Proceedings of the 2020 Winter Simulation Conference
K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, eds.

ASSESSING THE IMPACT OF HETEROGENEOUS TRAFFIC ON HIGHWAYS VIA AGENT-BASED SIMULATIONS

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ABSTRACT

Rules that govern highways are very different across countries. For instance, in the USA, most of the highway traffic is comprised of cars and trucks; whereas in India, there are more types of vehicles that use the highway. Each vehicle type has its characteristics and capabilities, thus causing variation in driver preferences, especially the preferred-speed. We investigate if this heterogeneity leads to an increase in the number of lane changes, which could potentially lead to an increase in accidents. We use Agent-Based Modeling to compare the interaction between vehicles in two simulations, one representative of the traffic in the USA and the second representative of traffic in India. The results show that increased heterogeneity in vehicle types causes a significant increase in the number of lane changes. These results have broader implications for traffic policy-making and bring into focus the need for minimum-speed limits and dedicated lanes for slower vehicles.

1 INTRODUCTION

In today's fast-paced world, highways help in connecting people, trade, and transportation of products. Highways play a very important role in disaster evacuations while also contributing towards the security of a country. Many developed nations already have highly efficient highway systems. India is catching up fast and building highways that are capable of supporting high speed and high volume traffic. Nevertheless, the current rules and regulations governing the traffic in Indian highways are different from that of developed nations and might require revisions to meet the fast growing demands. For example, some freeways in the United States have enforced limits for both minimum and maximum speeds (Michigan Legislature. 2006). Even when not explicitly enforced in some states, people refrain from accessing the freeways with slower vehicles like bicycles and mopeds. Whereas in India, there is no such implementation of a minimum speed limit on the Indian National Highways and people are free to access the highway with slower vehicles. Consequently, there is a considerable proportion of slow vehicles on Indian highways. Figure 1 illustrates the typical heterogeneous traffic condition in India. Drivers driving much faster and much slower than the general traffic stream are more likely to be involved in accidents (Finch 1994). In India, about 20-40% of fatalities on the highway consists of bicyclists and slower vehicles. There is a possibility that allowing slower vehicles on highways with high speed limits could cause more accidents.

A driver's preferred speed is dependent on the geometry of the road and vehicle characteristics, more so than individual driver characteristics (Quimby et al. 1999). Consequently, drivers tend to have different preferred-speeds based on the vehicle type and the geometry of the road. Highways in India experience more heterogeneity when compared to highways in the developed nations i.e. there are more types of vehicles

978-1-7281-9499-8/20/$31.00 ©2020 IEEE

on Indian highways in comparison to developed nations. This heterogeneity would in turn result in more differences in preferred speeds among drivers. The primary objective of this study is to explore the risks of higher heterogeneity in highway traffic. Through our simulations, we show that higher heterogeneity increases the number of lane changes drastically. It is known that lane changing is one of the primary causes of traffic oscillation and accidents. Taken together, this indicates that increase in heterogeneity could indirectly lead to more accidents and therefore, less safer conditions for highways.

