Risk-oriented Behavior Design for Traffic Simulation

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Abstract: With the advent of the autonomous vehicle and the transformation of the automobile sector in the next decade, road traffic simulation has taken off again, and behavioral testing represents a significant area. A collision is a potentially complex phenomenon that is very difficult to study. In most tools, collisions are predefined phenomena, preventing the study of behavioral factors' impacts on these collisions. The notion of risk-taking is essential in individual driving behavior to obtain realistic traffic at both the macroscopic (flow) and microscopic (individual behavior) levels. We propose a model where collisions are unpredictable emerging phenomena resulting from individual deterministic behaviors where risk-taking parameters ease the design of various behaviors.

1 INTRODUCTION

Behavioral testing represents a significant area in traffic simulation. To test a vehicle, it must face various vehicles characterized by different behaviors within an environment. However, creating environments is not an easy task. Many tools, e.g., like SUMO (Krajzewicz et al., 2006), generate by default regular flows of vehicles with homogeneous behavior most of the time. As it is often the case, extensions can alter the default simulator behavior (e.g., via Traci (Wegener et al., 2008) in this case) to get around this issue, but this requires an entirely different skill set.

We can also study the impact of behavioral factors on collisions. However, a crash is a potentially complex phenomenon that is very difficult to analyze: a driver taking many risks will not necessarily have an accident, while others driving more cautiously may suffer from one. Databases of insurance companies, police, or governmental institutions (e.g., databases from ONISR[1]) are purely factual and only contain information about the context of accidents, but nothing indicates the triggering element. Most tools simulate accidents either as predetermined or stochastic events and not as interactions between deterministic behaviors leading to an accident. Although studies of risk-taking behavior exist (such as (Iversen, 2004) or (Ram and Chand, 2016) for example), they always start with a few surveys of the number of drivers and do not provide tools or models to test hypotheses.

Many models exist such as Krauss (Krauß, 1998), Gipps (Gipps, 1981) or IDM ("*Intelligent Driver Model*") (Treiber et al., 2000) as car-following models or MOBIL (Kesting et al., 2007) for lateral displacements, to name only the most widely known. The vast majority of these models start from a physical description of the phenomena (including parameters such as turning radius, longitudinal/lateral velocities, grip/slope of the road). Writing a specific driver behavior proves to be an arduous task for a non-specialist. Many tools exist and do not consider the same level of details. Low-level details tools only consider undifferentiated vehicle flows (vehicles have a decorative role) while others, on the contrary, focus on physical phenomena. In both cases, behavioral hypothesis testing is difficult: the non-specialist has to identify how the new behavioral parameter affects all parameters from the model. These impacts are difficult to identify since the number of parameters is high.

We position ourselves at the image Scanner (Champion et al., 1999), Sumo (Krajzewicz et al., 2006), Vissim (Fellendorf, 1994), Trafficgen (Bonhomme et al., 2016), Movesim (Treiber and Kesting, 2010) or MATISSE (Al-Zinati and Wenkstern, 2015) at an intermediate level of details where vehicles are individualized and endowed with their own behavior.

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[1] ONISR: Observatoire National Interministériel de la Sécurité Routière – https://www.onisr.securite-routiere.gouv.fr/

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The environment is a flat and perfect road network whose topology is provided by geographic information systems like *OpenStreetMap* or *GoogleMaps*. These tools developed from both an academic and an industrial point of view often have a different objective than ours. Some of them focus on infrastructure testing such as (Fellendorf, 1994), coordination between vehicles (Bonhomme et al., 2016) (Tlig et al., 2012) or simulation of realistic vehicle flows (Kesting et al., 2007).

We argue that the notion of risk-taking is essential in individual driving behavior to obtain realistic traffic at both the macroscopic (flow) and microscopic (individual behavior) levels. Without risk-taking, accidents (resulting from interactions between vehicles) never occur, but neither is there realistic traffic allowing behavioral testing. In this study, we unify drivers' behavior and vehicles' behavior as assumed in most models. We seek to model driving behavior to study the factors leading to accidents. We aim to capture the core of the phenomenon by identifying the minimal model capable of bringing out accidents resulting from interactions between vehicles.

