s)	Desired Deceleration B (m/s/s)	Reaction Time T (s)
Cautious	4	12	1.4	2.0	1.8
Aggressive	4	18	2	3.0	1.2
Truck	9	8	0.9	1.0	1.8

Table 2: IDM Parameter for our Experiments

Different mixtures of these drivers were run for both the experimental cases to determine the steady state number of cars in simulation for each mixture. Mixtures denoted as “Mostly Aggressive” have aggressive cars being drawn with an 80% chance and cautious at 20%. The inter arrival times can be generated from any distribution, and for these experiments a couple of options were utilized. The results of these experiments are in the figures below.

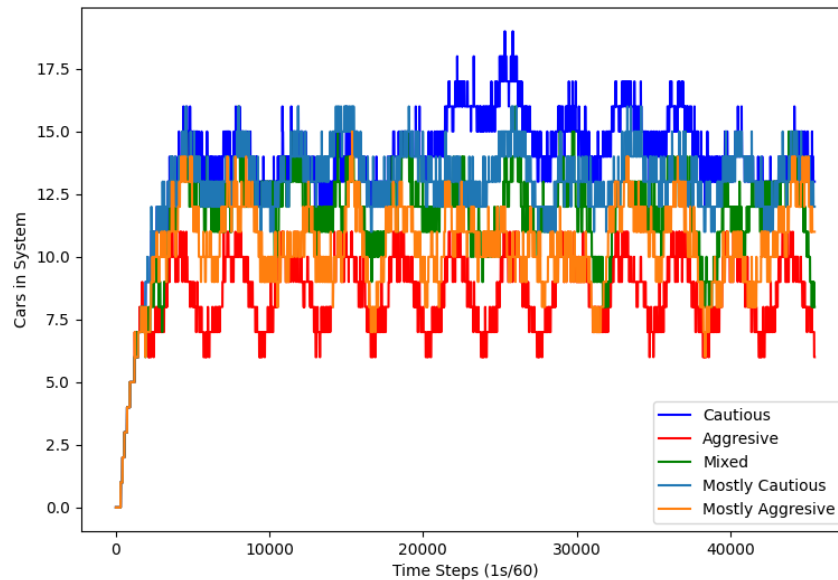


Figure 3: On Ramp with no Trucks

For this figure we see a periodic steady state behavior where if you add more aggressive drivers the number of cars in the simulation decreases indicating increased flow rate. The average number of cars for each category after time step 10,000 is 14.4 for cautious, 8.5 for aggressive, 11.8 for mixed, 13.2 for mostly cautious, and 10.3 with mostly aggressive. The interarrival times for figure 3 were, for the first 10 terms generated from a uniform distribution between 2 and 6, then for the next 10 terms from a uniform distribution between 1 and 4 to simulate periodic boundary conditions on the simulation. All runs of different mixtures of drivers were run with the same interarrival times.

