Microscopic Evaluation of Extended Car-following Model in Multi-lane Roads

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This paper describes a micro-simulation model which combined car following with lane change model. For that, we proposed a new car-following model which is an extended of velocity-separation difference model (VSDM) by introducing a new optimal velocity function, named a modified velocity-separation difference model (MVSDM) which react better in braking case. The problems of collision in urgent braking case existing in the previous models were solved. Furthermore, the simulation results show that (MVSDM) can exactly describe the driver's behavior under braking case, where no collision occurs.

Povzetek: Članek opisuje mikrosimulacijski model avtonomne vožnje, ki kombinira sledenje avta z zamenjavo voznega pasu.

1 Introduction

The accelerated growth of the urban population and the extension of cities, the intensification of economic exchanges have made road traffic and its management one of the major challenges of sustainable development. Recently, there has been a strong focus on improving the efficiency and safety of transportation and this has led to the development of the Intelligent Transportation Systems (ITS) (1). Among the most notable urban transport problems:

- Traffic congestion occurs when, at a specific point in time and in a specific section, there is an imbalance between transport demand and supply .
- Environmental impacts includes the pollution and noise problems generated by circulation.
- Accidents and safety problems due to growing traffic in urban areas with a growing number of accidents and fatalities.

In this context, traffic flow modeling and simulation has become a famous area of research in recent years, and constitute efficient tools to evaluate different tasks such as traffic prediction, traffic control and forecasting, the repercussion of the construction of new infrastructure onto the global behavior of the traffic flow. For studying the traffic problem, traffic flow are classified into two different types of approaches, namely, macroscopic and microscopic ones (2). Macroscopic models describe traffic flow as a continuous fluid, which describe entities and their activities and interactions at a relatively low level of detail and established relationships between speed, flow and density. In contrast, microscopic model attempts to model the motion of individual vehicles and their interaction at a high level of detail and describe the reaction of every driver (accelerating, braking, lane changing, etc) depending on the surrounding traffic. Microscopic models are better adapted to the description of more punctual elements of the network, while macroscopic models are adapted to the representation of networks of large sizes. On the other hand, mesoscopic models characterized by the high level of aggregation, low level of detail, and typically based on a gas-kinetic analogy in which driver behavior is explicitly considered (3). Figure 1 presented the different simulation approaches of traffic flow. In this context, we are mainly interested with the microscopic approach which road traffic is modeled by individual motion of each vehicle. In this model, the speed of a vehicle is directly according to the distance that separates it from the leading vehicle, modulo a delay time. This delay time is generally assimilated to the reaction time of the driver in order to take into account the variations in behavior of his leading vehicle. This is a car-following process also known as longitudinal driving behavior. The modeling of traffic in the broader sense proposes to describe more finely the flow of vehicles on a road. For that, it is necessary to understand two behavioral sub-models which are responsible for vehicle movement inside the network: Car Following (CF) and Lane Changing (LC) models. Car-following process were developed to model the manner in which individual vehicles follow one another in the same lane where the driver adjusts his or her acceleration according to the conditions in front and following each other on a single lane without any overtaking (2). The purpose of this paper is to propose a extended car-following model taking into account the effects of lane changing behavior. The work presented in this paper is devoted to overcome the shortcomings such as the unrealistic deceleration and the collisions in braking cases of many existing car-following models. However, we implemented the proposed approach using the open source simulator for traffic flow (4), in order

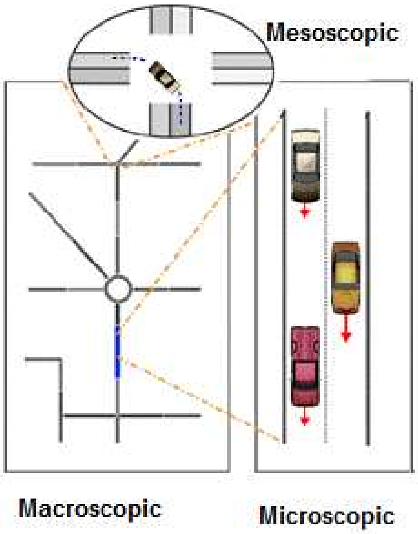

Figure 1: Traffic flow approaches

to improve the efficiency of a proposed approach compared with the existing ones.

The paper is organized as follows. The state-of-the art of car-following and lane changing models will be introduced in Section 2. The proposed approach will be presented in Section 3. In section 4, the simulation results are carried out. At last, the conclusion is given in Section 5.

