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Master's Thesis

Microscopic simulation of road traffic

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Master's Thesis

MICROSCOPIC SIMULATION OF ROAD TRAFFIC

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Abstract

Microscopic simulation models have been widely used as tools to investigate the operation of road traffic and different intelligent transportation systems applications. The conformity of microscopic simulation tools depends on the driving behavior models that they implement. We desire to model and simulate road traffic using cellular automata (CA). Our model explains traffic occurrences as well as possible and simulate real traffic. The successful model allowed us to optimize requirements for traffic (to take controlling action) and to plan changes without actually having to try out all the possible variations that occur in reality. It is almost self-evident that these different necessities partially compete with each other. Also we try to understand the concept of intelligent driver model (IDM) and try to simulate this concept and compare our model to other models of traffic simulation.

Abbreviations

q_{max} = maximum flow
v_{max} = optimal speed
k_{max} = optimal density
v = speed (km/h)
k = density (veh/km)
v_f = free mean speed (veh/km)
k_j = jam density (veh/km)
$S_{0,i}$ = minimum expected distance between vehicles.
$v_{0,i}$ = maximum expected speed of a vehicle.
δ = it controls the acceleration 'smoothness'.
T_i = the reaction time of the driver of the car.
a_i = the maximum acceleration of the vehicle.
b_i = the car comfortable deceleration.
S^* = the actual desired distance between vehicles

Chapter 1

Introduction

Traffic modeling is aimed to accurately recreate traffic as observed and measured on roads. Traffic modeling assumed the appearance of a traffic system without replicating. We are no longer interested completely in the standard value of significant traffic parameters for a roadway such as the velocity v in km/h, the flow f in veh/h or the density ρ in veh/km. To control the flow, we amount the number of vehicles transitory by a check point per unit time. For the density, we consider the number of vehicles per leg on a domination section. At the microscopic simulation, we want to determine the traffic down to the individual traffic partaker to "microscopic" precision in mandate to consider the individual behavior. From the point of assessment of the individual driver, this is significant in the case for route planning. This should be as lively as possible and be reliant on the current traffic situation. It must also account for individual possessions such as the maximum speed of each driver's automobile. A person traveling a lot can effortlessly understand that, in particular, the properties of traffic can strongly depend on the individual or on individual classes of vehicle kinds. Driving in the country with slight view of the road ahead, a single tractor or truck can instigate a long vehicle line since the other traffic participants are offered little chance for transitory for our macroscopic model that was considered, there always occurred the implicit possibility to permit.

1.1 Relevance of the Problem

The first approach on microscopic modeling techniques for road traffic were the so-called car-following models. Now, separate traffic members are modeled via partial differential equations which has the important benefit that for simple variants the model is systematically soluble.

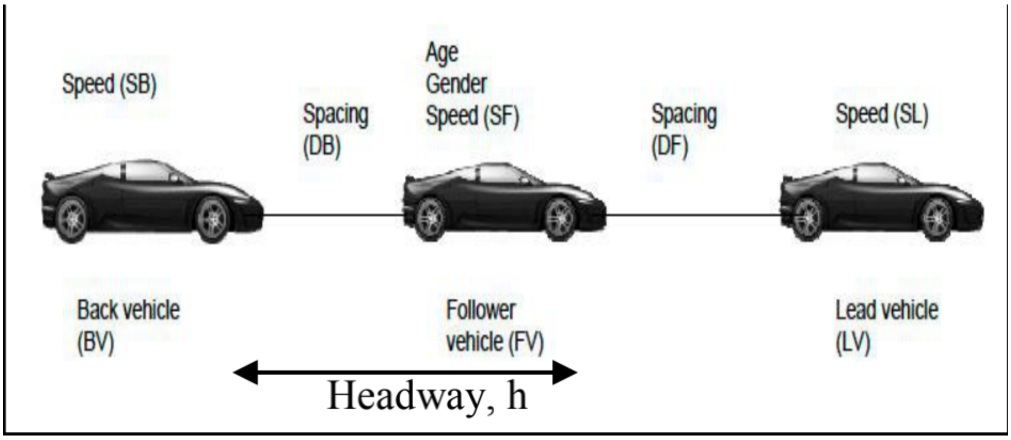


Figure 1.1: Car following model

1.2 Problem Statement

From the viewpoint of the traffic planners, on a highway it is of concern to know the consequence that a no-passing regulation has on the overall traffic, if it is applied only to a quota of the traffic participants, for instance, only for trucks. In addition, the behavior of trucks and cars on the road is meaningfully diverse. These are all motives to reflect the traffic microscopically. If we also involve the goal to exactly resolve and exemplify a road network (for example of a larger city), formerly a macroscopic recreation based on wave propagation replicas, and it becomes computationally very intense. In order to predict traffic congestion, it must be possible to simulate at a faster rate than real time since otherwise the results would effectively become obsolete during their computation. At minimum from a historical point of opinion the macroscopic simulation has reached its limits.

1.3 Aim of the Research

In this research we want to introduce a model that is based on stochastic cellular automata. It models and explains different traffic phenomena and it is very useful in applications. We transfer the concept of cellular automata to the traffic simulation. Also, we introduce the idea of intelligent driver model (IDM) and we compared this model to other known models.

1.4 Research Materials

In this thesis work the software tools that we will use for our simulation are matlab and python.

1.5 Description of the Model

For the modeling of road traffic, we at foremost want to contemplate a modest, closed, single lane road. We will later extend the model to more classy and accurate cases which, in principal, are progressed from such simple structure blocks. In addition, we permit only standard cars as traffic participants. Now, the state of a cell is not alive or dead, but a cell may or may not contain a car with some velocity. Therefore, the cell state is also a car with a velocity value (0, if it presently stands still) or there is “no car”. With respect to the set of states, it is imaginable to allow for an arbitrary velocity for engaged cells.

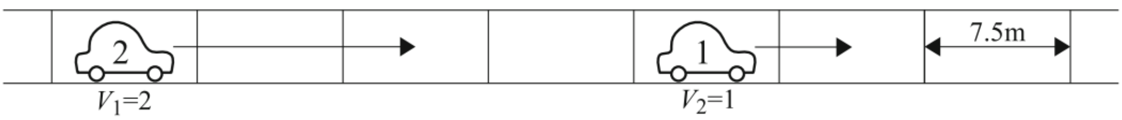


Figure 1.2: Car moving with velocity

Through this, however, it could then happen that a vehicle that is moving comes to a halt somewhere amid two cells. Thus, in our model we amount the velocity in cells/time step and allow solitary for distinct velocity levels. For the following, the maximum admissible velocity of the model will be $v_{max} = 5$ cells/timestep. A cell should match to the smallest space that a car dominates on the road, including its safety distance. In order to persuasively standardize this parameter, we turn to the real world for assistance. Clarifications on highways have revealed that in traffic overcrowding situations, i.e., for maximum density, one has to assume around $7.5m$ per car. This corresponds to a maximum density ρ max of about 133.3 cars/km (214.5 veh/mile). In severe circumstances and, in specific, for city traffic, the highest density can also be higher which we disregard and eliminate from our model.

1. First is the traffic flows. In traffic movements, another routes can be acknowledged based on the quantity of vehicles. By exploiting the simulation model, modeller can develop on how to decrease the levels of overcrowding of certain roads.

2. Second output is the network element. Network component in traffic simulation contains of connection, merge, link cross and other fundamentals of the road. This is associated to the algebraic layout of the road. Using suitable simulation package, the road algebraic design can be changed to see how it can affect the present traffic situation.

3. Third output is the skim category. Simulations model can help to estimate the time and price of travel. This is especially used when the valuation of traffic development is desired to be measured. The transport planner can easily make a presentation assessment without any extra cost of money and time.

Chapter 2

Literature review

A large number of cellular automata (CA) based traffic flow models have been proposed in the recent years. Often, the speed-flow-density relations obtained from these models are only presented and their apparent similarities with observed relations are cited as reasons for considering them as valid models of traffic flow. Hardly any attempt has been made to comprehensively study the microscopic properties (like time-headway distribution, acceleration noise, stability in car-following situations, etc.) of the simulated streams. This research work proposes a framework for such evaluations. It also presents the results from the evaluation of six existing CA-based models. The results show that none of them satisfy all the properties. A new model proposed by the authors to overcome these shortcomings is briefly presented, and results supporting the improved performance of the proposed model are also provided.Literature search on microscopic analysis of CA-based traffic flow models yields some papers which study certain (not all) microscopic properties of some of the CA-based traffic flow models. For example, Knospe et al. (2000, 2004) have studied the time-headway distribution as well as distance headways for traffic streams simulated using many of the CA-based traffic flow models. Recently, Bham and Benekohal (2004) conducted the stability analysis of their model (CELLSIM) and also compared the individual vehicle trajectories and speeds from simulation with field data. A search of literature yielded little work on the development of a framework for the evaluation of any microscopic traffic flow model. Many studies, not necessarily related to CA-based traffic flow models, have only studied individual vehicle trajectories and speeds of the simulated vehicles and compared them with the test track data (e.g. Benekohal and Treiterer, 1988; Aycin and Benekohal, 1998; Brockfeld et al., 2004; Ranjitkar et al., 2004). Others like Kikuchi and Chakroborty (1999), Wu et al. (2003) and

Panwai and Dia (2005) have only concentrated on car-following behaviour.