The remainder of this article follows the structure: Section 2 details the type of situations we aim to simulate. We explicitly consider risk-taking in the modeling to achieve this, as formulated in Section 3, while Section 4 brings an empirical evaluation. The explicit consideration of risk-taking factors allows to exhibit a wide range of behavior, based on a single deterministic behavioral model, and to observe the most common phenomena (traffic jams, aggressive drivers, etc.). Section 5 concludes and describes the perspectives of this work.

2 ARE ALL ACCIDENTS INTERESTING?

An accident model is required to evaluate a behavioral hypothesis. Most tools benefit from a safety mechanism preventing collisions if they should nevertheless occur (e.g., a teleportation mechanism in SUMO). Most traffic simulation tools do not allow accidents/collisions between vehicles. In these platforms, vehicle behaviors' design ensures collision-free traffic. Indeed, their driving models usually need a perfect and complete knowledge of the environment. Each vehicle always perceives others, no matter how far apart they are. These models do not consider risk-taking factors.

SUMO (Krajzewicz et al., 2006), MITSIMLab (Ben-Akiva et al., 2010) and MATISSE (Al-Zinati and Wenkstern, 2015) allow collisions. In SUMO, collisions occur artificially: accidents may arise depending on a dedicated parameter. A vehicle can ignore the minimum bumper-to-bumper distance to maintain and collide with another. In MITSIMLab, collisions are predefined events characterized by a location and a time. In MATISSE, accidents are due to driver distraction (using perceptions' disruption). None of these tools proposes an accident model that explicitly considers risk-taking factors. In all cases, accidents are intended and declared by the user.

Simulators can generate any accident type, but not all are interesting. When studying the taxonomy of road accidents, two categories appear according to the nature and origin of accidents. The first category is completely context-independent and can be considered an endogenous phenomenon: the crash is only due to a unique vehicle, even within dense traffic, which does not mean it won't impact the traffic. It means that even if the driver had been alone on the road, the accident would have happened too. '*A tire bursts*' or '*a driver falls asleep*' are examples of the causes of such crashes. A random generator can simulate such accidents; we do not study a specific endogenous origin like phoning while driving. Thus, we unify all endogenous causes.

The second category is context-dependent and results from interactions between several vehicles. Indeed, it depends on each of the vehicle behaviors present in the simulation: an initial event (e.g., an emergency braking or an inappropriate lane change) leads to a series of consequences that leads to a collision. A crash resulting from sudden braking in a line of vehicles may not occur if their order in that line varies. Since the accident results from a cascade of interactions, one cannot foresee their time and place. This work focuses on this second category, fully supporting simulations since an analytic model based on equations would hardly provide a solution.

A central notion for considering this type of accident in simulation is risk-taking. Driving requires taking more or less risk. If no vehicle takes any risk, the resulting traffic flow isn't realistic: all vehicles respect their safety distance. However, a crash will not necessarily occur even if one takes risks. An accident is a complex phenomenon that is context-dependent (inter-vehicle space, capacities of drivers, duration of braking...). If a vehicle slams on the brakes, it may not have/cause an accident, but a chain of interactions may lead another vehicle further down the lane to a crash. An accident emerges from various interactions according to the risk taken by each vehicle.

3 DRIVING MODEL

3.1 Model Description

As often in literature, the environment $\mathcal{E}$ is a finite set of n lanes: $\mathcal{E} = (\mathbb{R} \times \mathcal{L})$ with $\mathcal{L} = \{\ell_i\}_{i=0}^{n}$. The longitudinal component of the environment is continuous while the lateral component is discrete: a position is an x-coordinate coupled to a lane number.

A vehicle A is characterized by four status parameters and three behavioral parameters. The status parameters are factual and describe the vehicle within its environment by:

- its position: $p_A(t) = (x_A(t), \ell_A(t)) \in (\mathbb{R} \times \mathcal{L})$;
- a perception function φ_A which defines a functional field of vision (considered constant and uniform here) of radius r_A in which A collects relevant information for its decision-making: $\varphi_A : \mathcal{E} \times t \to \mathcal{E}$ such that $\varphi_A(\mathcal{E}, t) = \mathcal{E}_A(t)$;
- an instantaneous speed: $v_A(t)$ bounded such that: $v_A(t) \in [0, v_A^{\max}]$, where $v_A^{\max}$ represents the maximum speed of A;
- an instantaneous acceleration: $\gamma_A(t)$. We assume here that acceleration and braking are constant functions: $\gamma_A(t) \in \{-\gamma_A^{\text{BRA}}, 0, \gamma_A^{\text{ACC}}\}$.