2 Related work

2.1 Car-following models

The most widely known class of microscopic traffic flow models is so-called the family of car-following or follow-the-leader models. Car-following theories describe the way in which each vehicle follow another in the same lane. The most car-following models have a significant impact on the ability of traffic micro-simulations to replicate real-world traffic behavior (5). Various models were formulated to represent how a driver reacts to the changes in the relative positions of the vehicle ahead. Figure 2 describes the vehicular traffic sketch. We denote as i the car whose behavior is currently under investigation, at instant t, such vehicle is at a position $x_i(t)$, and travels with a speed $v_i(t)$, that means its instantaneous acceleration can be expressed as $a_i(t)$. Index $i-1$ identify the front vehicles with respect to i , which are located at $x_{i-1}(t)$ and travel at speed $v_{i-1}(t)$ at time t. The front bumper to back bumper distance between i and $i-1$ is identified as $S(t) = \triangle x_i = x_{i-1} - x_i$.

Since the 1990s, car following models have not only been of great importance in an autonomous cruise control system, but also as important evaluation tools for intelligent transportation system strategies (6). The car-following models have been designed for single-lane roads, based essentially on the following ordinary differential equation

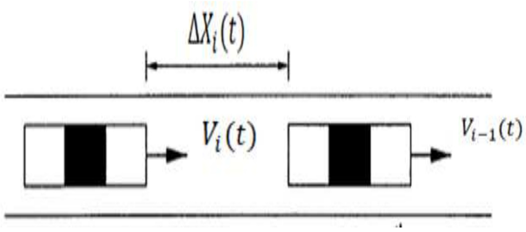

Figure 2: Car following process notation

(ODE):

$$a_i(t) = \frac{v_{i-1}(t) - v_i(t)}{T} \tag{1}$$

This model is based on the idea that the acceleration $a_i(t)$ of the vehicle i at time t depends on the relative speed of the vehicle i and its leader $i-1$ by means of a certain relaxation time T. However the previous equation describes a phenomenon is not stable enough in the case of road traffic. Hence the appearance of several variants of this model includes:

- Safe-distance models or collision avoidance models try to describe simply the dynamics of the only vehicle in relation with his predecessor, so as to respect a certain safe distance.
- Stimulus-response models based on the assumption that the driver of the following vehicle perceives and reacts appropriately to the spacing and the speed difference between the following and the lead vehicles (7).
- Optimal velocity models are another approach generally based on the difference between the driver's desired velocity and the current velocity of the vehicle as a stimulus for the driver's actions.

In this paper, we focused on optimal velocity models and we give here a state of art of the famous ones. For more detailed information with respect to microscopic models, particularly, car-following models can be found in the overview of (5) (8) (9)(10)(11) (12)(13)(14)(15). The optimal velocity models attempt to modify the acceleration mechanism, such that a vehicle's desired speed is selected on the basis of its space headway, instead of only considering the speed of the leading vehicle (16). The first model defined the optimal velocity function using an equilibrium relation for the desired speed as a function of its space headway is (17). The acceleration of Newell model is determined by the following equation:

$$a_i(t) = V_{opt}(x_{i-1}(t) - x_i(t)) \tag{2}$$

Bando et al. later improved this model, by introducing the notion of desired velocity, chosen as a function of relative spacing or headway (18). They distinguished two major types of theories for car-following regulations. The first type called follow-the leader theory which was used by (17), based on the idea that each vehicle must maintain the legal safe distance of the preceding vehicle, which depends on the relative velocity of these two successive vehicles. The other type for regulation is that each vehicle has the legal velocity, which depends on the following distance from the preceding vehicle. Based on the latter assumption, the authors (18) investigated the equation of traffic dynamics and found a realistic model of traffic flow, resulting in the following equation that describes a vehicle's acceleration behavior:

$$a_i(t) = k * [V_{opt}((S(t)) - v_i(t)] \tag{3}$$

In which $V_{opt}(S(t))$ is the optimal velocity function which depends on the headway $S(t)$ to the car in the front. The stimulus here was a function of the relative spacing and the sensitivity k was a constant. The optimal velocity function, generally, must satisfy the following properties: it is a monotonically increasing function and it has an upper bound (maximal velocity). The optimal velocity adopted here calibrated by using actual measurement data proposed by (19) as follows :