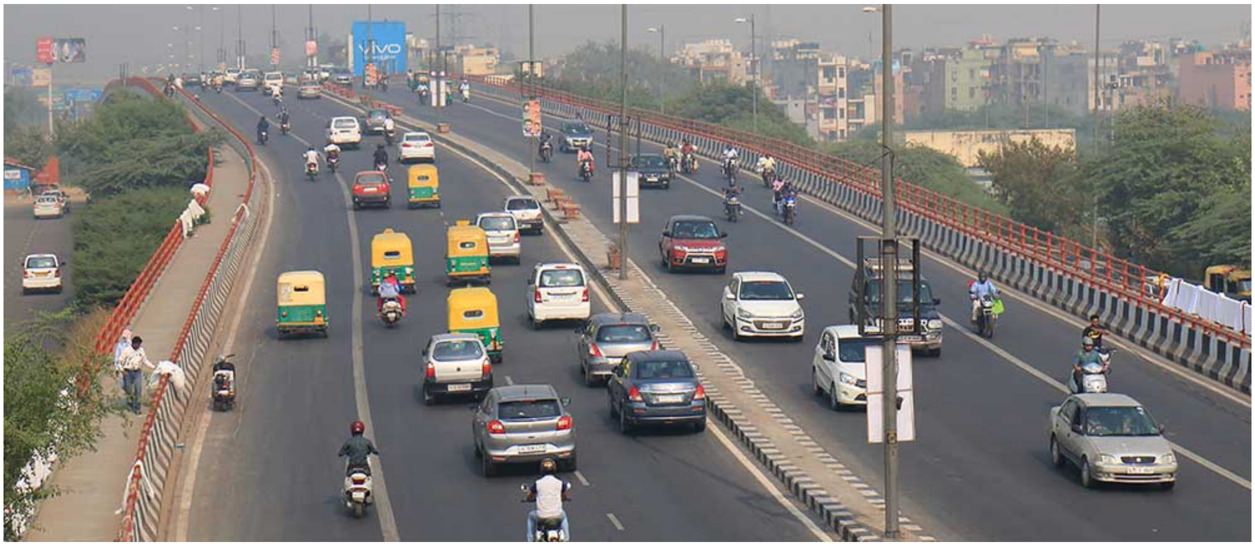

Figure 1: Highways in India (Kumar 2018).

Previous studies investigated the safety effects of differential speed limits on highways (Garber et al. 2003) and compared various strategies for differential speed limits (Ghods et al. 2012). Wilmot and Khanal (1999) analyzed driver behavior in adhering to posted speed limits. More recently, Raju et al. (2019) and Asaithambi et al. (2018) studied vehicle following behaviour in heterogeneous traffic conditions in India and compared the trajectory data to validate various car following models. But, to our knowledge, there have been no studies which explores the safety implications of heterogeneous traffic in Indian Highways.

Several Transportation research studies have used Agent-based modeling for microscopic traffic simulations and to study emergent phenomenon (Ghods et al. 2012; Nguyen et al. 2014; Lansdowne 2006). ABM allows simulation of driver behavior according to a predefined set of rules. NetLogo (Wilensky, U 1999), TRANSIMS (Smith et al. 1995), and MATSim (Axhausen et al. 2016) are some of the widely used agent-based modeling platforms for traffic simulation. In this study, we use NetLogo (Wilensky, U 1999), which has been used successfully in several traffic simulation studies (Schindler 2013; Lansdowne 2006). Schindler (2013) used NetLogo to run microscopic simulations using data from traffic studies to propose with a frugal adaptive cruise control strategy for autonomous traffic-jam clearance. Lansdowne (2006) designed a detailed traffic simulator using NetLogo. He analyzed the effect on traffic congestion when various different lanes of traffic are introduced using lane-changing, sources, sinks and traffic lights. We have implemented the Intelligent-Driver Model(IDM) (Treiber et al. 2000) for car-following and Minimizing Overall Braking Induced By Lane change(MOBIL) (Kesting et al. 2007) for lane-change decisions in NetLogo. Additionally, we incorporated a method to simulate estimation errors from the Human Driver Model(HDM) (Treiber et al. 2006). Finally, we took the idea of level-of-service from the Intelligent Driver Model with Memory(IDMM) (Treiber and Helbing 2003) and have used it to calibrate MOBIL, to simulate the effects of driver frustration in lane changing decisions.

The remainder of the paper is structured as follows: First, we present the components of the model. Second, we look at the NetLogo platform and the details of our model implementation. Third, we present and analyse the results of our simulations, and discuss the implications. Finally, we present our conclusions along with our plans for future work.

2 MODELING DRIVER BEHAVIOR

We model human driving behavior on a one-way road section of a two lane highway. Our model consists of multiple vehicular agents interacting with each other. When modeling driver behavior, we need to consider car-following dynamics and lane-change decisions. Moreover, to understand the causes that could lead to accidents, the model should incorporate a mechanism to simulate human imperfections in estimating distance and speed. Furthermore, humans have emotions that play an important role in their behaviour and any accurate model of human driver should incorporate this. Thus, our model consists of 4 major components:

1. **Intelligent Driver Model(IDM)** (Treiber et al. 2000) as the car-following model.
2. **Minimizing Overall Braking Induced By Lane change(MOBIL)** (Kesting et al. 2007) as the lane-changing model.
3. **Human Driver Model (HDM)** (Treiber et al. 2006) to simulate the imperfect estimations of human drivers.
4. An adaptation of the **Intelligent Driver Model with memory (IDMM)** (Treiber and Helbing 2003) on MOBIL to simulate the non-instantaneous adaptation of the driving behaviour towards making lane-change decisions.