Since vehicles are associated with an instantaneous position, the distance between A and any element e within its perception radius can then be calculated as $\delta_A(e,t) = \sqrt{|x_A(t) - x_e(t)|^2}$. In other words, $\mathcal{E}_A(t) = \{e \in \mathcal{E} | \delta_A(e,t) < r_A\}$. Any vehicle outside the functional field of vision is not part of the vehicle's reasoning and can be considered unknown by the vehicle.

Behavioral parameters characterize the actions of a vehicle by:

- a desired speed $v_A^*(t)$ that vehicle A is willing to achieve;
- an inter-vehicle distance $\delta_A^*(t)$ that A wishes to maintain;
- a risk-taking vector $k_A = (k_A^0, \dots, k_A^4) \in [0,2]^5$ in which each component corresponds to the risk-taking factor towards a different decision-making aspect:
  - k_A^0 represents the compliance with the speed limit required by the environment;
  - k_A^1 defines the FFOV, i.e., the distance below which A uses its perceived information in its decision-making;
  - k_A^2 corresponds to the respect of safety distances and can be used to simulate drivers that put pressure on others by reducing the bumper-to-bumper distance to a minimum;
  - k_A^3 represents the minimum space that A considers necessary with the other vehicles already in the left lane that it wishes to join;
  - k_A^4 is the same space but to the vehicles in the right lane that A wishes to join.

$\forall i \in \{0..4\}, k^i = 1$ represents a driver compliant with the safety regulation. The lower k^i is, the more risk the driver takes regarding the i-th aspect in its reasoning. For example, $k_A^0 = 0.5$ means that A is willing to exceed the speed limit by half. As soon as $k^i > 1$, the driver is overly cautious. However, even if such a driver is not willing to take risks, it does not mean that it cannot suffer from a collision.

3.2 Regulation Mechanism

The status parameters control the movement of a vehicle according to well-known physical laws. The future position of a vehicle A depends on its current position and instantaneous speed:

$$p_A(t+1) = p_A(t) + \frac{dv_A(t)}{dt}$$

Similarly, its future speed depends on its current speed and instantaneous acceleration:

$$v_A(t+1) = v_A(t) + \frac{d\gamma_A(t)}{dt}$$

The speed variation of a vehicle A results from an acceleration choice. Behavioral parameters are involved in the mechanisms of acceleration or speed regulation.

The acceleration of a vehicle A is determined according to the inter-vehicle distance $\delta_A^*(t)$ that this vehicle is willing to maintain if a vehicle B is perceived at front. Otherwise, if A does not perceive other vehicles or if other vehicles are outside its FFOV, the acceleration depends on the cruising speed to achieve. When a vehicle A does not perceive anyone, it aims at driving at the maximum possible speed: $v_A^*(t) = v_A^{\max}$. In other words, if $\mathcal{E}_A(t) = \emptyset$ or $\forall B \in \mathcal{E}_A(t), \delta_A(B,t) > \delta_A^*(t)$, then:

$$\gamma_A(t+1) = \begin{cases} \gamma_A^{\text{ACC}} & \text{if } v_A(t) < v_A^*(t) \\ 0 & \text{if } v_A(t) = v_A^*(t) \\ -\gamma_A^{\text{BRA}} & \text{otherwise} \end{cases}$$

However, if another vehicle $B \in \mathcal{E}_A(t)$ is in a close neighborhood, the acceleration regulation mechanism is based on the inter-vehicle distance and is written:

$$\gamma_A(t+1) = \begin{cases} -\gamma_A^{\text{BRA}} & \text{if } \delta(B,t) < \delta_A^*(t) \\ 0 & \text{if } \delta(B,t) = \delta_A^*(t) \end{cases}$$