$$V_{opt}(S(t)) = V_1 + V_2 \tanh[C_1(S(t) - l) - C_2] \tag{4}$$

With V_1, V_2, C_1, C_2 parameters calibrated and l is the length of the car. Unfortunately, the model produces many problems of high acceleration, unrealistic deceleration and is not always free of collisions. For this reason, Helbing and Tilch proposed an extended model considering the headway and the velocity of the following car and the relative velocity between the preceding vehicle and the following vehicle when the following vehicle was faster than the preceding vehicle (19). To solve the OVM problems, they added a new term which represents the impact of the negative difference in velocity on condition that the velocity of the front vehicle is lower than that of the follower. The GFM formula is:

$$a_i(t) = k * [V_{opt}((S(t)) - v_i(t)] + \lambda H(-S\dot{(t)})S\dot{(t)} \tag{5}$$

Where $H(.)$ is the Heaviside function, λ is another sensitivity coefficient, and $S\dot{(t)} = v_{i-1}(t) - v_i(t)$ means the velocity difference between the current vehicle and the vehicle ahead. The main drawback of GFM doesn't take the effect of positive velocity difference on traffic dynamics into account and only considers the case where the velocity of the following vehicle is larger than that of the leading vehicle (15). The basis of GFM and taking the positive factor $S\dot{(t)}$ into account. In 2001, the authors (20) obtained a more systematic model called Full Velocity Difference Model (FVDM), one whose dynamics equation is as:

$$a_i(t) = k * [V_{opt}((S(t)) - v_i(t)] + \lambda S\dot{(t)} \tag{6}$$

In 2005, the authors in ref (21) introduced a weighting factor which makes the OV model more reactive to braking . They extended the OVM by incorporating the new optimal velocity function obtained by the combination of optimal velocity function Eq (8) with the weighting factor. The modified optimal velocity function expressed as:

$$V_{opt}^{new}(S, \dot{S}) = V_{opt}(S(t)) * W(S(t), S\dot{(t)}) \tag{7}$$

Where the weighting factor is as follows:

$$W(S(t), S\dot{(t)}) = \frac{1}{2} + \frac{1}{2}\tanh B(\frac{\dot{S}(t)}{S(t)} + C) \tag{8}$$

In which B and C are the calibrated parameters. The dynamic equation of the system is obtained as:

$$a(t) = \kappa(V_{opt}^{new}(S(t), S\dot{(t)}) - v_i(t)) \tag{9}$$

In 2006, (6) conducted a detailed analysis of FVDM and found out that second term in the right side of Eq (6) makes no allowance of the effect of the inter-car spacing independently of the relative velocity. For that, they proposed a velocity-difference-separation model (VDSM) which takes the separation between cars into account and the dynamics equation becomes:

$$\begin{aligned} a_i(t) &= \kappa(V_{opt}(S(t)) - v_i(t)) \\ &+ \lambda H(S\dot{(t)})S\dot{(t)}(1 + \tanh(C_1(S(t) - l) - C_2)^3 \\ &+ \lambda\Theta(-S\dot{(t)}(t))S\dot{(t)}(1 - \tanh(C_1(S(t) - l) - C_2)^3 \end{aligned} \tag{10}$$

2.2 Lane changing models

The transfer of a vehicle from one lane to adjacent lane is defined as lane change. Lane change, as one of the basic driver behaviors, can never be avoided in the real traffic environment. Lane changing models are therefore an important component in microscopic traffic simulation Modeling the behavior of a vehicle within its present lane is relatively straightforward, as the only considerations of any importance are the speed and location of the preceding vehicle. Therefore the understanding of lane changing behavior is important in several application fields such as capacity analysis and safety studies. These lane changing models are categorized into four groups:

– Rule-based models are the most popular ones in microscopic traffic simulators include those reported in (22),(23). For this type of models, the subject vehicle's lane changing reasons is evaluated first. If these reasons warrant a lane change, a target lane from the adjacent lane(s) is selected. The gap acceptance model used to determine whether the available gaps should be accepted.

– Discrete-choice-based models based on logit or probit models. The lane changing process is usually modeled as either MLC or DLC. Mandatory lane changes (MLC) are considered those which occur because of a blocked lane, traffic regulations or in order to follow one's route to destination. Discretionary changes (DLC) are made in order for the subject vehicle to achieve better lane conditions (24). Discrete-choice-based lane changing models follow three steps: 1) checking lane change necessity, 2) choice of target lane, and 3) gap acceptance.