In what follows are summaries of the components along with the description of our model implementation.

2.1 Car-following Model

Intelligent Driver Model (IDM) (Treiber et al. 2000) allows the simulation of human car following behavior. IDM is able to reproduce all essential traffic phenomena observed on highways. Raju et al. (2019) found that IDM resembles Indian traffic behavior reasonably well, especially under mixed traffic conditions. Furthermore, IDM features a small number of parameters which are easy to interpret and therefore allow for a intuitive characterization of different driver-vehicle classes (e.g., cars and trucks) and heterogeneous driving behavior. IDM sets the acceleration a equal to the free-flow acceleration for reaching the preferred speed v_0, subtracting a braking-term which increases proportionally based on the current distance s to the preceding vehicle. The acceleration decreases as s becomes smaller than the desired-distance $s^*(v,\Delta v)$. The acceleration of each vehicle is computed based on the following equation.

$$a = a_{\max}\left(1-\left(\frac{v}{v_0}\right)^4-\left(\frac{s^*(v,\,\Delta v)}{s}\right)^2\right)$$

where $a_{\max}$ is the maximum possible acceleration of the vehicle, v is the speed of the vehicle, v_0 is the preferred speed of the driver, $s^*(v,\,\Delta v)$ is the distance the driver would like to maintain with the preceding vehicle, and s is the distance of the vehicle from the preceding vehicle.The desired distance s^* of each vehicle is based on the following equation.

$$s^*(v,\,\Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{a_{\max}b}} \tag{1}$$

where s_0 is the minimum allowed distance between vehicles, Δv is the speed difference to the preceding vehicle, b is the comfortable deceleration of the driver, and T is the safe time headway. Thus, using IDM we can easily simulate car-following behavior of different vehicle classes and different driver preferences by calibrating the five model parameters: maximum acceleration($a_{\max}$), the safe time gap(T), the comfortable deceleration(b), the preferred speed(v_0), and the minimum jam distance(s_0).

2.2 Lane Changing Model

Minimizing Overall Braking Induced By Lane change (MOBIL) (Kesting et al. 2007) is a lane change decision model which works alongside a wide class of car following models including IDM. In MOBIL, the decision to change lanes is derived based on the utility of being in a lane and the associated risks of a lane change. MOBIL incorporates the utility and risks via two criteria to decide whether to change lanes - a safety criterion and an incentive criterion. To change the lane, both must be satisfied. The safety criterion assures that the potential new follower does not have to brake too abruptly. In mathematical terms: if $\tilde{a}_n >= -b_{\text{safe}}$, where $\tilde{a}_n$ is the acceleration of the new follower after changing the lane and b_{safe} is the critical deceleration. The incentive criterion assures that the lane change is actually beneficial, using a utility measure. The utility is measured using the changes in accelerations of the vehicle, the new follower, and the old follower as shown in the following equation.

$$\tilde{a}_v - a_v + p\left(\tilde{a}_n - a_n + \tilde{a}_o - a_o\right) \geq \Delta a_{\text{th}}$$

where a_v, a_n, and a_o are the current accelerations of the vehicle, the new follower, and the old follower respectively and $\tilde{a}_v$, $\tilde{a}_n$, and $\tilde{a}_o$ are the anticipated future accelerations of the vehicle, the new follower, and the old follower respectively. The decision to change lane is made once the utility measure exceeds the threshold parameter Δa_{th}. The politeness of the driver is denoted using the second model parameter p which ranges between 0 and 1. p regulates the degree to which the driver considers the gains and losses of other drivers. When p is closer to 0, it signifies the driver having an egoistic lane change behavior and not considering the effect of his decision to change lanes on other drivers. When p is closer to 1, it signifies a very polite driver who is considerate of the consequences of his lane-changing decision on other drivers, more so than his own gains.