3.3 Calibration of Behavioral Parameters

Some parameters like the desired inter-vehicular distance δ^* or the FFOVradius can be calibrated according to a threshold value that ensures a vehicle safety. We have chosen to calibrate our parameters on the stopping distance, which represents the distance required to stop the vehicle completely. The stopping distance of a vehicle A (denoted as Δ_A) depends on its instantaneous speed and braking capacity:$\Delta_A(t) = \frac{-v_A(t)^2}{-\gamma_A^{\text{BRA}}}$. This distance Δ_A therefore depends on the speed of a vehicle. The faster it drives, the greater the distance.

Maximum Speed $v^{\max}$. The risk factor k^0 determines the maximum speed a vehicle is willing to drive. It can simulate respectful drivers as well as unconstrained ones. The maximum speed $v_A^{\max}$ must consider the physical speed limit that the vehicle can reach $v_\varphi^{\lim}$ as well as the driver's interpretation of the limit imposed by the environment $v_\mathcal{E}^{\lim}$ (which it can respect or not). We can thus calibrate $v_A^{\max}$ according to the following relationship:

$$v_A^{\max} = \min((2-k^0)v_\mathcal{E}^{\lim}, v_\varphi^{\lim})$$

Functional Field of Vision Width r. The risk factor k^1 impacts the perception radius r_A and can simulate aware drivers or some that have difficulties perceiving their surroundings. The width of this FFOVcould depend on external factors such as visibility, but that is out of this study's scope. This radius can be indexed to the stopping distance $\Delta^{\max}$ when the vehicle is driving at its maximum speed $v_A^{\max}$. If $\Delta_A^{\max}(t) < r_A$, A's perception area is narrower than its stopping distance: there is a risk of a front-accident, not perceived soon enough. The driver drives too fast regarding its perception and braking abilities.

$$r_A = k^1 \Delta_A^{\max}(t)$$

Desired Inter-vehicle Distance δ^*. The risk factor k^2 is coupled to the stopping distance to define the inter-vehicle distance desired by a driver. It can simulate drivers that urge others either to free the lane/accelerate or peaceful drivers that fear proximity to other vehicles.

$$\delta_A^*(t) = k^2\,\Delta_A(t)$$

In real life, almost no driver strictly complies with the safety distance (otherwise, there would be no such traffic density on the roads). A vehicle A distances himself from a preceding vehicle B depending on the situation: not based on $p_B(t)$ but on $p_B(t+1)$. In other words, a vehicle must stop before the preceding vehicle, otherwise, there will be a collision.

To calibrate δ^*, two thresholds can be defined: the first one based on the stopping distance Δ, the second one on the distance known as *reasoned*, denoted $\widetilde{\Delta}$:

$$\widetilde{\Delta}_A(t) = \frac{v_A(t)^2}{2\gamma_A^{\text{BRA}}} - \frac{\widehat{v_B(t)}^2}{2\widehat{\gamma_B^{\text{BRA}}}}$$

Let us note that this reasoned distance (denoted by $\widetilde{\Delta}$) no longer depends only on instantaneous characteristics of A, but also those of the front vehicle B. $\widehat{v_B}$ and $\widehat{\gamma_D^{\text{BRA}}}$ represents the estimation of B's characteristics by A, depending on the information available (using VANETs or measure equipment). Several cases are possible:

- if $\delta_A^*(t) > \Delta_A(t)$: no risk of collision. The safety distances are maintained such that even if the vehicle in front were to stop instantly, A would still have time to brake without causing a collision.
- If $\widetilde{\Delta}_A(t) < \delta_A^*(t) < \Delta_A(t)$: moderate risk. If the vehicle in front brakes normally, no collision occurs. However, the vehicle in front collides himself with another, he would brake abnormally and cause a new collision at the rear.
- If $\delta_A^*(t) < \widetilde{\Delta}_A(t)$: very significant risk. Collision is not guaranteed, but depends completely on the behavior of other vehicles, especially on the duration of the braking they may perform. The longer they brake, the higher the risk of collision.