– Artificial intelligence models are fundamentally different from the rule-based and discrete choice-based models. A major advantage of them is that they can better incorporate human experience and reasoning into the development of lane changing models.

– Incentive-based models have been recently proposed to modeling lane changing behavior. From their perspective, the attractiveness of a lane based on its utility to the driver, and a safety criterion captures the risk associated with the lane change (25). A variety of factors included in these models such as the desire to follow a route, gain speed, and keep right (26), in addition to politeness factors that can describe the different driver behaviors (25).

In this paper, we describe briefly one the important incentive-based lane changes models. We chose MOBIL (25) as it is the only lane changing model which takes into account the effect of lane change decisions on the immediate neighbors. This model based on the simplistic control rules and it was more appropriate to analyze the affects of usual lane change behaviors of drivers on the overall traffic (24). The lane changing algorithm MOBIL (Minimizing Overall Braking Induced by Lane Changes) is among the most important components of a microscopic traffic simulator based on a microscopic longitudinal movement model. A lane change model depends on the two following vehicles on the present and the target lane, respectively as shown in Fig. 3. A specific MOBIL lane change based on the accelerations on the old and the prospective new lanes.

To formulate the lane changing criteria shown in Fig. 3 we use the following notation: the vehicle i refers to the lane change of the successive vehicles on the target and present lane referred by n (new one in the target lane) and o (old follower in the current lane). The tildes $\tilde{a}_i$, $\tilde{a}_o$ and $\tilde{a}_n$ denotes the new acceleration of vehicle i on the target lane, the acceleration of the old and new followers after the

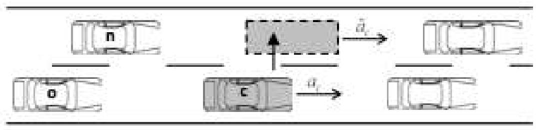

Figure 3: Vehicles involved in lane changing process

lane change of vehicle i, respectively. All the accelerations involved are calculated according to the car-following model (27). A lane change model based on a safety and incentive criterion. The safety criterion is satisfied, if the car-following braking deceleration $\tilde{a}_i$ imposed on the old vehicle o of the target lane after a possible change does not exceed a certain limit b_{safe} this means:

$$\tilde{a}_i > -b_{safe} \tag{11}$$

The second criterion determines the acceleration advantage that would be gained from the event. This criterion based on the accelerations of the longitudinal model before and after the lane change and focused on improving the traffic situation of an individual driver by letting him drive faster or avoid a slow leader (24). For symmetric overtaking rules, they neglect differences between the lanes and propose the following incentive condition for a lane changing decision of the driver of vehicle i as follows:

$$\overbrace{\tilde{a}_i - a_i} + p(\overbrace{\tilde{a}_n - a_n} + \overbrace{\tilde{a}_o - a_o}) > \triangle a_{th} \tag{12}$$

Equation (11) states that the acceleration advantage to be gained by the lane change, must be greater than both a threshold acceleration $\triangle a_{th}$ used to dampen out changes with marginal advantage, and a politeness factor p determines to which degree these vehicles influence the lane-changing decision. The factor p controls the degree of cooperation while considering a lane change, from a purely egoistic behavior (p = 0) to an altruistic one (p ¿ 1) (25). The politeness factor can be thought of as accounting for driver aggressiveness. It is this balancing of accelerations that gives rise to the name MOBIL, as Minimizing Overall Braking Induced by Lane changes (27).

3 Proposed approach

In comparison with the existing works above, our proposal in this paper provides a extended car following model with an interaction of lane change behavior that mainly important to simulating and to representing the traffic flow in the real manner. The proposed approach is detailed in the following section.

3.1 Flowchart of the proposed approach

For an ideal flow of a dynamic traffic simulation study, we proposed the basic algorithm presented in Fig. 4 which based on three major steps given as:

- Preparation of the traffic flow simulation: in this step, we must define the road environment and also we must specify the initial parameters and variables, including initialization of position, velocity, and so on.
- Implementation of the model and validation of its different scenarios: in this stage, we adopt our MVSD model to compute acceleration for each car and then compute the new speed and position on both lanes for the next time step. At the same time, we start lane changes rules, we determine which car change whereto and add these cars to the correct position on the lane and removed changed cars from their old lane.
- Analysis of results: for the next time step, we update the network and information state to get a new velocity and position state; then we jump to step 2, and we begin an another cycle.