2.3 Human Driver Model

Humans make systematic errors while estimating speeds of other vehicles and distance between vehicles (Schmidt and Tiffin 1969; Gordon and Mast 1970). To simulate this, we introduced human imperfections into our model as described in the Human Driver Model (HDM) (Treiber et al. 2006). Humans can not perform an indefinite number of decisions per unit of time. Hence, at every time step Δt, the drivers observe the traffic and make a decision whether to accelerate or slow down. This acceleration value would remain constant for the next interval Δt. For our experiment, Δt is equal to one tick, which was roughly equal to the tenth of a second. There are two types of estimation errors : an error in calculating the distance between vehicles, and the other in approximating the differences in speed. The estimated distance was calculated using the following equation.

$$s^{\text{est}}(t) = s(t)\exp\left(V_s w(t)\right)$$

where s^{est} is the driver's estimation of distance from preceding vehicle, $s(t)$ is the actual distance from preceding vehicle, and V_s is the distance error constant. The estimated speed difference was calculated using the following equation.

$$v^{\text{est}}(t) = \Delta v(t) + s(t) r_c w(t)$$

where v^{est} is the driver's estimation of speed difference to the preceding vehicle, $\Delta v(t)$ it the actual speed difference to the preceding vehicle, and r_c is the estimation error constant. $w(t)$ is a stochastic variable following a Wiener process of variance 1 with correlation time τ. HDM uses independent Wiener processes for distance and time estimation. Whereas, in our implementation, for simplicity, we use the same Wiener process for both. The Wiener process is implemented using the approximations, as shown in the following equation.

$$w(t) = e^{-\Delta t/\tau} w(t-\Delta t) \;+\; N(0,1)\sqrt{\frac{2\Delta t}{\tau}}$$

where $N(0,1)$ is the normal random variable with mean equal to 0 and variance equal to 1. HDM augments basic physics oriented traffic model with (i) finite reaction times, (ii) estimation errors, (iii) spatial anticipation, and (iv) temporal anticipation. For sake of simplicity, in our microscopic simulation, we have only incorporated estimation errors using the equations shown above.

2.4 Driver Adaptation Model

Intelligent Driver Model with memory (IDMM) (Treiber and Helbing 2003) models a memory effect in drivers using a level of service parameter $\lambda(t)$. It simulates the changes in model parameters like safe time headway(T), demonstrating the "frustration effect" caused due to congested traffic. For instance, it was observed in Netherlands that the average safe time headway(T) increased with congestion (Treiber and Helbing 2003). This effect occurs due to inability to drive at preferred speeds. The level of service parameter $\lambda(t)$ is the exponential moving average of the ratio of speed(v) to preferred speed(v_0). IDMM uses a continuous form of exponential moving average to vary the level of service parameter. Changes in safe time headway (T) are discussed as a function of the level of service parameter. The level of service parameter can also be used to vary other IDM parameters like preferred-speed(v_0), max-acceleration($a_{\max}$), and comfortable-deceleration(b). We take inspiration from IDMM and use $\lambda(t)$ to vary the politeness from MOBIL. As our model is discrete, we use the discrete form of exponential moving average to compute $\lambda(t)$ (Hunter 1986). The politeness parameter (p) was calculated using minimum politeness($p_{\min} = 0$), maximum politeness($p_{\max} = 1$), and the level of service parameter $\lambda(t)$. The following equation was used to compute politeness with time.

$$p(t) = (\lambda(t) * p_{\max}) + ((1-\lambda(t)) * p_{\min})$$

The level of service parameter $\lambda(t)$ is a function of the discrete form of Exponential Weighted Moving Average(EWMA)(Hunter 1986) of the ratio of speed to preferred speed. The level of service parameter at time t was calculated using the following equation.

$$\lambda(t) = \left(\alpha * \left(\frac{v}{v_0}\right)\right) + ((1-\alpha) * \lambda(t-1))$$

Here, α is the weighting factor. It determines the contribution of older politeness values. As the minimum and maximum politeness were 0 and 1 respectively, the politeness parameter (p) became equal to the level of service parameter $\lambda(t)$. Note that the level of service parameter in our model is not used to vary any of the IDM parameters in this model as that IDM does not contribute much towards inter vehicular interaction, which is the focus of this paper.