Safety during Lane Changes. A vehicle changes from one lane to another as soon as the space available satisfies its criterion. This space is calibrated based on the estimation of the stopping distance of the targeted lane's vehicle. k^3 is dedicated to left-lane changes, whereas changing to a right-lane involves k^4. The decision-making in both cases is different. Indeed, a vehicle changing to the left lane is usually slower than the ones already in it. In contrast, the vehicle changing to the right lane is usually faster. Thus, the space that one may require will vary. As soon as $\delta_A(B,t) \geq k^3\widehat{\Delta_B}(t)$, A considers that the inter-vehicle space is sufficient to safely change lane to the left one. The reasoning is similar when changing to the right lane with k^4.

4 SIMULATION RESULTS

Each risk-taking parameter is illustrated next through an environment designed specifically. Some vehicles (colored in black in the sequel) are used to design a specific context. Then, is added the vehicle we want to study: parallel simulations are used to evaluate various settings for the tested vehicle, within the same context.

Except when explicitly set, all vehicles used in the next simulation correspond to the best-selling vehicle in France (*Clio 4*)'s technical data. A plausible acceleration capacity varies between $2.3m/s^2$ to $3.1m/s^2$ (during a passage of $0km/h$ to $100km/h$ by varying the engine and finishes). Braking varies between $-8.5m/s^2$ and $-11m/s^2$ that corresponds to the average braking capacity respectively on wet (with grip reduced) and dry environments. We choose to set the default acceleration capacity $\gamma^{\text{ACC}} = 3m/s^2$ and the default braking capacity to $\gamma^{\text{BRA}} = -9m/s^2$.

Besides the vehicle parameters, neutral risk-taking parameters are used by default to produce a safety-compliance behavior. The risk-taking vector is then defined as: $k = (1.0, 1.0, 1.0, 1.0, 1.0)$. Only one risk-taking parameter in each experiment series is updated to identify their impact. A simulation tick is sampled to 0.01 seconds in real-time.

4.1 Impact of k^0: Interpretation of Speed Limitation

The environment only requires a single lane with different speed limit sections, as depicted by Figure 1. All vehicles driving in this environment aim at the maximal speed they are willing to drive (computed according to the limit suggested by the environment and the risk-taking factor k^0).

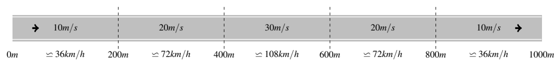


Figure 1: Single lane road with different speed limit section.

Two vehicles A and B are characterized by the following risk-taking vector: $k_A = (1.5, 1.0, 1.0, 1.0, 1.0)$ represents the behavior of a vehicle A that does not take risk and bound its cruising speed to half the speed limitation while $k_B = (0.5, 1.0, 1.0, 1.0, 1.0)$ corresponds to a driver that exceeds the speed limit by half. A third vehicle R, which follows a neutral behavior, is also added for comparison purposes. This third vehicle has instantaneous acceleration and braking. Moreover, while vehicles A and B have the same acceleration capacity ($\gamma_A^{\text{ACC}} = \gamma_B^{\text{ACC}} = 3m/s^2$), B has a braking capacity weaker than A: $\gamma_A^{\text{BRA}} = -11m/s^2$ and $\gamma_B^{\text{BRA}} = -9m/s^2$.

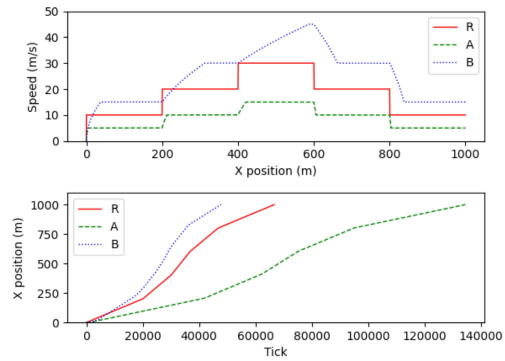


Figure 2: Speed and position of vehicles A and B on the environment described Figure 1, compared to a vehicle R always driving at maximum speed.