In the past, the experimental findings are consistent with a recently proposed theoretical phase diagram for traffic near on-ramps D. Helbing, A. Hennecke, and M. Treiber, Phys. Rev. Lett. 82, 4360 (1999). Also the single-lane car-following models have been successfully applied to describe traffic dynamics. Particularly collective phenomena such as traffic instabilities and the spatio-temporal dynamics of congested traffic can be well understood within the scope of single-lane traffic models. But real traffic consists of different types of vehicles, such as cars and trucks. Therefore, a realistic description of heterogeneous traffic streams is only possible within a multi-lane modeling framework allowing faster vehicles to improve their driving condition by passing slower vehicles. Hence, freeway lane changing has recently received increased attention. Moreover, since lane-changing maneuvers often act as initial perturbations, it is crucial to understand their impact on the capacity, stability, and breakdown of traffic flows. Particularly near bottleneck sections such as on-ramps and off-ramps, lane changing is often a significant ingredient in triggering a traffic breakdown (provided that the traffic volume is high). In addition, drivers' lane-changing behaviour has a direct influence on traffic safety. Despite its great significance, lane changing has not been studied nearly as extensively as longitudinal acceleration and deceleration behaviour. One reason is the scarcity of reliable data. To measure lane changes, cross-sectional data from detectors are not sufficient and therefore only a few empirical studies about lane changing rates as a function of traffic flow or density are available. Sparmann (2012) investigated lane-changing rates on a German two lanes autobahn. Data for a British motorway were presented by Yousif and Hunt (2013). Recent progress in video tracking methods, however, allows for a collection of high-quality trajectory data from aerial observations. These two-dimensional data will become more and more available in the future and will allow for a more profound understanding of the microscopic lane-changing processes.

Chapter 3

Methodology

3.1 Microscopic Modeling

Microscopic modeling based on the features of numerous vehicle actions such as cars, buses, motorcycles and so on in the traffic movement. Microscopic modeling envisioned to assemble data factors, such as, flow, density, speed, travel and delay time, elongated queues, stopovers, pollution, fuel utilisation and tremor waves. The features of microscopic modeling approaches were based on car-following model, lane-changing models and gaps of the separate drivers. In the micro model, the driver model is used to designate the performance of the vehicle. Consequently, it must be a multi-agent scheme, that is, each vehicle routes on its own using input from its location. In the

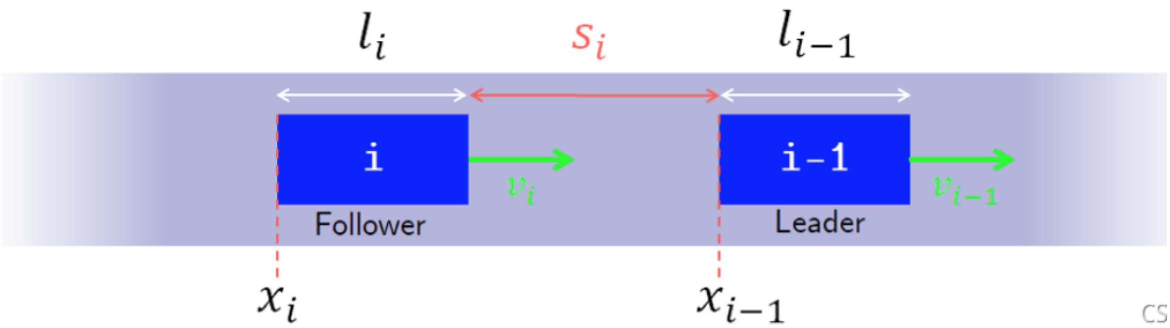


Figure 3.1: Two moving vehicles

microscopic model, individual car is numbered i. The first car i follows the $(i-1)$ vehicles. For the first i vehicles, we will use x_i to indicates its location along the road, and we use v_i to indicates its speed, as well as l_i indicates its length. Every car is like this.

$$S_i = x_i - x_{i-1} - l_i \tag{3.1}$$

$$\Delta v_i = v_i - v_{i-1} \tag{3.2}$$

Where v_i indicate the speed of the following vehicle, v_{i-1} is the speed of the leading vehicle and S_i is the distance between the two vehicles i and $i-1$

3.2 Cellular Automata

Cellular automata is a model that comprises of the following components:

1. **Cell space:** A discrete, in most cases one- or two-dimensional cell space. Every cells have the similar geometry such that in the two-dimensional case commonly rectangular (cartesian), hexagonal or triangular grids.

2. **Set of states:** Each cell of an automaton can assume only one (typically discrete) state from a set of states.

3. **Neighborhood relation:** Each cell can only sense the state of the cells in its neighborhood.

4. **Discrete time:** The state of the CA changes in discrete time steps δt. new state is computed in parallel for all cells.

3.3 Analysis of the model.

There are two central model assumptions that our model shall satisfy, they are:

1. Absence of collision

2. Conservation of vehicle.

Absence of collisions means that two vehicles may never drive within the identical cell within a time step or between two-time steps. This applies, specifically, that a vehicle must be able to decelerate without any time lag. If a car travels at $v = v_{max} = 5$ and, at time step t, arrives in the cell directly behind a non-moving car, then it must be assured that in the next time step it reduces its velocity to $v = 0$ and also stops moving. Hence it holds for the neighborhood connection. For this modest model it is necessary for a vehicle to look ahead the highest step width in the driving direction, i.e., five cells. Let the vehicles be numbered with regard to the driving route, i.e., vehicle i drives with velocity v_i behind vehicle $i + 1$ with velocity $v_(i + 1)$, let $d(i, j)$ be the distance of vehicle i to vehicle j in driving direction, i.e., the number of cells between i and j. Two cars that stand sprightly one after the other have distance zero. The rules of the change function hold in parallel for all vehicles.

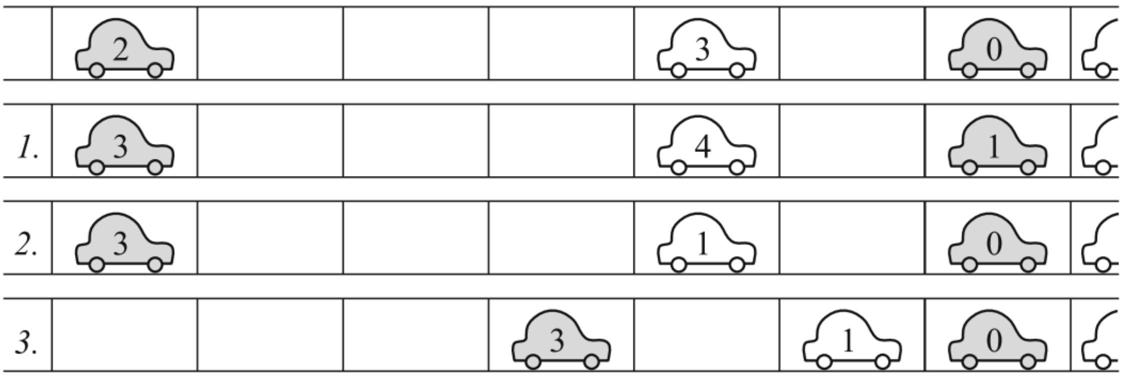


Figure 3.2: Car with traffic jam

Two cars that stand sprightly one after the other have distance zero. The rules of the change function hold in parallel for all vehicles.

3.3.1 The rules of the CA model.

Update for vehicle i with $j = i + 1$:

1. **Accelerate:** $v_i := \min(v_i + 1, v_{max})$
2. **Decelerate:** $v_i := d(i, i + 1)$; if $v_i < d(i; i + 1)$
3. **Randomize:** $v_i := \max(v_i - 1, 0)$ with probability $p < 1$
4. **Move:** vehicle i moves v_i cells forward,

In the basic step, all drivers try to accelerate in order to get the maximum permitted velocity v_{max}. Now, we suppose idealized drivers and vehicles in that all want to, and can, get the allowed maximum velocity. In the next step, the lack of collisions comes to bear. The vehicle must be decelerated in the case that the previous car is too close and thus driving at vi is not permitted. Finally, in the third step all vehicles move. It is noteworthy that vehicles only need to know their own velocity and not that of the other vehicles. In certainty, one typically tries to come up with an uneven estimate of the velocity of the other traffic participants in order to modify one's own behaviour.