3 MODEL IMPLEMENTATION

NetLogo consists of 3 types of agents - Turtles, Links, and Patches. Out of these, we only use turtles and patches for our simulation. Turtles are free agents. They have a defined shape, size and can move freely. Turtles can have different properties by being classified using breeds. Patches are stationary agents. Patches can be of different colors, but all patches will have the same size. Time in NetLogo is measured in terms of ticks. We use patches to set up the lanes and to measure distances.

In our simulation, each vehicular agent is a turtle. Their shape and characteristics, such as speed and acceleration, depend on the type of vehicle. The vehicle types include cars, trucks, buses, and motorbikes. For the behavior of the vehicular agents, we have implemented the car-following model IDM, the lane-changing model MOBIL, imperfect estimations from HDM, and a memory effect similar to IDMM, as described in the previous sections.The model parameters for each vehicle type can be controlled via the

NetLogo interface shown in Figure 2. The interface consists of a *view*, *sliders*, *buttons* and a *drop-down*. The parameters are as follows:

1. **[vehicle]-max-acceleration(a_{max}):** Acceleration of a vehicle. It is measured in $patches/tick^2$.
2. **[vehicle]-comfortable-deceleration(b):** Deceleration most vehicles follow for that vehicle type. It is measured in $patches/tick^2$.
3. **[vehicle]-max-deceleration(b_{safe}):** The maximum deceleration a vehicle type can have. It is measured in $patches/tick^2$.
4. **[vehicle]-preferred-speed(v_0):** The preferred speed of the vehicle type. It is measured in $patches/tick$.

Other parameters, which are common for all vehicle types are as follows:

1. **lane-change-threshold(Δa_{th}):** The threshold of acceleration benefit at which a vehicle changes lanes.
2. **weighting-factor(α):** The contribution of past politeness towards current politeness.
3. **estimation-error(r_c):** Average estimation of the time to collision.
4. **distance-error(V_s):** Variation co-efficient of the distance estimate.

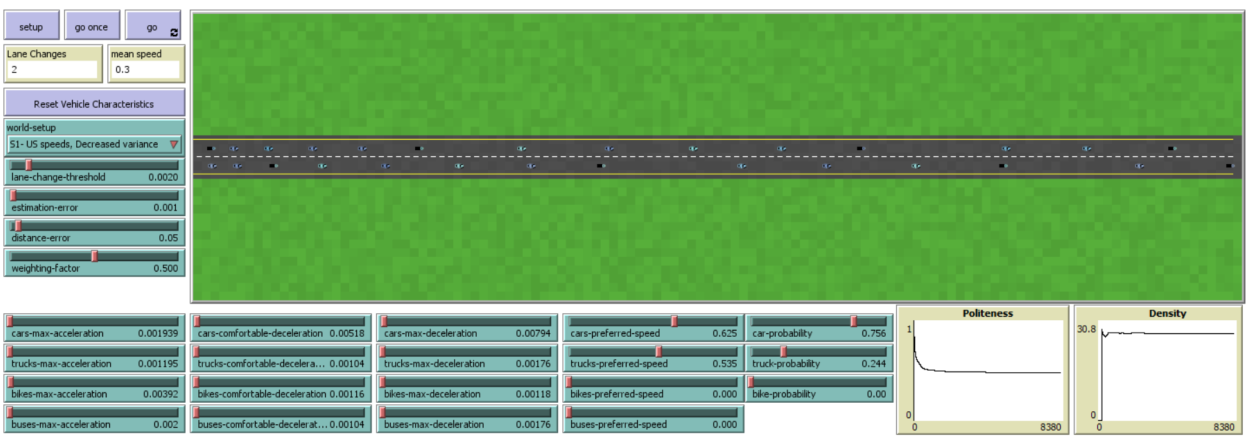

Figure 2: NetLogo model interface.

The NetLogo Traffic 2 Lanes model (Wilensky, U., and N. Payette. 1998), which can be found in the NetLogo models library, is free for use and provided the basic design for the environment of the model. When the model is initialized, patches are assigned as lanes, grass and intermediary patches between lanes that show the dividing line. For spawning, each vehicle had it's own probability based on traffic compositions.