The top-most part of Figure 2 shows the speed of A and B compared to the reference vehicle R always driving (instantaneously) at the maximum speed allowed by the environment. It shows that all vehicles adapt their speed according to their interpretation of the speed limitation advised in each section. B bounds its speed to half the limitation, while A always exceeds the speed limit by half. When vehicles leave a road section (the one limited to $30m/s$ for instance), the slopes show that B brakes harder than A and for less time in order to achieve the new desired speed.

The lower part of Figure 2 represents the progression over the kilometer-long road. Because B drives the fastest, it covers the kilometer faster than others. The steeper slope of his progression reflects his constant and faster speed. On the contrary, the shallower slope indicates a lower speed: A needs a lot more time (almost 140000 simulation ticks) to travel the same distance.

4.2 Impact of k^1: Functional Field of Vision

To illustrate the impact of the functional field of vision (FFOV), an environment consisting of a single lane-road is sufficient, as depicted by Figure 3. This figure also describes the context of the case studied. In a single lane road environment, vehicles can only brake when facing a much slower vehicle. These simulations aim to study the vehicles' reactions as soon as they perceive an obstacle according to their risk-taking parameter k^1.

Figure 3: One lane road where the speed is bounded to $20m/s$ ($\simeq 72km/h$). .

All simulations start with a reference vehicle R driving at $10m/s$ only, while the studied vehicle drives at $20m/s$. Different behavioral settings are compared: A is a cautious vehicle $k_A = (1.0, 1.0, 1.0, 1.0, 1.0)$. B takes a little more risk $k_B = (1.0, 0.5, 1.0, 1.0, 1.0)$, whereas C takes a lot more risk since its FFOVwidth is only a quarter of its stopping-distance: $k_C = (1.0, 0.25, 1.0, 1.0, 1.0)$.

Figure 4a shows that A does not take risks: it perceives far enough and thus starts braking in advance to progressively adapt its speed to the slower pace of the front vehicle. B has a shorter range of perception and starts braking later. Its speed decreases abruptly, down to $8m/s$ because the inter-vehicular distance to the front-vehicle is not large enough. Once far enough from R, it accelerates until it matches R's speed. C takes a lot of risk by driving at $20m/s$ while suffering from a small FFOV. It starts braking too late and collides with R.

Figure 4b reproduces the same situation except that R is immobile on the lane. A is still able to stop safely, and C still collides with R after taking too much risk. However, while B was safe before, it now collides with R even if its behavior and setting do not change. Indeed, an accident depends on the context. In both cases, B does not drive according to its perception, but, during the first experiment, R was moving at a slow pace, allowing B to stop soon enough to avoid the collision. However, during the second experiment, B brakes as soon as it perceives R, which is immobile, but too late, and the collision is unavoidable.

Identical behaviors can either lead to a collision or not, depending on the context. Facing a slow-driving vehicle, it can avoid a collision even if it takes some risks. However, the same vehicle driving according to the same behavior will collide when facing an obstacle, e.g., a broken-down vehicle.

4.3 Impact of k^2: Inter-vehicle Distance

The environment required to illustrate the impact of the inter-vehicle distance is similar to the one used to demonstrate the impact of the FFOV, depicted in Figure 3. In these simulations, all vehicles have sufficient perception even to stop facing an obstacle. However, vehicles control the desired inter-vehicular distance, according to k^2. Shortening this distance may represent reasonable behavior under the assumption that nothing unexpected arises (like the preceding vehicle not braking too abruptly). The simulation settings are identical to the ones described in Subsection 4.2. Indeed, all simulations start with a reference vehicle R driving at $10m/s$ only while the studied vehicle drives at $20m/s$. Different behavioral settings are compared: A is a cautious vehicle $k_A^2 = 1.0$. B is a little riskier $k_B^2 = 0.5$), whereas C is significantly riskier because the inter-vehicular distance it is willing to allow with the preceding vehicle is only a quarter of its stopping-distance: $k_C^2 = 0.25$.