3.4 Component of the system.

In order to determine the flow f , one measures the number of vehicles N that pass a prescribed measuring station during a certain time interval δT , e.g., with the support of an induction loop in the road or a radar at a bridge. One then determines the measured value as

$$f = \frac{N}{\delta T} \tag{3.3}$$

Measuring the density ρ is, however, slightly more involved: The number of vehicles N_i on a section of the road having length L must be determined at the point in time i of the measurement. We then computes the number of traffic participants in the measuring region. Since the flow has also been averaged over a time interval δT , one can also average the density over m measurements in the time interval δT and obtains

$$\rho = \frac{1}{M} \sum_{i=1}^{m} \frac{N_i}{L} \tag{3.4}$$

We can continue exactly the same way for the model, we choose a checkpoint on the circular road and a time interval, e.g, $\delta T = 3min = 180$ simulation steps. For each step we consider the $k \geq v_{max}$ cells behind the checkpoint so that we don't lose a vehicle. We then count for each measurement the vehicles in the roadway section of length $L = k.7.5m$. In order to obtain measured values covering the entire density spectrum between $\rho = 0$ and $\rho = \rho_{max}$, we must systematically populate our circular road with vehicles. We start with an empty road and insert a new vehicle at an ordered intervals until the road is occupied. If we always insert the vehicles at $x = 0$, we immediately obtain traffic jams at low densities which are always caused at this location by a new car. In order to interrupt the traffic flow as little as likely through this supplement technique, we can insert the new traffic participant at the speed v_{max} and in the middle of the largest free interval. For only a single lane, at most one vehicle can pass the sensor per time step. Thus we would have a maximum flow

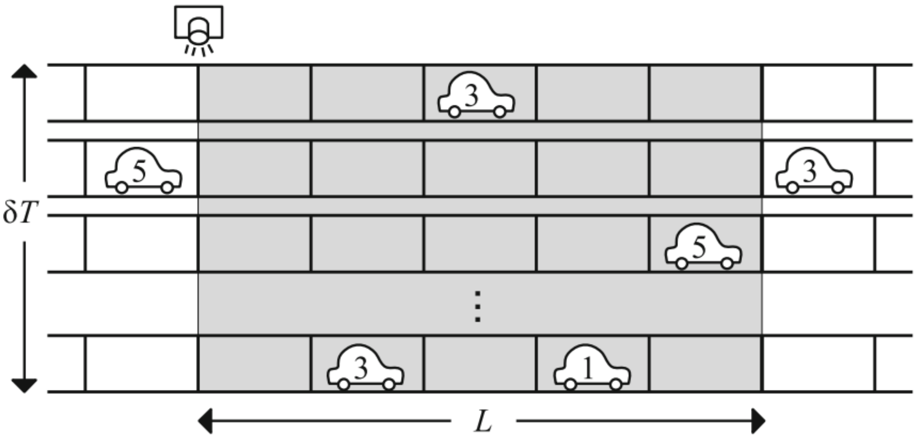


Figure 3.3: Measurement of flow and density in the simulation

$f_{max} = 1veh/s = 3600veh/h$. We will never reach it. Let us assume that all traffic participants have the same velocity, v. To allow as many as likely to pass the sensor in the determining time span, they must drive as closely as possible to one another, i.e., with v free cells in-between. This means that every $(v+1)^{st}$ time step no vehicle passes the sensor, so we observe the flow of $f_{max} = \frac{v}{v+1} veh/s$. This is maximal at $v = v_{max}, p = 0$ and the critical traffic density of $\rho = 22.2$ Vel/km and is reached in our model scenario at

$$f_{max} = 5/6veh/s = 3000veh/h \tag{3.5}$$

The elementary progression shows in each case that there is a large increase for small densities, a sharp bend and a decrease with noise until the highest density is gotten. In contrast to the simulation, tangible measurement values at very extreme densities are usually a rare commodity. These conditions ascend in reality only for a whole traffic jam and are avoided by all involved parties by all means and are therefore not that frequent. Subsequently, our virtual car drivers are significantly less prone to suffering, we can measure values even for extremely great densities in the simulation.

3.5 Build Model

To analyse and optimize the transportation system, we must first model the transportation system mathematically. This model should be based on input parameters (road network geometry, vehicles per minute, speed, etc). Truly represent traffic flow. Traffic flow system models are mostly distributed into three categories, it varies on the level at which they run:

1. **Miniature models**: Characterise each vehicle distinctly, and try to replicate the driver's behaviour.
2. **Macro model**: From traffic density (vehicles per kilometer) and traffic movement (vehicle per minute) angle explains the overall movement of the vehicle. They are generally similar to the movement of a fluid.
3. **Meso model**: It is a mixed model merging the features of micro and macro models, the flow is demonstrated as the flow of the vehicle.

3.6 Intelligent Driver Model (IDM)

Years ago, Treiber, Hennecke and Helbing developed a model called intelligent driver model (IDM), it describes the second vehicle i, the acceleration of a vehicle as a function of its variable and the vehicle in front. The dynamic equation is defined as:

$$\frac{dv_i}{dt} = a_i \left[1 - \left(\frac{v_i}{v_{0,i}}\right)^{\delta} - \left(\frac{S^*(v_i, \Delta v_i)}{S_i}\right)^2\right] \tag{3.6}$$

where $S^*(v_i, \Delta v_i)$ in equation (3.6) is given by

$$S^*(v_i, \Delta v_i) = S_{0,i} + v_i T_i + \frac{(v_i, \Delta v_i)}{\sqrt{2a_i b_i}} \tag{3.7}$$

We have talked about S_i, v_i, and Δv_i as other parameters are clearly defined in the abbreviation list.
First, We are going to look at S^*, This consists of three parts.

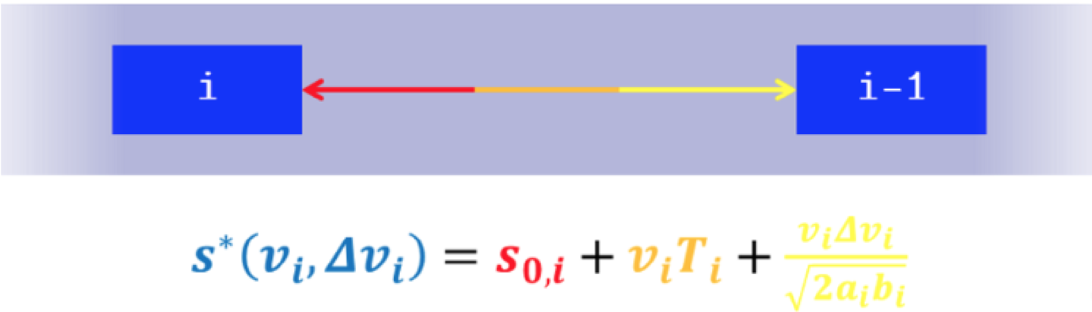


Figure 3.4: Desired distance between vehicles

$S_{0,i}$ is the minimum distance required and $v_i T_i$ is the safe distance of reaction time (brake). Since speed is the distance maintained over time, distance is speed times time, it can be deduced as.

$$v = \frac{d}{T} \rightarrow d = vT \tag{3.8}$$

also, $\frac{(v_i, \Delta v_i)}{\sqrt{2 a_i b_i}}$ means that the vehicle is braking without emergency (the deceleration shall be less than b_i), The distance required without hitting the vehicle in front.

How the intelligent driver model works?. The vehicle is assumed to travel along a straight road, and assume that the following equation:

$$\frac{dv_i}{dt} = a_{free\ road} + a_{interaction} \tag{3.9}$$

where

$$a_{free\ road} = a_i \left(1 - \left(\frac{v_i}{v_{0,1}}\right)^{\delta}\right) \tag{3.10}$$

and

$$a_{interaction} = -a_i \left(1 - \left(\frac{S^*(v_i, \Delta v_i)}{S_i}\right)^2\right) \tag{3.11}$$

To better understand this equation, we can divide it in two. We have a free road acceleration and an interactive acceleration.

$$a_{free\ road} = a_i \left(1 - \left(\frac{v_i}{v_{0,1}}\right)^{\delta}\right) \tag{3.12}$$

The free road acceleration is the acceleration on the free road, that is, an empty road without vehicles. If we plot acceleration as a_i over the velocity v_i we have:

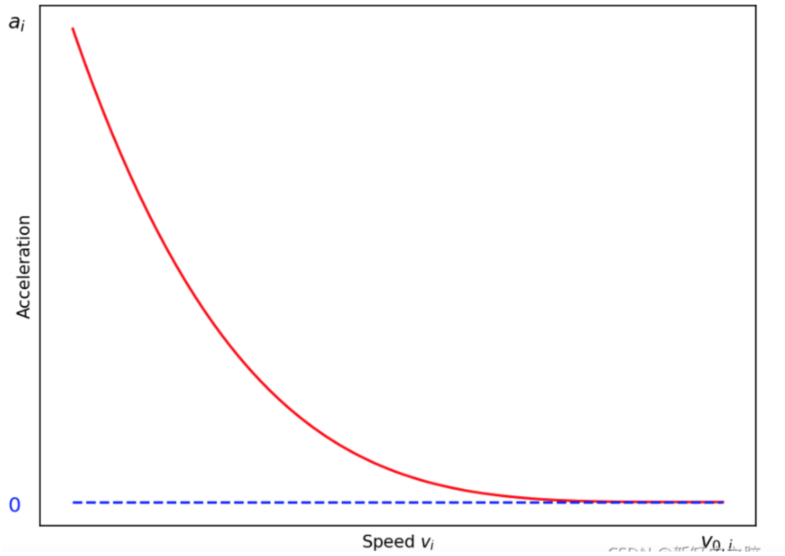


Figure 3.5: Free road acceleration

We noticed that, when the vehicle is stationary ($v_i = 0$), acceleration is at the greatest. When the vehicle approaches the maximum speed, acceleration becomes 0. This shows that, the free road acceleration will accelerate the vehicle to the maximum speed.
If we plot different values δ for the $v - a$ chart we have,