3.2 Modified velocity separation difference model

In this paper, we proposed a modified car following model introducing the lane changing rules just as other studies. In ref (21), the authors modified an OV model, introducing the new OV function without using the lane change behavior to get a model more reactive on braking situation called modified optimal velocity model (MOVM). The motivation for our paper comes from the key idea behind the new optimal velocity function proposed by (21) which we incorporating this latter on the VSDM model using the lane changing behavior. However, the new OV function combined between the OV function the reference Eq (2) and the weighting factor Eq (8) that depends on the inverse of time to collision (TTC). The TTC concept was introduced by the US researcher (28) and it was used in different studies as a time based surrogate safety measure for evaluating collision risk (29)(30)(31). In car following situations the TTC indicator is only defined when the speed of the following vehicle is higher than the speed of the lead vehicle (31). Rear end collision risk is defined as the time for the collision of two vehicles if they continue at their present speed and on the same lane and at the same speed (see Fig. 5). The time to collision of a vehicle driver combination n at instant t with respect to a leading vehicle$n1$ can be calculated with:

$$TTC = \frac{S(t)}{\dot{S(t)}}; \forall \dot{S(t)} > 0 \tag{13}$$

The new optimal velocity function $V_{opt}^{new}(S, \dot{S})$ is expressed as the combination of the optimal velocity function proposed by (18) based only on headway stimulus and the weighting factor established the inverse of time to collision to make the model more reactive in braking case.

$$V_{opt}^{new}(S, \dot{S}) = V_{opt}(S) * W(S, \dot{S}) \tag{14}$$

Where the weighting factor is :

$$W(S, \dot{S}) = [A(1 + tanhB(\frac{\dot{S}}{S} + C)] \tag{15}$$

The weighting factor must satisfies some proprieties:

- When the relative speed is positive $\dot{S(t)} > 0$, the weighting must maintain the reference OV function unchanged.
- For negative decreasing relative speed $\dot{S(t)} < 0$, it has to be decreasing and has to go toward zero when $\dot{S(t)} -> infini$.

There are several functions which behave similarly with varying only the headway stimulus. Therefore, Here the new OV function modulates the reactivity of the car following model according to the actual headway and relative speed between the follower and ahead car. In our contribution, we revised and extended a velocity separation difference model by incorporating the new OV function to get a new model that called a Modified Velocity Separation Difference (MVSDM). The MVSD model is expressed by the equation of motion as:

$$\begin{aligned} a_i(t) &= \kappa(V_{opt}^{new}(S(t), \dot{S(t)}) - v_i(t)) \\ &+ \lambda H(\dot{S(t)})\dot{S(t)}(1 + \tanh(C_1(S(t) - l) - C_2)^3 \\ &+ \lambda\Theta(-\dot{S(t)}(t))\dot{S(t)}(1 - \tanh(C_1(S(t) - l) - C_2)^3 \end{aligned} \tag{16}$$

To describe real driving behavior on multilane roads, we need the car following process and the lane changing process. The lane changing behavior has a significant effect on traffic flow. Therefore the understanding of lane changing behavior is important in several application fields such as capacity analysis and safety studies. We interested, particularly, the lane changing algorithm MOBIL (Minimizing Overall Braking Induced by Lane Changes) which is among the most important components of a microscopic traffic simulator based on a microscopic longitudinal movement model (25) and is adopted here.

4 Simulation results

In this study, we carry out the simulations to investigate whether MVSDM can overcome the shortcomings of previous models and compared MVSDM with MOVM proposed by (21). In this paper, for each model we establish the