3.1 Simulating Traffic Flow

The view in our simulation is analogous to a camera set in the sky to observe a stretch of a highway, where the traffic moves from left to right. So, in the simulation, when an agent is spawned at the right edge, it represents a vehicle coming into the view of the camera. Likewise, when an agent reaches the left edge, it is removed, representing the vehicle moving out of the camera view. Accordingly, the spawning (initial) speed of the vehicular agent should be representative of the speed of a vehicle entering the view of the camera in the real world. Our implementation for spawning an vehicular agent takes these factors into consideration. Vehicles are spawned only if there are no vehicles in the first two patches of each row. If the first two patches of a particular lane have no vehicles, a vehicle will try to spawn based on the vehicle's spawn-probability. Preferably, the speed of the vehicle is set such that there is no sudden braking, to simulate freely moving traffic. We use the distance between the spawned vehicle and the preceding vehicle, to compute *comfortable speed*(v_c). The speed is computed by reversing Equation (1) and setting the desired distance $s^*(v,\Delta v)$ equal to s, the current distance. Thereby, the comfortable speed guarantees that a vehicle does not go through sudden drastic deceleration after spawning, as the distance between itself and the preceding vehicle is already at a comfortable range. The following equation is used to calculate the comfortable speed. Note that all the parameters in this equation are from IDM.

$$v_c = \frac{v_{\text{front}} - 2T\sqrt{a_{\max}b} + \sqrt{(2T\sqrt{a_{\max}b} - v_{\text{front}})^2 - 8(s-s_0)\sqrt{a_{\max}b}}}{2}$$

where v_{front} is the speed of the preceding vehicle and s is the distance from the preceding vehicle. The stretch of road in the vision of the camera was 121 patches wide, each lane was one patch wide and each vehicle was one patch long.

According to NHTSA(National Highway Traffic Safety Association), rear-end collisions account for approximately 30% of all crashes; Out of which distracted drivers caused 87 percent of rear-end collisions (Lee et al. 2007). This served as an inspiration to focus on read-end collisions. A rear-end collision is detected when two vehicles collide i.e. the agents have their x or y coordinate within 1 patch of each other. After a collision, a vehicle turns into a crashed vehicle and is removed from the model after 3 ticks.

NetLogo does not enforce an order in which turtles are updated. The turtles are updated in a random order. But for synchronicity, vehicles need to be updated in a specific order. As the vehicles in our model move from left to right, we implemented a procedure to update the agents in the order from right to left to ensure synchronicity of the model. For model simplicity, we made the following assumptions:

1. All vehicular agents of the same type have the same characteristics (such as preferred speed and acceleration) to reduce unwanted randomness that could affect the results. The values used for each type of vehicle are shown in Tables 1, 2, 3 and 4.
2. The acceleration characteristics of buses are the same as trucks, as shown in Table 2, because of similar engine characteristics in India.
3. All vehicles have the same patience and error characteristics, as shown in Table 6, irrespective of the vehicle type.
4. All vehicles have the same size as we are not interested in the contribution of vehicle dimensions in accidents at this point of time.
5. Vehicles instantaneously change lanes, eliminating the occurrences of sideways collisions. Similar assumptions were made by multiple studies (Schindler 2013; Kesting et al. 2007).

4 EXPERIMENTS AND ANALYSIS

4.1 Experiment 1

Our goal was to compare the highway conditions in developed nations, with less heterogeneous traffic, to developing nations with more heterogeneity. For experiment-1, we consider USA highways as a representative example of developed nations and India as the example for developing nations.

Setup 1 simulates the highway condition in USA. Here, the speed limits of Michigan Urban Interstates from Governors Highway Safety Association (2018) is used as the preferred-speed parameters. We use acceleration values from Yang et al. (2015). The traffic composition for this setup is taken from Hallenbeck et al. (1997). According to Pew research findings, 88% of U.S households own a car where only 14% own a motorcycle (Poushter, J 2010). Also, as shown in Hallenbeck et al. (1997), the percentage of motorcycles on US highways is 0.2%. Hence, we ignore motorcycles for this setup, because of the low probability. We do not consider buses in setup-1 for a similar reason. The only types of vehicles considered for this setup are cars and trucks, because of their significant presence.

Setup 2 simulates the condition in India. We use the speed parameters from a spot speed survey conducted in Ludhiana, Punjab, India (Naidu 2018). We use acceleration values from Bokare and Maurya (2017). The types of vehicles simulated are cars, trucks, motorbikes, and buses. The composition for this setup is taken from Jain et al. (2011).