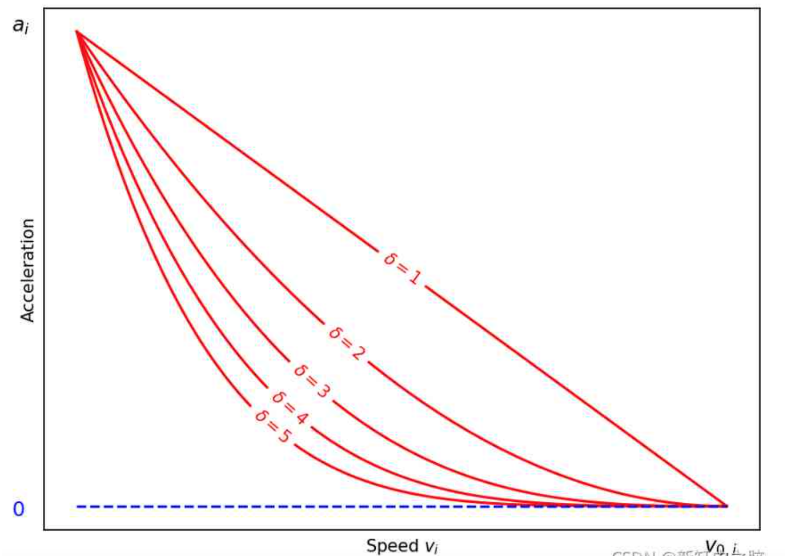


Figure 3.6: At different acceleration

We observed that δ controls the speed at which the driver decelerates near the maximum speed. This in turn controls the acceleration or smoothness of deceleration

$$a_{interaction} = -a_i \left(\left(\frac{S^*(v_i, \Delta v_i)}{S_i} \right)^2 \right) = -a_i \left(\frac{S_{0,i} + v_i T_i}{S_i} + \left(\frac{(v_i, \Delta v_i)}{2S_i\sqrt{a_i b_i}} \right)^2 \right) \tag{3.13}$$

The interaction acceleration is associated to the interaction with the vehicle upfront. To comprehend how the whole thing, let us consider the following

1. On the road to freedom ($S_i >> S^*$) when the vehicle ahead is far away, namely S_i far greater than the required safe distance between vehicles S^*, the interaction acceleration is almost 0. This means that the vehicle is reduced to a free road acceleration.

$$\frac{dv_i}{dt} \approx a_{free\ road} = a_i \left(1 - \left(\frac{v_i}{v_{0,1}} \right)^\delta \right); \left(\frac{S^*(v_i, \Delta v_i)}{S_i} \right)^2 \approx 0 \tag{3.14}$$

2. At high approach rates Δv_i, when the speed difference is large, the interaction acceleration attempts to pass through the $(v_i, \Delta v_i)^2$ item for brake compensation.

$$a_{interaction} = -a_i \left(\frac{S_{0,i} + v_i T_i}{S_i} + \left(\frac{(v_i, \Delta v_i)}{2S_i\sqrt{a_i b_i}} \right)^2 \right) \approx -\frac{(v_i \Delta v_i)^2}{4b_i S_i^2} \tag{3.15}$$

3. At small distances ($S_i << 1$ and $\Delta v_i \approx 0$) acceleration becomes a simple repulsive force.

$$a_{interaction} = -a_i \left(\frac{S_{0,i} + v_i T_i}{S_i} + \left(\frac{(v_i, \Delta v_i)}{2S_i\sqrt{a_i b_i}} \right)^2 \right) \approx -a_i \left(\frac{(S_{0,i} + v_i T_i)}{S_i} \right)^2 \tag{3.16}$$

So all these described the relationship between one vehicle following the other.

3.7 The Lane-Changing Model

Lane changes take place if another lane is more attractive ('incentive criterion'), and the change can be performed safely ('safety criterion'). In our lane-changing model MOBIL we base both criteria on the accelerations in the old and the prospective new lanes, as calculated with the longitudinal model (that is the IDM in the simulation). The safety criterion is satisfied if the IDM braking deceleration -a^{IDM} imposed on the new follower f' of the target lane after a possible change does not exceed a certain limit b_{safe},

3.8 Mathematical Structure of the IDM

The mathematical form of the IDM model equations (1) and (2) is that of coupled ordinary (non-linear) differential equations:

1. They are differential equations since, in one equation, the dynamic quantities $v(t)$ (speed) and its derivative dv/dt (acceleration) appear simultaneously.
2. They are coupled since, besides the speed v, the equations also contain the speed $v_{lead} = v - \Delta v$ of the leading vehicle. Furthermore, the gap s obeys its own kinematic equation, $ds/dt = -\Delta v$ coupling, again, the (time derivative) gap to the leading speed.

Simulation means to numerically integrate, or to solve the coupled differential equations of the model. Specifically, we consider a finite and fixed numerical update time interval Δt, and integrate over this interval assuming constant accelerations. This so-called ballistic method reads
new speed: $v(t + \delta t) = v(t) + dv/dt\Delta t$;
new position: $x(t + \Delta t) = x(t) + v(t)\Delta t + 1/2dv/dt\Delta t^2$
where dv/dt is the IDM acceleration calculated at time t, and x is the position of the front bumper. Strictly speaking, the model is only well defined if there is a leading vehicle and no other object impeding the driving. Nevertheless, generalizations are straightforward:

- If there is no leading vehicle and no other blocking object ('free road'), just set the gap to a very big value such as 1000 m. The bound of the gap tending to infinity is well-defined for any significant car-following model such as the IDM.
- If the next obstructing object is not a leading vehicle but a red traffic light or a stop-signalized intersection, just model these objects by a standing virtual vehicle of length zero positioned at the stopping line.

Chapter 4

Results and Analysis

We consider the analysis of road traffic based on cellula automata (CA) for both one lane and double lane. We also simulate the intelligent driver model (IDM) and compare these models to other known models.

4.1 One Lane Simulation

Road traffic simulation using cellula automata, what is of interest is that this simple model can actually be simulated. We simulate a one lane unidirectional highway section. For this model, as usual we need the initial as well as the boundary conditions for the simulation. On the boundary the question arises which addresses when new vehicles enter the roadway as well as what occurs to vehicles that drive outside the last cell at the end. For some simulations it is beneficial to recommend the flow at the start and to let vehicles disappear when they leave the simulation domain. In the following, we use the simplest options and choose periodic boundary conditions: All vehicle that leaves the roadway at the end returns at the beginning. In particular, this allows one to simulate a constant number of vehicles over an extended period. For a single time step we visualize the simulation as in the figure below.

4.1.1 Description of the single lane traffic

We visualize the state of this model over time and to show how traffic jams can appear when traffic density is high enough. We put into consideration so many traffic terminologies for the simulation, for this single lane simulation we define

1. Maximum velocity = 5.
2. Road length = 100,
3. Density = 0.2,
4. Slow probability = 0.3

For single time step we have. This demonstrates the velocity at which a

```
.1...3.0.....50..2...0.1...3.1...3...1......4...1.....4...20.0.........5.00......5..10.000.....5...3
```

Figure 4.1: One time step for single lane.

car moves into the lane, with each number representing the velocity of the moving car from left to right. The acceleration just drags on a little longer. The vehicle will reach v_{max} eventually despite dallying. For example,

$$0 \to 1 \to 2 \to 3 \to 4 \to 5$$

can become

$$0 \to 1 \to 1 \to 2 \to 2 \to 2 \to 3 \to 4 \to 4 \to 5.$$

So if we have $0 \to 0 \to 0 \to 0 \to 0$, this means cars with 0 velocities, and this is when traffic jam occur. So, we plot the graph of flow rate to the density for one lane traffic with one time step. To have more visualization we increase the time steps to 25 for a single lane, we have The randomization step incorporates into the model three fundamental phenomena of road traffic:

1. Delay when accelerating: A vehicle that does not drive with highest velocity v_{max} and has an open road, i.e., one that would supposedly accelerate, does not do so as soon as possible but barely with some time delay to a later step. One notes that the velocity is not condensed in the acceleration phase.
2. Dallying on an open road: Drivers who drives v_{max} for a longer period of time on an open road tend to not preserve their velocity constant. Again, the model neglects that a vehicle suddenly decelerates entirely in various steps.