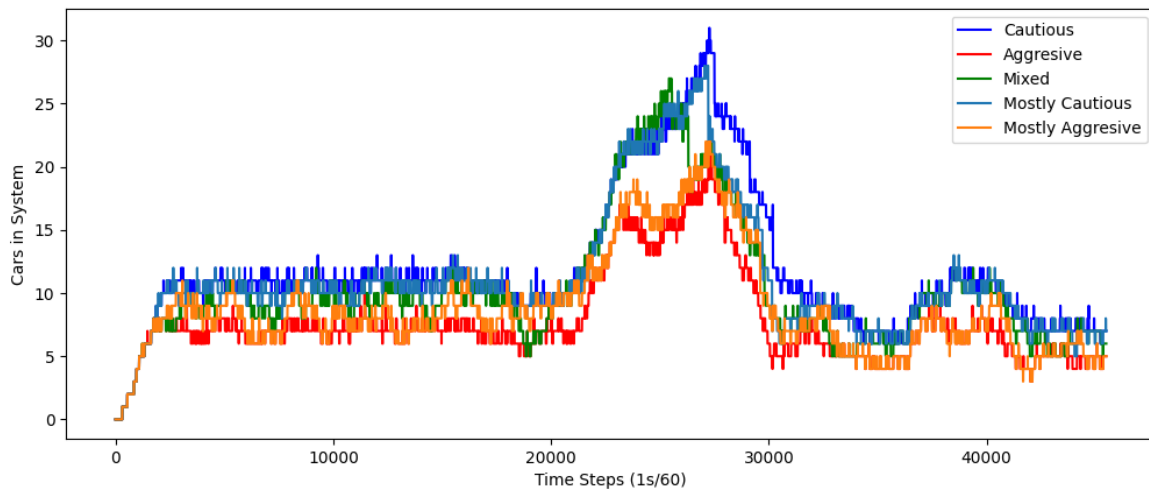


Figure 4: On Ramp no Trucks, burst arrival

In this experiment we attempted a burst of traffic to see how the different mixtures responded. This burst was generated in the interarrival times by having a random uniform distribution between 2 and 6 seconds for the first 100 terms, then random uniform between 1 and 4, for 50 terms, then a relaxation for 100 terms between 1 and 8. Here again we see the same effect of more aggressive drivers leading to more throughput.

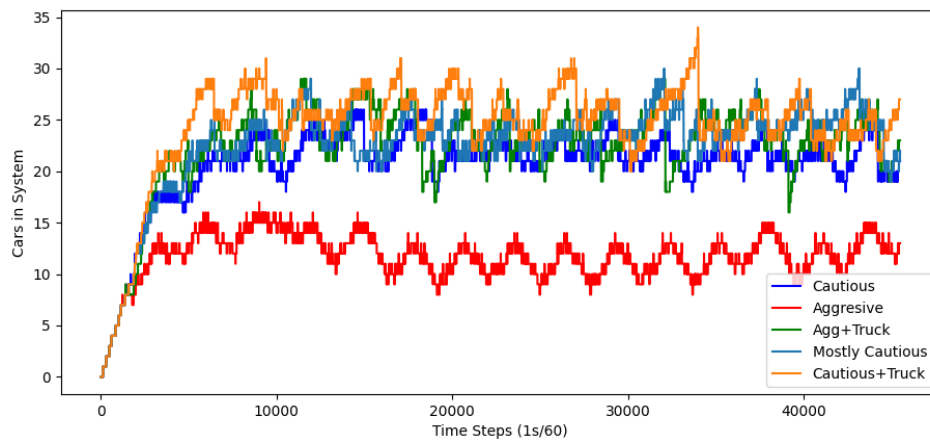


Figure 5: On Ramp with Trucks

We can see here that trucks slow down the throughput significantly for the on-ramp scenario, only being slightly better if aggressive drivers are included with the trucks.

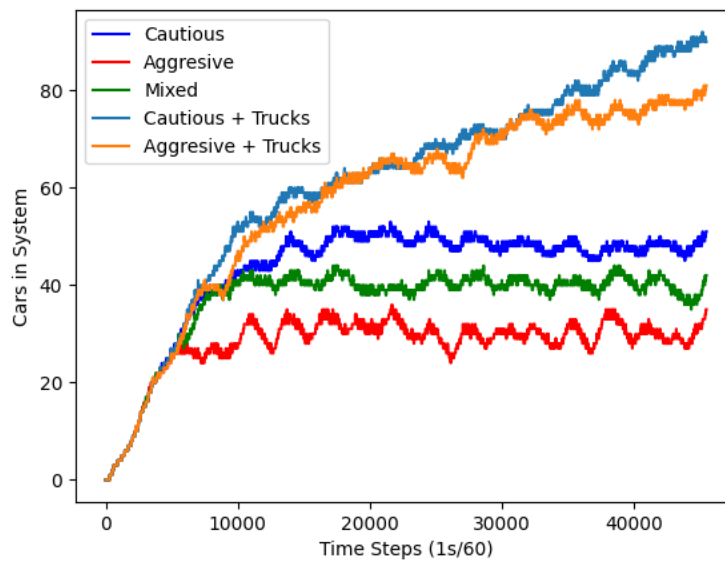


Figure 6: Traffic Light with different Mixtures

For the traffic light scenario, the differences between the types of drivers becomes even more pronounced. As the traffic waves are much more consistent in the stop light scenario due to the periodic stopping, the effects of acceleration limits for each type of driver become more apparent. One may think the difference in throughput is only a function of the desired velocity for each driver type, and that would be true on an open road with no merges or traffic waves, but when there is any form of stopping the acceleration terms guide the behavior. An example of this is shown in the figure below.