All speed and accelerations values were converted into m/s and m/s^2. In the simulation, 1 patch equals 5 meters and 1 tick corresponds to 0.1 seconds. The values were scaled appropriately and shown in Tables 1, 2, 3 and 4. Table 5 shows the vehicle composition used for each setup. Other values used in the model were scaled down and are shown in Table 6.

Table 1: Acceleration conversions from Yang et al. (2015) for Setup 1.

Vehicle	**Reported** (m/s^2)	**Scaled** ($patches/tick^2$)
Car	0.97	0.001939
Truck	0.6	0.001195

Table 2: Acceleration conversions from Bokare and Maurya (2017) for Setup 2.

Vehicle	**Reported** (m/s^2)	**Scaled** ($patches/tick^2$)
Car	2.24	0.00448
Truck	0.87	0.00174
Motorbike	1.96	0.00392

Table 3: Speed conversions from Governors Highway Safety Association 2018 for Setup 1.

Vehicle	**Reported** (m/s)	**Scaled** ($patches/tick$)
Car	31.291	0.626
Truck	26.821	0.535

Table 4: Speed conversions from Naidu (2018) for Setup 2.

Vehicle	**Reported** (m/s)	**Scaled** ($patches/tick$)
Car	20.833	0.416
Truck	15.278	0.305
Motorbike	19.444	0.389
Bus	18.056	0.361

Table 5: Vehicle composition of each setup.

Vehicle	**Setup 1 Composition**	**Setup 2 Composition**
Cars	0.756	0.385
Trucks	0.244	0.275
Bikes	0	0.245
Buses	0	0.095

Table 6: Values used for vehicle-following and lane-changing models.

Parameter	**Reported Value**	**Used Value**
Minimum Distance(s_0)	2	0.4
Safe time headway(T)	1.6	16
Estimation error(r_c)	0.01	0.001
Distance error(V_s)	0.05	0.05
Lane change threshold(Δa_{th})	0.1	0.002

Each setup was run for 10 iterations. Each iteration was run until 10,000 vehicles entered the vision of the camera(*view*).

4.1.1 Results

We recorded the number of lane-changes, the average politeness of all vehicles, and the average number of vehicles in the view(Average Vehicle Count) until 10,000 vehicles spawned. Results of Setup 1 and Setup 2 are shown in Table 7 along with Setup 3 which we discuss in Experiment 2. Likewise, Figure 3 shows the visual representation of the number of lane changes for all three conditions.

The results are consistent with our hypothesis. Setup 2, the Indian Highway condition, has significantly more number of lane-changes than Setup 1. However, Setup 2 has higher average politeness when compared to Setup 1. We explain the reasons for this latter in the discussion section. The lower preferred speeds in setup 2 explains the lower average Vehicle Count. Obviously, vehicles with low speeds will take more time to cover the distance and require less gap from the preceding vehicle. The results of the two setups were compared using a independent samples single tailed t-test. There was a significant difference in the number of lane changes for Setup 1 (M=134.40, SD=13.3267) and Setup 2 (M=1,178.70, SD=68.2447); t(9)=-47.49, $p < 0.00001$.

4.2 Experiment 2

Some newer expressways in developing countries have regulations that restrict slower vehicles. For instance, Ahmedabad-Vadodara Expressway in India doesn't allow two-wheelers on the expressway. This rule is yet to be seen on National Highways in India. This served as motivation for another setup which would restrict vehicle types but with the same speed and acceleration parameters as Setup 2. Moreover, we wanted to test the contribution of difference in preferred-speed alone towards increasing lane changes.

Setup 3 simulates a hypothetical highway in India without motorcycles and buses. The composition used was that of Setup 1 (USA), while the vehicular characteristics such as speed, acceleration, deceleration were same as Setup 2 (India).

4.2.1 Results

The results for Setup 3 are shown in Table 7. Surprisingly, Setup 3 had a much lower number of lane-changes when compared to Setup 2. But Setup 3 consistently had more lane-changes than Setup 1. As

Table 7: Results for all the setups.