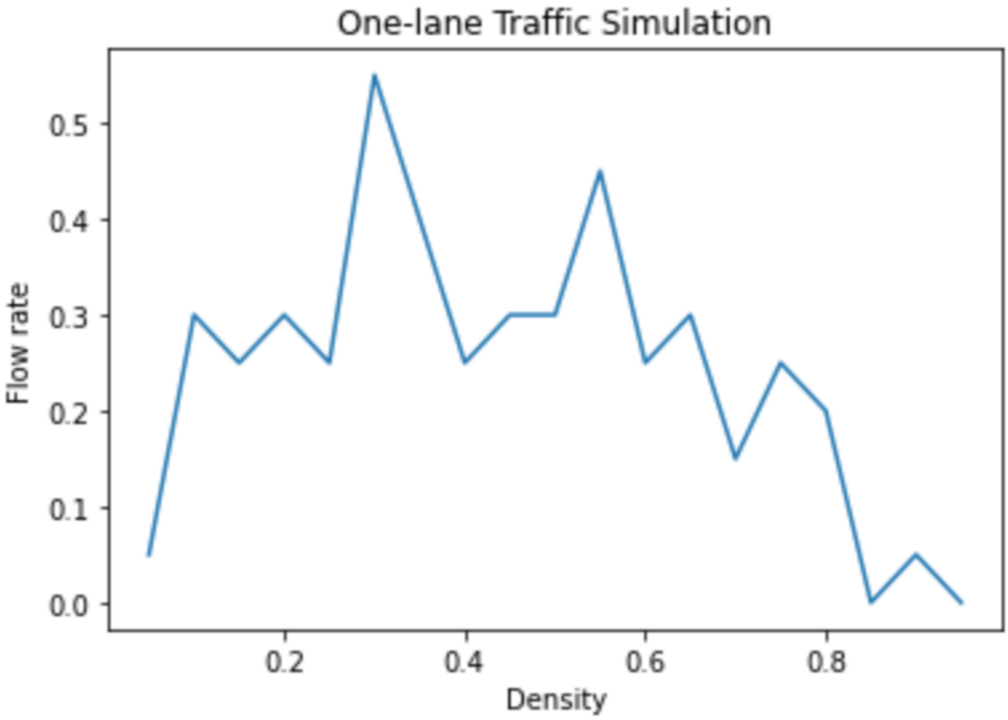
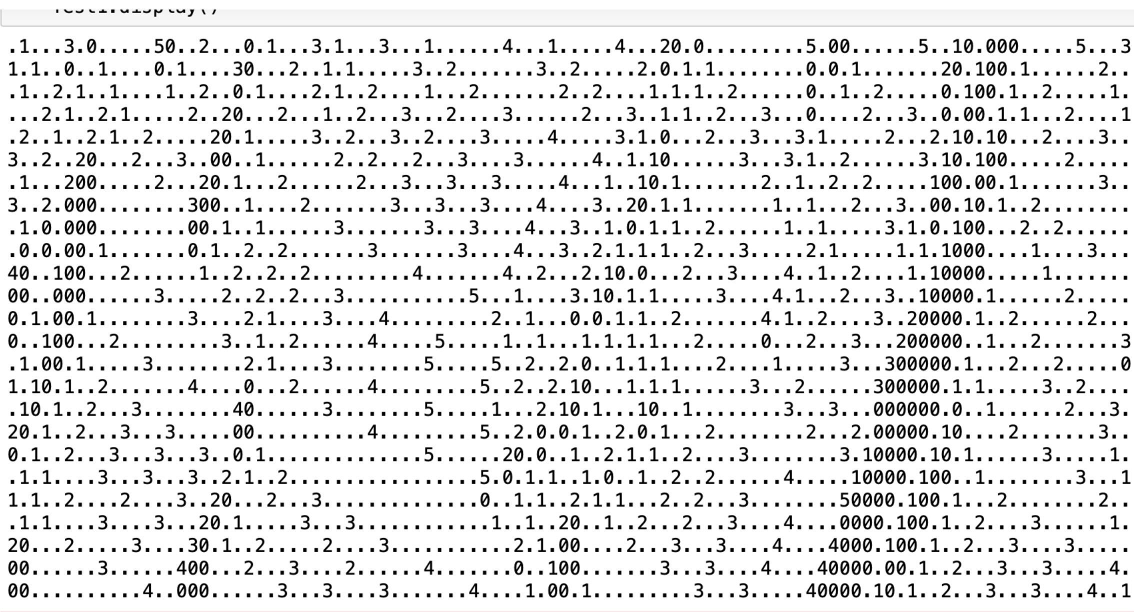


Figure 4.2: Average flow rate of one time step for single lane.



```
.1...3.0.....50..2...0.1...3.1...3...1.....4...1.....4...20.0.........5.00......5..10.000.....5...3
1.1..0..1....0.1....30...2..1.1.....3..2.......3..2.....2.0.1.1........0.0.1.......20.100.1......2..
.1..2.1..1....1..2..0.1....2.1..2....1...2.......2..2....1.1.1..2......0..1..2.....0.100.1..2.....1.
...2.1..2.1.....2..20...2...1..2...3...2...3......2...3..1.1..2...3...0....2...3..0.00.1.1...2....1
.2..1..2.1..2.....20.1.....3..2...3..2....3.....4.....3.1.0...2...3...3.1.....2...2.10.10...2....3..
3..2..20...2...3..00..1......2..2...2...3....3......4..1.10......3...3.1..2......3.10.100.....2.....
.1...200.....2...20.1...2......2...3...3...3.....4...1..10.1.......2..1..2..2.....100.00.1.......3..
3..2.000........300..1....2.......3...3...3....4....3..20.1.1.......1..1...2...3..00.10.1..2........
.1.0.000........00.1..1......3.......3...3....4...3..1.0.1.1..2......1..1.....3.1.0.100...2..2......
.0.0.00.1.......0.1..2..2.......3.......3....4...3..2.1.1.1..2...3.....2.1.....1.1.1000....1....3...
40..100...2......1..2..2..2.........4.......4..2...2.10.0...2...3....4..1..2....1.10000.....1.......
00..000......3.....2..2..2...3...........5...1....3.10.1.1.....3....4.1...2...3..10000.1......2.....
0.1.00.1........3....2.1....3....4.........2..1...0.0.1.1..2.......4.1..2....3..20000.1..2......2...
0..100...2.........3..1..2......4.....5.....1..1...1.1.1.1...2.....0...2...3...200000..1...2.......3
.1.00.1.....3........2.1....3........5.....5..2..2.0..1.1.1....2....1.....3...300000.1...2...2.....0
1.10.1..2.......4....0...2......4.........5..2..2.10...1.1.1......3...2......300000.1.1.....3..2....
.10.1..2...3........40......3........5.....1...2.10.1...10..1........3...3...000000.0..1......2...3.
20.1..2...3...3.....00..........4.........5..2.0.0.1..2.0.1...2........2...2.00000.10....2.......3..
0.1..2...3...3...3..0.1..............5......20.0..1..2.1.1..2....3........3.10000.10.1......3.....1.
.1.1....3...3...3..2.1..2.................5.0.1.1..1.0..1..2..2......4.....10000.100..1........3...1
1.1..2....2....3..20...2...3..............0..1.1..2.1.1...2..2...3........50000.100.1...2........2..
.1.1....3....3...20.1.....3...3............1..1..20..1..2...2...3....4....0000.100.1..2....3......1.
20...2.....3....30.1..2.....2....3...........2.1.00....2...3...3....4....4000.100.1..2...3....3.....
00......3......400...2...3....2......4.......0..100.......3...3....4....40000.00.1..2...3...3.....4.
00..........4..000......3...3....3.......4....1.00.1.........3...3.....40000.10.1..2...3...3....4..1
```

Figure 4.3: 25 time steps for single lane.

3. Overreaction when decelerating: A vehicle is stalled by a slower vehicle in front and must modify its velocity appropriately. For example, drivers tend to the brakes too hard since they misinterpret the distance or speed or because they drive too cautiously with respect to what is deemed an optimal traffic behavior. The condition considering an underreaction that leads to rear end collisions is excluded in the

model.

So, we plot the graph of flow rate to the density for one lane traffic with 25 time steps.

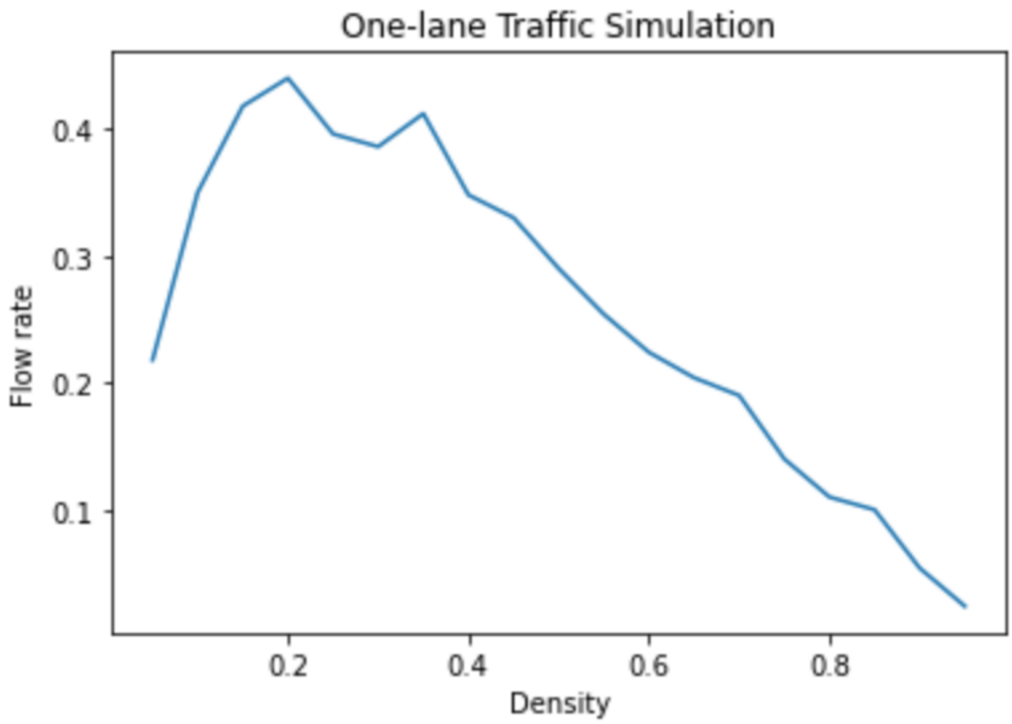


Figure 4.4: Average flow rate for 25 time step. For the one-lane model, the maximum flow rate is: 0.425 and it's reached at the density of: 0.04

4.2 Two-Lane Simulation

For two lane the randomization step is very useful sufficient for the model to demonstrate realistic traffic behaviour. We can detect that traffic jams form which disappear again after a short time. Especially the fact that the model can explain so-called traffic jams out of nowhere, traffic jams that appear spontaneously and, from an outsider perspective, without any reason. With other models these are usually not easy to observe without additional effort and must be modelled explicitly.