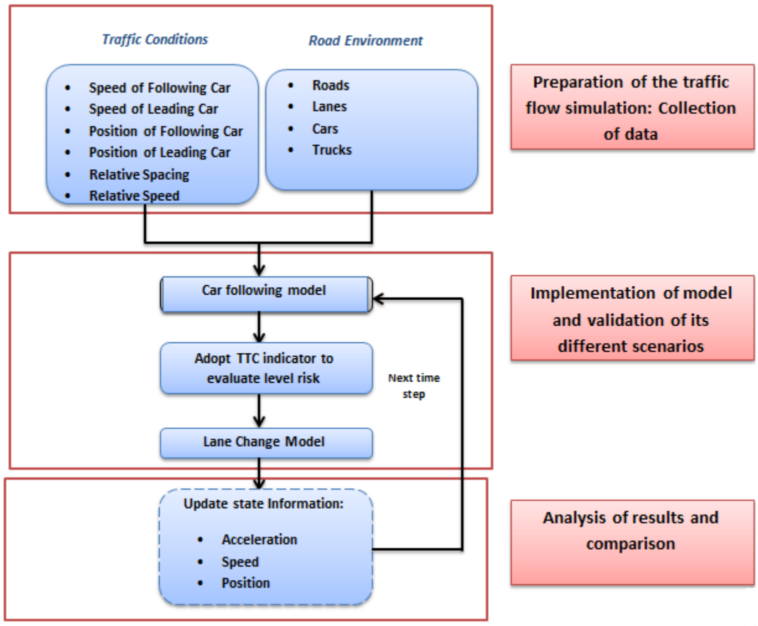

Figure 4: Flowchart of the proposed approach

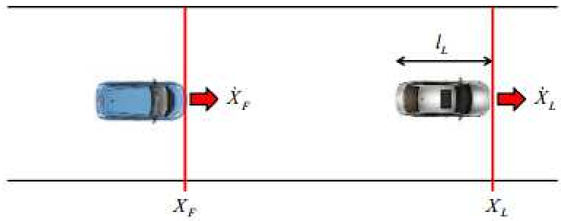

Figure 5: Time to collision for rear end collision sketch

simulation results for two different scenarios. In the following, we will test the proposed approach (accelerating and braking behavior) using an open source microscopic simulator proposed by (4) to validate our approach using these scenarios. We used two vehicle classes: cars and trucks. For all simulations, the parameter values used for optimal velocity function Eq (4) and are adapted from (19) are $V_1 = 6.75m/s$, $V_2 = 7.91m/s$, $C_1 = 0.13m^{-1}$, and $C_2 = 1.57m^{-1}$. The parameter values calibrated for weighting factor (21) are $A = 0.5$, $C = 0.5$, and $B = 5s$. The sensitivities parameters values are $a = 0.6m/s^2$, and $\lambda = 0.45m/s^2$. The parameters values for cars are the desired velocity $V_0 = 120km/h$, the safe time headway $T = 1.2s$, the minimum gap $S_0 = 2m$, and the vehicle length $l = 6m$. The parameters values for trucks are the desired velocity $V_0 = 80km/h$, the safe time headway $T = 1.7s$, the minimum gap $S_0 = 2m$, and the vehicle length $l = 10m$. The parameters values for lane changing are the politeness factor $p = 0$, the changing threshold $\triangle a_{th} = 0.2m/s^2$, the maximum safe deceleration $b_{save} = 12m/s^2$, and the bias for the slow lane $\triangle a_{bias}$.

For more information about the simulation results, we built a video to visualize clearly the validity of our proposed model MVSDM and the existing model MOVM and VSDM in the following link `https://www.youtube.com/watch?v=LJ5ddRGVbgA&feature=youtu.be`.

When starting the simulation, we extract the necessary data in excel format in order to represent them in graph form, and this is done for each car following model and for each scenario. Figure 6 shows the resulting data (speed, acceleration, position, type of car, length, etc.)

4.1 Ramp scenario: behavior in stop and go traffic

Stop and go scenario demonstrates the traffic breakdown provoking on the main road of the on-ramp. Usually, the traffic jam occur when the leading car decelerate for certain reasons. For that, it's important to study the vehicle behavior when simulating in such case. Simulation results depicted in Fig. 7d show that the proposed model avoids the collision when the leading car decelerate hardly. However, simulating traffic flow with MOV model occurs crashes between different cars as we can see in Fig. 7b.

At $t = 0$, all cars start up according to the MOVM, VSDM, and MVSDM, respectively. From Fig. 8, it can be seen that the speed maximum of MVSDM is under of MOVM and VSDM. We can see that MFVDM velocity begins to decrease before MOVM and VSDM velocity reaches its maximum. The simulation results demonstrate that MOVM and VSDM provokes crashes. In contrast, our proposal MVSDM avoid it and the traffic jams disappear.

To simulate the car motion and to describe the traffic flow, we examine certain properties of traffic from each car.