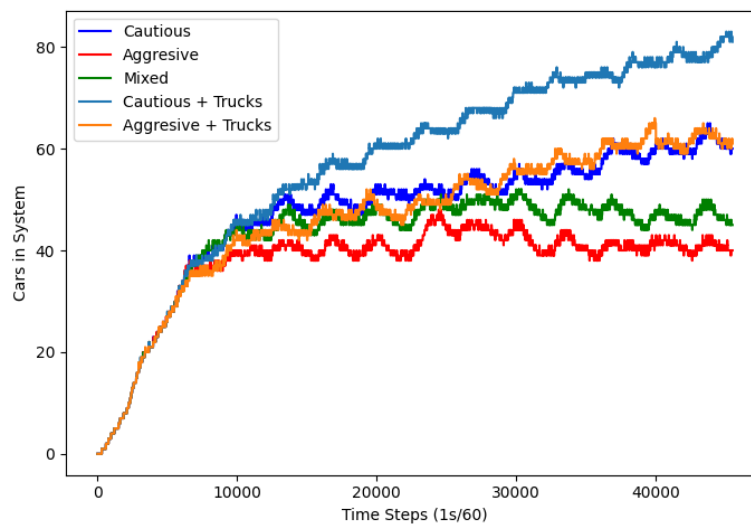


Figure 7: Traffic Light with same Desired Velocities

In this case we used the same desired velocity ($v_0 = 12\text{m/s}$) for every type of driver. Because the traffic light scenario is heavily dependent on re acceleration for throughput, there is still a large difference between the types of drivers. Interestingly the aggressive driver + trucks scenario performed similarly to the only cautious driver scenario despite the much slower acceleration of trucks, while in the previous experiment cautious + trucks was much closer to aggressive + trucks.

Conclusion and Discussion

In conclusion a general framework for evaluating parameters of an intelligent driver model or similar car follower models. We evaluated two road scenarios, an on-ramp and traffic light to examine the effects of types of drivers on throughput. It was found in general that more aggressive drivers, primarily due to their propensity for acceleration and deceleration improve the flow of traffic in these scenarios.

Some limitations of this framework are synonymous with the limitations of car follower models. Those being capturing traffic dynamics for lane merging are difficult, and potentially inaccurate. In this simulation the implementation of roads with queues for the cars on them and checking if the next road has room for the car alleviated some concern and allowed for evaluation of a highway on ramp. Further extensions of this framework could include building more complex and interconnected road networks to track larger scale dynamics in a mesoscopic model, but simulation does slow down when there are more than 150 cars in simulation.

References

Treiber, M., Hennecke, A., & Helbing, D. (2000). Congested traffic states in empirical observations and microscopic simulations. *Physical Review E*, 62(2), 1805–1824.
<https://doi.org/10.1103/physreve.62.1805>

The intelligent-driver model and its variants. *Microsimulation of Traffic Flow: Onramp*. Retrieved December 10, 2021, from https://traffic-simulation.de/info/info_IDM.html

L J Pignataro.
 Traffic Engineering: Theory and practice.
 Prentice-Hall, Englewoods Cliffs,N.J., 1973.

Himite, B. (2021, September 7). *Simulating traffic flow in Python*. Medium. Retrieved December 10, 2021, from <https://towardsdatascience.com/simulating-traffic-flow-in-python-ee1eab4dd20f>.

Malinauskas, Rachel, "The Intelligent Driver Model: Analysis and Application to Adaptive Cruise Control" (2014). *All Theses*. 1934.
https://tigerprints.clemson.edu/all_theses/1934

Matthew, T. V. *Microscopic traffic flow modeling*. Retrieved December 10, 2021, from https://www.civil.iitb.ac.in/~vmtom/1100_LnTse/509_InTse/plain/