4.2.1 Description of the double lane traffic

For the simulation of two lanes simulation, we define the following traffic terms that we use to set up our model.

1. Road length = 100,
2. Density = 0.2,
3. Maximum velocity = 5,
4. slow probability = 0.3,
5. Lane probability = 0.8.

We set up two empty road with the vehicle moving randomly into the two lanes. We populate cars on the lanes according to initial probabilities and that with symmetric model, a car only changes lanes when there is someone in front of it and that the other lane is free. For one time step with the two lanes simulation we have.

```
....4.0....4.......3...........2....40...2......................2.10................4...........2.10
4.....4...1...3...2........1...1..........4.....3...........3.1......1.............5.0.....4..10....
```

Figure 4.5: One time step for two-lane traffic simulation.

So, we plot the graph of flow rate to the density for two lane traffic with one time step.
We also increase the time steps to 25 to have a better visualisation of the simulation, and we have in the graph.

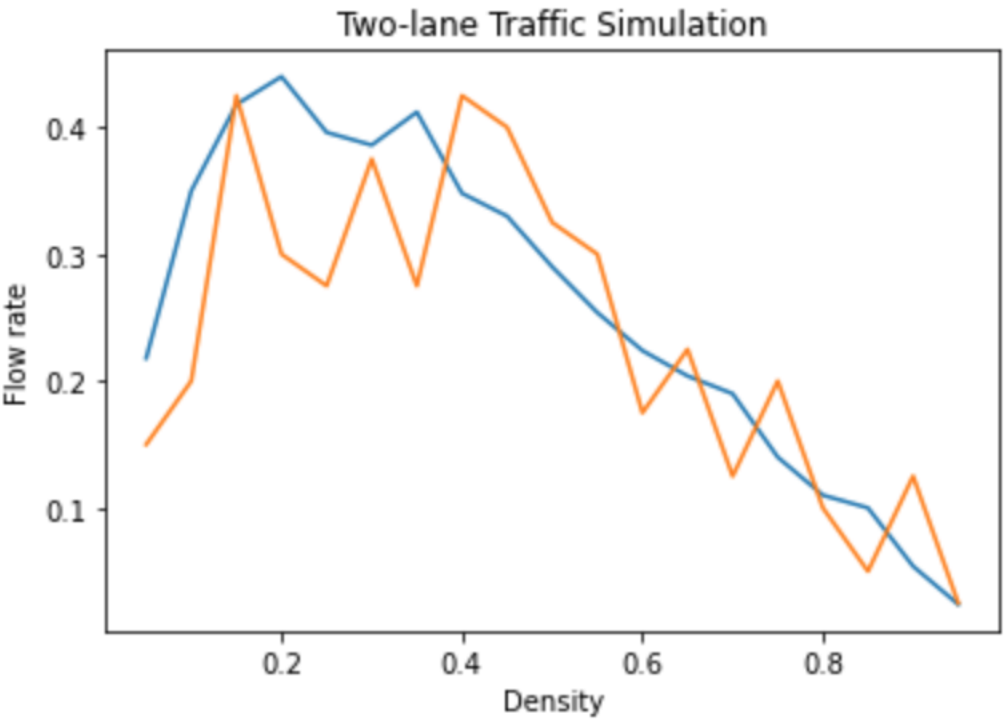


Figure 4.6: Average flow rate one time step for two lanes.

```
....4.0....4.......3...........2....40...2.....................2.10...............4..........2.10
4.....4...1...3...2........1...1.........4.....3..........3.1......1............5.0.....4..10....
1...0..1.......4.......4.........3.00.....2...................10.1.................4.......10.
.....5...3..2....3...3......1...1.............5...3.........1.1......1.............1.1......20.1...
..2.0...10.........4........5......100........3.................0.1.1......................5...00.
..............3....3....4...1....2.............2....3......0...2......2...........1..2....0.1..2.
...10...00............4.........5.00.1..........4..............1.1..2......................2.00.
.3...............3.....4..2...2.....3.............3.....4..0.....2.......3..........2...3.0..1...
.....1..00.................5....0.00..1..............5..........1..2...3..................0.0.1
..10.................4...2...3...3......4.............4...2.1......2.........4.........3.10...1..
.20...1.0.1...................3..10.1...2.................5.......1....3....4...............0..1.
...0...................2....3...3....4.......5...........3.1..2......2..........4.......100....1.
.0.1...1.1..2...................20.1.1.....3..................5....2......4.....5............1..1
....1.......................3....3....4.....5.......5.......1.1....3.....2.............5..00.1....1
10..1...1..2...3................0.1.1..2.......4....................4...3........5....4........1..
1....1.........................4...3......5.....5.......5....1.1......3.....3............20.1.1....
00....2...2...3...3.............0.0...2...3.........5..................3....4.......3......5......2
..2....2........................3...3........5.....5.....3.0...2........4.....4.........0.1.1.1...
0.1......3...3...3...3............1.1.....3....4.........5................4....4.......4.......5.0
....2.....3.........................3....4.........5....4..10......3.........5.....5.....1.1.1.1..
.1..2......2....3...3....4.........1.1.......3......5.........5..............3.....4.......4....10
.......3......4.........................4.....5.......3..1.0.1.........4..........5....4..1.1.1..2
1.1...2.......3...2.....4.....5.....1..2.........4.......5..........5............3.......5......40.
..3.......3.......4.........................5.....5....2.1.1..2............5.........4..2.1.1.1..
0...2....3.......3...3.......5.....5..2...3..........5......4.........4............4........5.00.
......4.......4.......5.........................4....3.0..1..2...3.............4........2.10..1..2
0......3.....4......3....4........5..2...3....4.............5......5..........5..............5...0.0.1
..3........5......4.........5........................4.1.1...2..2.....4..............5....100....2.
.1.........4......5.....4.....5.....2...3...3.....4............5.....4..........5...........3.10.0
.3...3..........5.....4.........4......................1.1..2...2...3.......5.............400.1.....
```

Figure 4.7: 15 time-step for two lanes

We can realise that the rate at which we have traffic jams has reduced due to ability to change lane. So, we plot the graph of flow rate to the density for two lane traffic with 15 time steps.

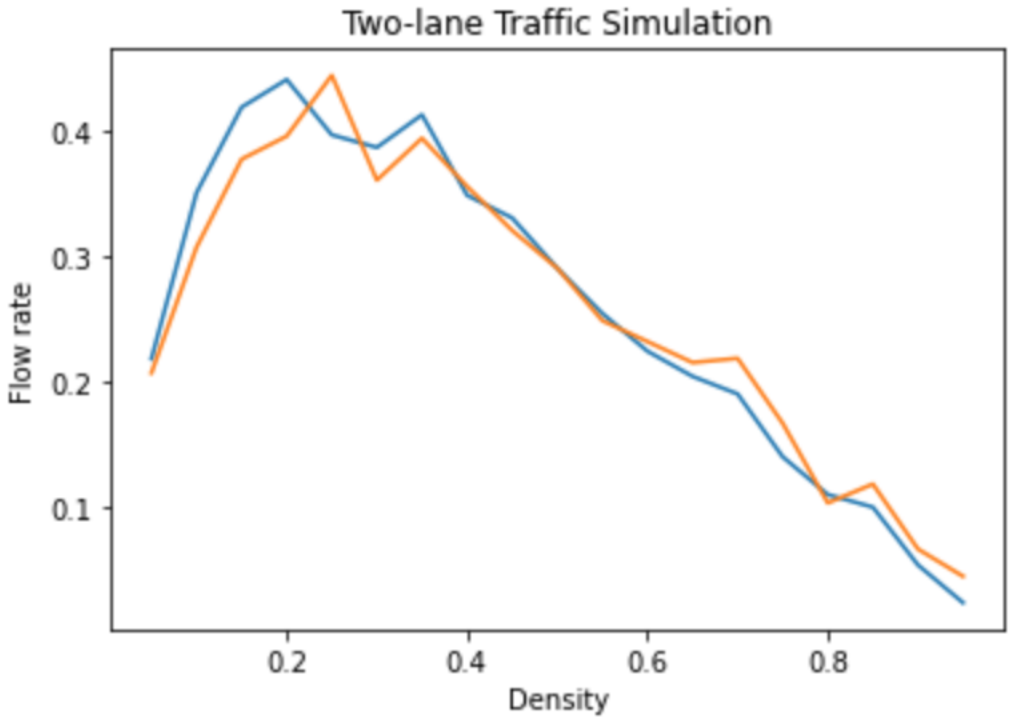


Figure 4.8: Average flow rate for 15 time steps for two lanes. For the two-lane model, the max flow rate is: 0.4400000000000001 and it's reached at the density of: 0.06