	A	B	C	D	E	F	G
1	Position	Speed	Accelerati	N° of vehicle	Time	Lane	Lenght
2	7,913354	14,57122	0,022237	2	0,2	0	6
3	10,8276	14,57527	0,020261	2	0,4	0	6
4	13,74265	14,57897	0,018487	2	0,6	0	6
5	16,65845	14,58235	0,016894	2	0,8	0	6
6	19,57491	14,58544	0,015465	2	1	0	6
7	22,492	14,58828	0,014183	2	1,2	0	6
8	0	14,56188	9,28E-10	1360544799	1,4	0	6
9	25,40966	14,59088	0,013035	2	1,4	0	6
10	2,912377	14,56188	8,35E-10	1360544799	1,6	0	6
11	28,32783	14,59328	0,012006	2	1,6	0	6
12	5,824753	14,56188	7,52E-10	1360544799	1,8	0	6
13	31,24649	14,5955	0,011085	2	1,8	0	6
14	8,73713	14,56188	6,77E-10	1360544799	2	0	6
15	34,16559	14,59755	0,010262	2	2	0	6
16	11,64951	14,56188	6,09E-10	1360544799	2,2	0	6
17	37,0851	14,59946	0,009526	2	2,2	0	6
18	14,56188	14,56188	5,48E-10	1360544799	2,4	0	6
19	40,00499	14,60123	0,008869	2	2,4	0	6
20	0	14,56188	7,45E-10	248792245	2,6	1	10
21	17,47426	14,56188	4,93E-10	1360544799	2,6	0	6
22	42,92524	14,60289	0,008284	2	2,6	0	6
23	2,912377	14,56188	6,85E-10	248792245	2,8	1	10
24	20,38664	14,56188	4,44E-10	1360544799	2,8	0	6
25	45,84582	14,60444	0,007763	2	2,8	0	6

Figure 6: Example of resulting data according to MVSDM

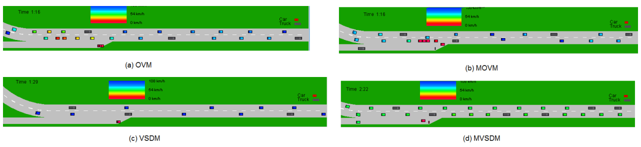

Figure 7: Simulation of ramp according to (a) OVM and (b) MOVM(c) VSDM and (d) MVSDM

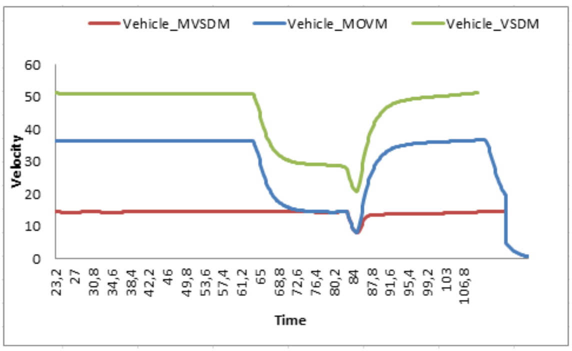

Figure 8: Time evolution of velocity variation according to MOVM, VSDM, and MVSDM

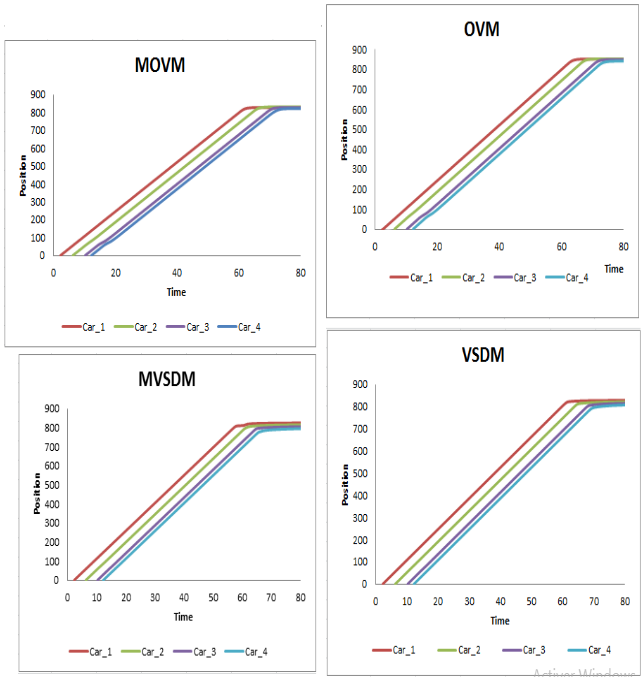

Figure 9: Position variation according to MOVM, VSDM, and MVSDM

Figure 9 gives the position evolution of four simulated cars, it's seen that the previous models provokes the collision. In contrast, our proposed approach avoids it.