Setup	**Lane Changes**	**Average Politeness**	**Average Vehicle Count**
Setup 1	134.4	0.474445	26.9003
Setup 2	1,178.7	0.5962999	46.2065
Setup 3	189.6	0.639154	31.5168

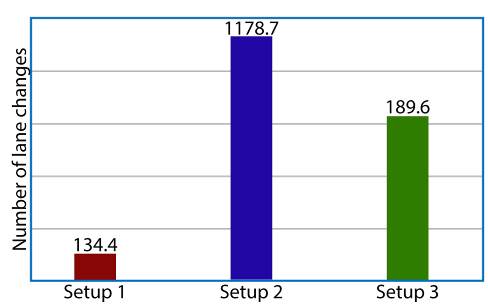

Figure 3: Lane changes in the three Setups.

we suspected, this could be because of the difference in preferred speeds. Setup 1 had a lower difference between the preferred speeds of cars and trucks when compared to Setup 3. Speed variance causing more vehicular interaction was first discussed by Solomon (1974). The results of the three setups were compared using a one-way between subjects ANOVA test. There was a significant difference in the number of lane changes for Setup 1 (M=134.40, SD=13.3267), Setup 2 (M=1,178.70, SD=68.2447) and Setup 3(M=189.60, SD=18.2708); f-ratio=2004.2773, $p < 0.00001$.

5 DISCUSSION AND FUTURE WORK

Results of Experiment-1 reveal that the increased heterogeneity (more types of vehicles) significantly contributes to increasing the number of lane changes on highways. Experiment-2 shows that the difference (or range) in preferred-speed between the fastest and the slowest vehicle on the highway is another factor that increases the number of lane changes. Even when the heterogeneity was decreased for setup 3, the number of lane changes were still higher than that of Setup 1. Also, we anticipated that frustration would be higher for Setup 2, with high heterogeneity. But, Setup 2 has more vehicles with lower preferred speed. Slower vehicles reach their preferred speed easily and this leads to higher average politeness. For instance, Setup 3 results show that politeness increases when the average preferred-speed is reduced. In the future, we plan to investigate more about the nature of this relationship.

Most of our model parameters are either from real world data or from prior peer-reviewed studies. While realistic parameters increase the overall accuracy, this affected the number of accidents. We noticed insignificant number of accidents for several experimental runs. We argue that this only validates our model and the drastic variation in the number of lane changes because of heterogeneity is interesting in its own right. To keep the simulation tractable, we use speed limits from the United States and assume it to be indicative of average speed of vehicles in the highway, but we use spot speed survey for simulating vehicles of India. This was because we found it difficult to obtain spot speed survey similar to Naidu (2018). Moreover, we found similar studies (Ghods et al. 2012) that used speed limits for their simulations. In addition, India has a poor record of speed limit compliance in comparison to western nations (Bains et al. 2013; Parker 1997). Accordingly, we decided to use spot speed surveys done by Indian Universities (Naidu 2018). Another simplification, is using MOBIL which does not simulate lane-change execution or trajectory. The transition between lanes are instantaneous, similar to many microscopic simulations using MOBIL (Schindler 2013; Kesting et al. 2007).

We believe Indian highways can be made safer by enacting dedicated lanes for vehicle-class wise traffic similar to some European countries (Basu and Vasudevan 2013). The class of the vehicle can be determined based on its speed characteristics. While some of our other policy proposals are in its nascent stage to present in detail, we note that there are many more that can be explored. In the future, we plan to expand our simulation to test new road-sharing policies and their impact on highway safety.

6 CONCLUSION

In this paper, we present the results of agent-based simulations, comparing highway traffic in developed nations and developing nations. We took United States and India as representative of developed and developing nations respectively. International Energy Agency (IEA) predicts that the passenger car ownership in India will grow significantly over the next two decades. As a result, this could lead to a potentially hazardous situation where the highways need to be shared between vehicles capable of very high speeds and low-speed vehicles, which are commonplace in India. Our results show how this could lead to an increase in the number of lane changes and thereby, indirectly contribute to an increase in the number of accidents. While there could be other factors, our analysis indicates that heterogeneity and range of preferred speeds as important factors that contributes to the increase in the number of lane changes. The study was done with the motive of improving safety of the Indian highway systems, but we notice that it broadly applies to highways on other nations, both developing and developed.

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