4.3 Simulation with the Intelligent driver model (IDM)

In the following, we describe the simulation scenarios, the main user interactions and observable traffic phenomena. At first we reformulated the IDM equation in [3.6] for $v' = x''_{n+1}$ and $v = x'_{n+1}$ so we have; and we solve equation [4.1]

$$x''_{n+1}(t)dt = a_i \left[1 - \left(\frac{x'_{n+1}(t)}{x_0} \right)^{\delta} - \left(\frac{S^*(x'_{n+1}(t), \Delta x'_{n+1}(t))}{S_{n+1}(t)} \right)^2 \right] \tag{4.1}$$

where $S^*(x'_{n+i}(t), \Delta x'_{n+i}(t))$ in equation (4.1) is given by

$$S^*(x'_{n+1}(t), \Delta x'_{n+1}(t)) = S_0 + max \left[0, \left(x'_{n+1}(t)T + \frac{(x'_{n+1}(t).\Delta x'_{n+1})(t)}{\sqrt{2ab}} \right) \right] \tag{4.2}$$

we solve this equations with using ode45 solver with Dirichlet boundary condition and using the following parameters.

- $x'_{n+1}, x''_{n+1}(t)$ is the velocity and the acceleration of the following car $n + 1$
- $S^*(x'_{n+1}(t), \Delta x'_{n+1}(t))$ is the desired gap between two cars
- $\Delta x'_{n+1}(t)$ is the velocity difference between the leading and the following car
- x'_0 is the free velocity [x'_0 30m/sec for a car]
- T is the nominal time between two cars [T=1.5sec]
- a is the acceleration [$a = 0.3m/sec^2$]
- b is the comfortable breaking deceleration in normal traffic scenario [$b = 3m/sec^2$]
- s_0 is the minimum distance between two cars [$s_0 = 2m$]
- $s_n = x_{n-1} - x_n - l_c$ where l_c is the length of the leading car [$l_c = 5m$]
- δ is the constant as acceleration exponent [$\delta = 4$]

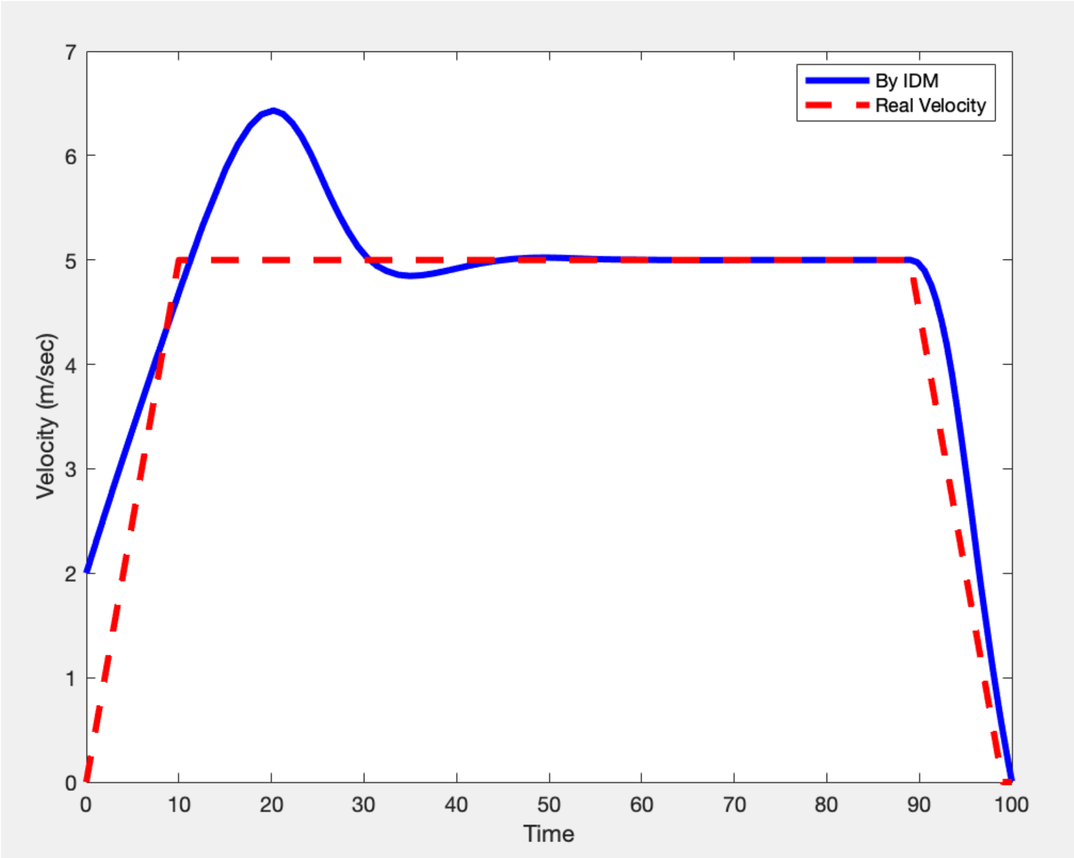


Figure 4.9: velocity-time graph of the road

We plot the graph of the velocity vs time for both the IDM and the real velocity of the road. We see observe that the car by the IDM and the car by the real velocity move freely on the road without collision as they started with a distance of 2m in between them.

4.3.1 Roundabout (close road)

We also perform the same simulation using IDM with python,JavaScript and pygame. and for this we try to simulate both vehicle and truck for better visualization. This simulation scenario shows multi-lane vehicular traffic in a closed system (ring road). For the close road as we randomly put cars into the road it got to a point that we can no longer put the car again because the closed system never give room to cars out of road.

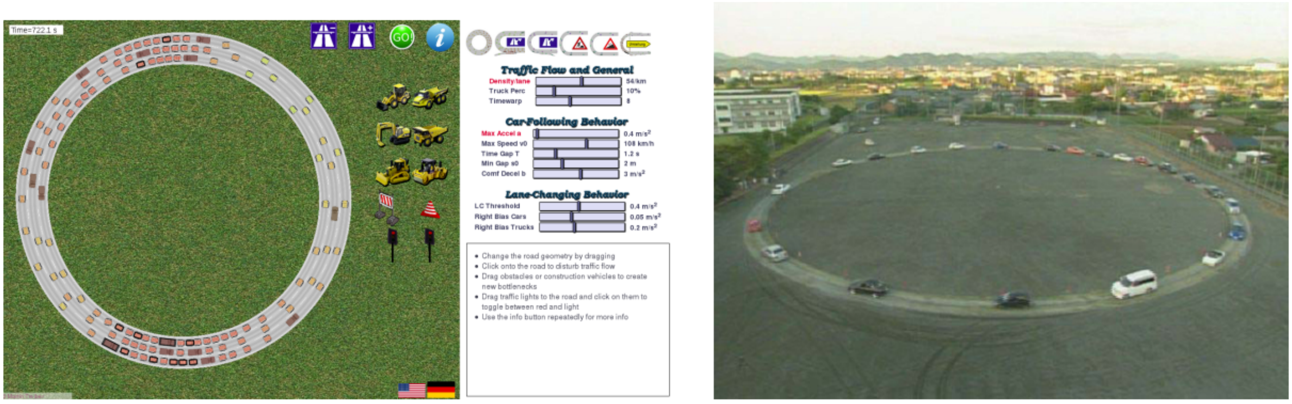


Figure 4.10: Simulation screenshot of a closed roundabout.

From the simulation, you can also lessen the number of lanes to 1 ('freeway minus' symbol) and/or eliminate the trucks (truck percentage to zero) to realize that neither lane changes nor driver-vehicle heterogeneity are relevant factors for this mechanism.

4.3.2 Open System Scenarios with different Bottlenecks

We also perform the same simulation for different bottlenecks. The simulator provides three scenarios with open boundaries and several forms of bottlenecks (in the screenshots below).