4.2 Traffic lights scenario: behavior at stopping and approaching traffic signal

The traffic lights scenario describes the driving behavior of the vehicle when approaching a traffic signal. First a traffic signal is red and a queue of vehicles is waiting which the optimal velocity is 0. When the signal turn to green, at $t = 0$, vehicles start. For that, the traffic lights signal is represented by virtual obstacles in each lane which is removed when the light turns to green. Figure 10 represents the velocity variation of two vehicles using the MVSDM in the case of several changes. At the beginning, vehicle 1 follows vehicle 2 in the same lane 0, after a few moments vehicle 1 change the lane 0 towards the lane 1 that is why two vehicles show themselves in parallel when approaching traffic lights at $t = 57$. In approaching phase, and at $t = 72$ vehicles should decelerate smoothly which clearly shown that the vehicles stopped completely at a red light, and their velocity goes to 0. When the signal changes to green, vehicles begin to accelerate.

Figure 11 shows the behavior of vehicle according MOVM, MVSDM, and VSDM. Through these results, we deducted that the velocity of vehicle applying MOVM doesn't go to 0 that means all vehicles don't stop at a red light. However, when we simulate applying VSDM and MVSDM, all vehicles behave correctly by stopping at a

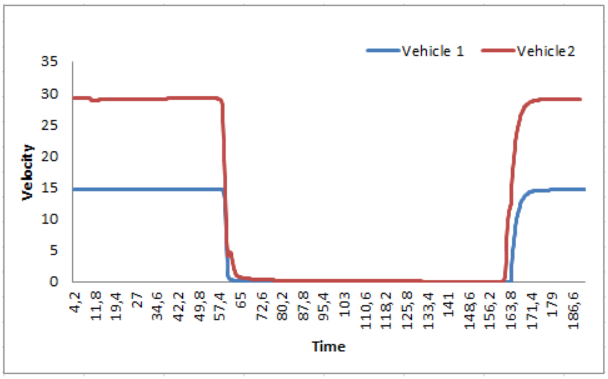

Figure 10: Driving behavior of two vehicles according MVSDM in each lane

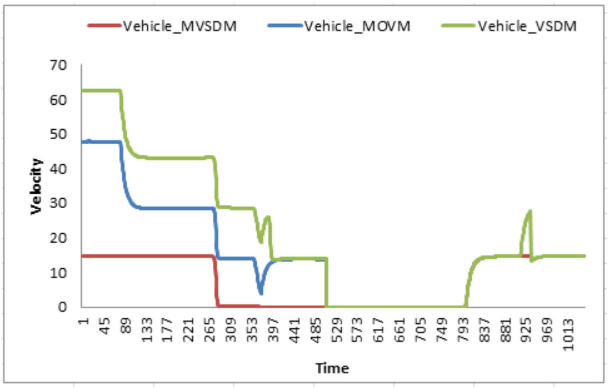

Figure 11: Simulation results according to MOVM, VSDM and MVSDM when approaching traffic lights signal

red light and moves when its turn to green. It's show clearly that the MVSD model react the realistic manner than MOVM and VSDM in braking case.

Figure 12 represents the snapshot of vehicle motion and their behavior according to MVSD, VSD, OV, and MOV models. Through these results, and when approaching traffic lights, it can be observed that the vehicles collide in the previous models. However, the problems of collision in emergency case were solved. Furthermore, the simulation results show that our proposed approach can exactly describe the driver's behavior when approaching traffic signal, where no crash occurs.

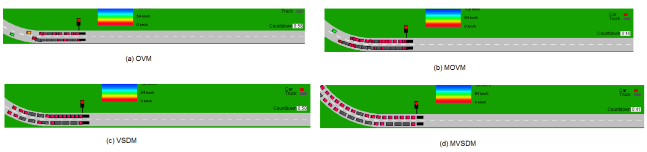

Figure 12: Simulation at traffic signal results according to OVM, MOVM, VSDM and MVSDM when approaching and stopping traffic lights signal

5 Conclusion

Through introducing the new optimal velocity function which takes into account not only the headway, but also the relative speed parameter into the VSDM, the modified velocity-separation difference model (MVSDM) is presented considering the driving behavior of the vehicle in braking case. In addition, to simulate in a realistic manner, we proposed to combine the proposed model with lane change model. The MVSDM can exactly describe the driver behavior under two proposed scenarios: when approaching traffic signal and an on ramp road, where no collision occurs. We can see that MVSDM is much close to the reality. However, the collision and crashes occur in the previous models. We proposed as a future work, to validate the model in bidirectional road scenario with multilane.

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