Figure 5a shows that a cautious vehicle like A does not collide facing a broken-down vehicle or a slow-moving one. C, which takes a lot of risks, crashes in both cases. Even if its perception is sufficient, such a vehicle does not react unless the inter-vehicular distance is insufficient to its liking. B, which is taking some risks, may or may not collide according to the context. If the preceding vehicle brakes too abruptly (e.g., colliding itself with its front-vehicle), B collides as illustrated in Figure 5b. Such behavior is commonly observed on a highway with dense traffic. Usually, no vehicle strictly complies with the safety distance imposed by regulation, but most maintain a reasonable inter-vehicular distance, allowing them to brake safely. However, as soon as one collides, its braking becomes unusual, and the next vehicle may crash if they take too much risk.

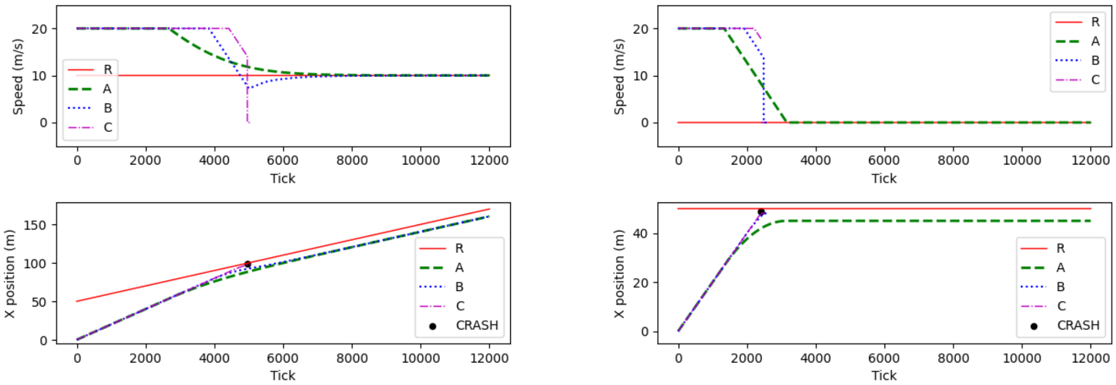
4.4 Within a Traffic Flow

To evaluate the risk-taking parameters within a flow of vehicles, we use generators that create an average vehicle number over a predefined period of ticks. For instance, Figure 6 represents the number of vehicles generated by periods of 2000 ticks. The generator uses the same generation rules and cycles three times. Such a generator can generate any traffic density (even real-data describing flows).

We use such generators (one per lane) in a two-lane environment to simulate congestion. However, since all vehicles take few risks (from neutral to a risk profile where $k^i = 0.75, \forall i \in \{0..4\}$). They adapt their speed in due time, and eventually, all vehicles drive at the same speed without colliding. Even if the initial speeds of vehicles are different, they quickly converge towards the same value.

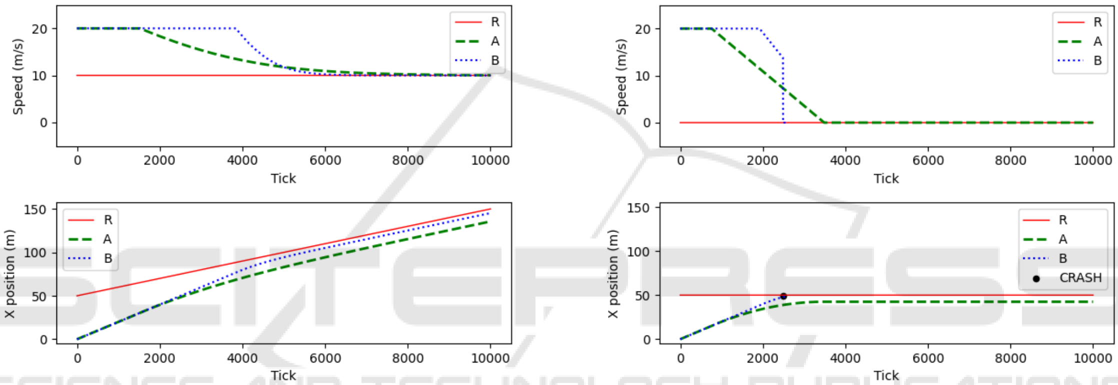
However, as soon as 10% of vehicles generated are willing to take more risks (down to a risk profile $k = (0.5, 0.5, 0.5, 0.5, 0.5)$), collisions occur. A lot of acceleration and braking (that mostly occurs when vehicles change from one lane to another). Uncaring vehicles do not consider the safety distance between themselves and the one in the other lane. A chain of braking interactions occurs and ends as soon as one in the chain takes a little more risk than others and crashes.