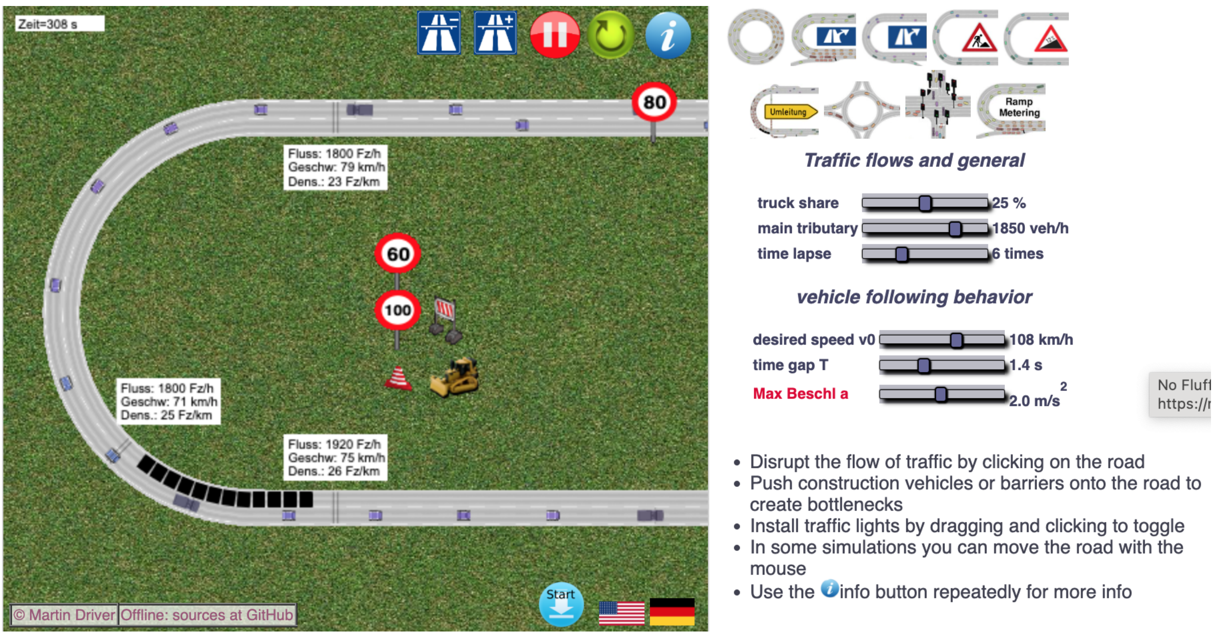


Figure 4.11: Simulation screenshot

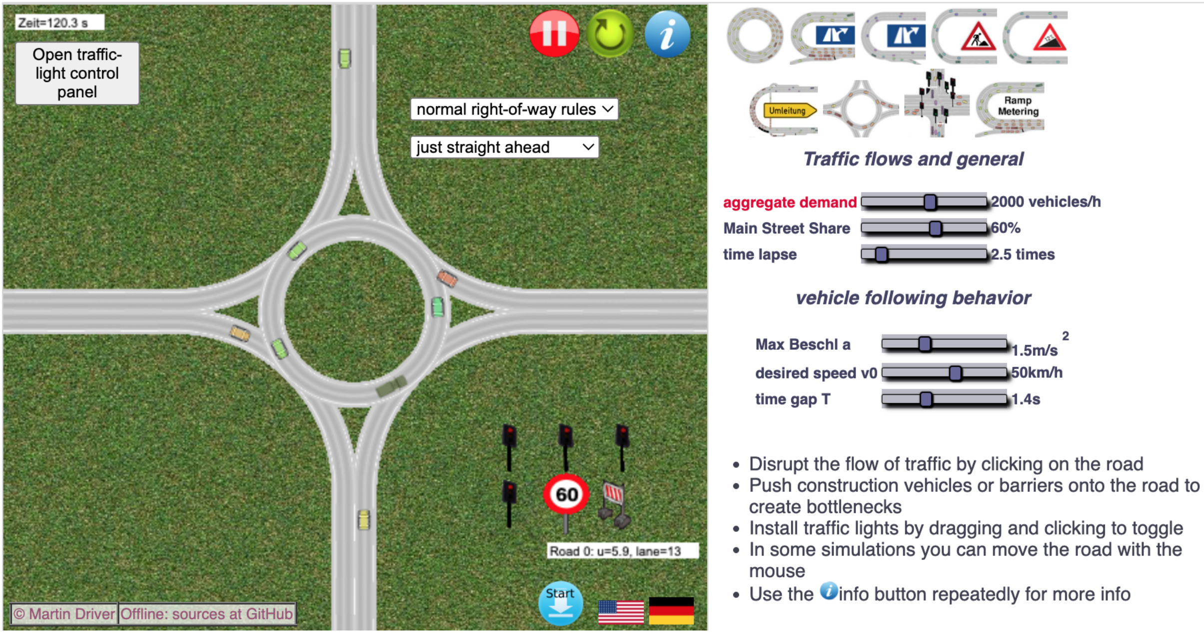


Figure 4.12: Simulation screenshot with open roundabout

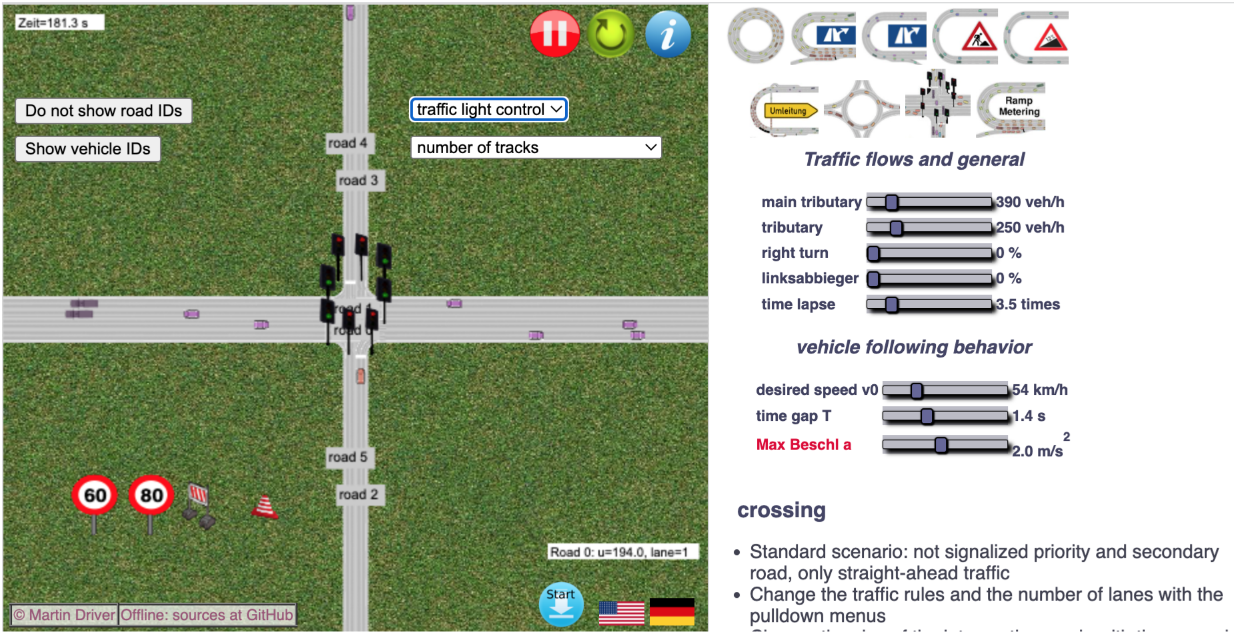


Figure 4.13: Simulation screenshot with intersection:

Notice that, all the above screenshots are the screenshots of the open-system scenarios with different bottlenecks. They all shows how a vehicles flow into the lane with and how they react to any barrier. The flow-conserving bottlenecks differ in their strength. We notice that when a vehicle noticed a barrier in its current lane, it will automatically change to another lane and the all the vehicles will change lane neglecting the lane where the barrier was placed. You can slow down the simulation speed, set your desired speed and click at an entering vehicle to observe how it encounters the traffic waves.

4.4 Comparing our simulation with other traffic simulations

Cellular automata (CA) with IDM models are widely used traffic simulation models because of their simplicity compare to other simulation [1]. Due to their fast performance when used in computer simulation, CA with IDM models are considered more advantageous over other models [2]. The knowledge of CA was commenced by Johann Louis von Neumann in 1948, when he used them to study living biological systems [3]. The CA were more commercialised in the nineteen eighties by the works of Stephen Wolfram [4]; The related CA models to all disciplines of sciences. Mostly, there are three kinds of CA models: stochastic models, deterministic model, and slow to start models. In 1992, Nagel and Schreckenberg proposed a CA model that can reproduce the most characteristics of traffic movement [5].

Conclusion

We have been able to simulate road traffic microscopically with the help of cellula automata for a single lane and two lanes, we discover that for single, as cars are moving randomly into the lane from left to right with their respective velocities, there experiences a traffic jam and this is due to different behaviour of the drivers. But in the case of two lanes traffic, the issue of traffic jam is reduced, this is as a result of the fact that drivers can change lane once there is free space in the second lane, the cellula automata helps us to assume that all cars are same with the assumption that the maximum velocity the car can attain is $5m/s$. In the IDM simulation, we successfully recreate the ideal intelligent of the driver. The IDM mainly simulate the distance between the leading and the following vehicles. We discover that the IDM is very accurate in maintaining the normal distance between the leading and the following vehicle. We also realize the automatic change of lane when a vehicle experiences any obstacle or barrier in the current lane of when its experience any traffic delay in the current lane.

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