The environment considered is a two-lane highway 3 kilometers long where the speed limit is at $35m/s$. A vehicle generator is placed at the beginning



(a) R driving at $10m/s$ (b) R immobile

Figure 4: Speed and position of vehicles A, B and C (all driving at $20m/s$) on the environment described Figure 3, facing a vehicle R (a) driving at $10m/s$ or (b) immobile, according to different k^1 values.



(a) R driving at $10m/s$ (b) R immobile

Figure 5: Speed and position of vehicles A, B and C on the environment described Figure 3, facing a vehicle R (a) driving at $10m/s$ or (b) immobile, according to different k^2 values.

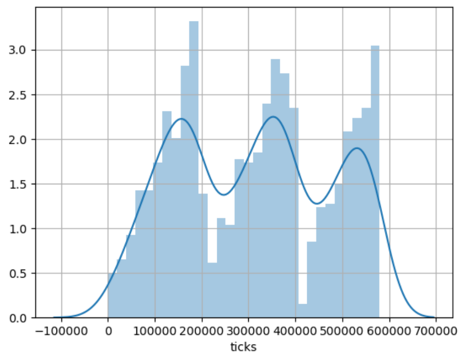


Figure 6: Number of vehicles generated per 2000 ticks-period, cycling three times.

of each lane to certify the traffic density on the road. These generators produce new vehicles regularly (every 250 ticks), which do not take risks with $k = (1.1, 1.1, 1.1, 1.1, 1.1)$. At tick 10000, an important increase in the generation rhythm, including uncaring vehicles, characterized by $k = (0.5, 0.5, 0.5, 0.5, 0.5)$ during 10000 ticks. As depicted by Figure 7, it is possible to evaluate the rate of vehicles crashing and identify their type. Accidents occur as soon as the proportion of uncaring vehicles in the environment increases. Indeed, the actions of a few of them are "swallowed" by the flow and others compensate for the mistakes of these few. However, even if the generation of uncaring vehicles stops after 10000 ticks, collisions continue to occur afterward. These vehicles generate waves of braking that persist even after they have passed.

5 CONCLUSION

Behavioral testing is becoming increasingly important, especially with the interest in autonomous vehicles. However, it is a difficult task as it requires

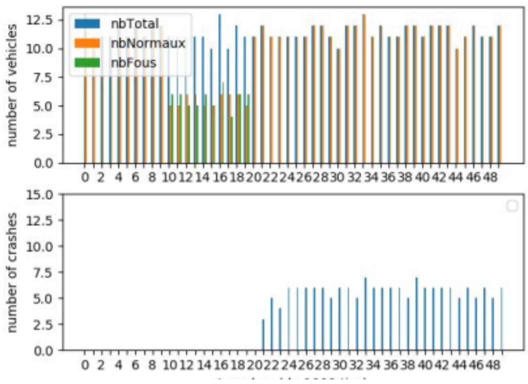


Figure 7: Number of vehicles within different status in time.

subjecting the behavior to a significant but realistic environmental stress to see how it reacts. Most of the existing tools have different objectives and do not focus on behavioral hypothesis testing, to study their impact on road traffic.

The model we propose allows easy behavioral hypothesis testing to generate realistic traffic whose behavior is individually configurable. This realistic traffic is a complex system that can lead to the emergence of accidents (unplanned, non-random). We argue that risk-taking is an essential criterion to be taken into account, but existing models are often based on physical phenomena, and their modification to integrate these new aspects is not accessible to non-specialists. The risk-taking profile is specific to each agent, so it is possible to create flows of vehicles with heterogeneous behavior that take more or less risk. The risk profile is based on five parameters and can be further extended.

We show that, thanks to the proposed model, it is possible to exhibit classic stylized facts in driving simulation and to study the behavioral factors that lead to accidents. After the description of the model, the simulation results clearly show classical phenomena as well as unpredictable accidents due to interactions between agents and their consequences on the traffic.

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