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# Cooperative highway traffic: multi-agent modeling and robustness assessment to local perturbations

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As cooperative systems, *a.k.a.* connected vehicles, enable the communication and exchange of information between vehicles and infrastructure, it is expected that their communication capabilities can lead to a better active traffic management on urban motorways. In such a context, technological constraints must be the basis for any management strategy. If it has been analytically proven that communication can help stabilize traffic flow at a microscopic level, it is interesting to evaluate realistic communication strategies taking into consideration multiple perturbations such as sensors faults or driver cooperation. In this paper, a three-layer multi-agent framework is used to model and control the homogenization of traffic flow. The physical layer coordinates the vehicles dynamics based on a cooperative car following model. This layer includes cooperation derived from the communication and trust layers that respectively manage information and its reliability. Simulation results highlight the positive impacts of communication and control on traffic flow stability.

# 1 Introduction

Cooperative systems, *a.k.a.* connected vehicles, are new technologies that allow vehicles communicate with other vehicles and with the infrastructure. They enable both capture and reports on vehicles' surrounding traffic conditions and environment. More specifically, they refer to vehicle integrated systems that aim to provide the driver with a more comfortable driving task, but also with a safer and more efficient traffic flow. In addition to autonomous technology like Adaptive Driver Assistance Systems (ADAS) [1], vehicles and infrastructure can be equipped with wireless communication devices. The recent developments of dedicated communication channels (cellular, Dedicated Short-Range Communication - DRSC, WIFI, WIMAX) increase the potential amount of information to be exchanged. All these technologies are part of the C2X framework [2], in which On-Board Units (OBU), Road Side Units (RSU), in-vehicle ADAS and on-road sensors (loop detectors, cameras..) would play their key role. Such a communication framework looks very suitable for a decentralized control approach, where vehicles are acting as mobile agents supplied by real time personalized and tailored recommendations, but also to a more centralized approach through the use of Road Side Units.

In this paper, we advocate that the vehicles' cooperation is likely to offer substantial additional benefits in terms of traffic safety, efficiency, level of service, reliability and reduction of negative impacts on the environment. To our belief, a multi-agent framework that inherits from the traffic theory knowledge would help to better assess the potentialities and limitations of cooperative systems at a local and microscopic level. The goal is to set up the modelling bricks of a cooperative auto-adaptive system, with the underlying stake that traffic physics and communication should interact to overcome modeling and technology uncertainties. We start this paper with a state of the art about the introduction of cooperative systems into traffic modeling (section 2). We also expose how agent-based modeling can be well adapted to our problem. In section 3, preliminary results related to microscopic models, calibration (see [3]), stability domains and instabilities conditions (see [4]) are briefly reported. This sets up the main ingredients of the multi-agent model. A three-layer framework with physical, communication and trust layers is used to achieve traffic flow homogenization. If traffic physics is modeled via a classical microscopic law, both communication and trust layers act upon physics through traffic models' parameters. The possibility of an online control is discussed. Finally, in section 4, we present promising numerical simulation results regarding the robustness of the Multi Agents System (MAS) to information reliability and the appearance of congestion. The simulation case allows us to foresee several research perspectives that would lead to a more realistic online cooperative traffic flow control, as discussed in section 5.

## 2 State of the art

### 2.1 Cooperation and traffic

The introduction of communication-based vehicle cooperation into classical traffic

models has been a recent topic of interest. One first area concerns traffic flow stability, meaning the study of traffic conditions likely to propagate traffic perturbations, *e.g.* shock waves. The information issued from cooperation has indeed a stabilizing effect if used as a complement of the driver's perception field. At a macroscopic level, pioneer work was part of the Automated Vehicle and Highway System (AVHS) effort where a link layer controller was designed based on macroscopic traffic states [5]. In [6], Ngoduy et al. derived a multi-class gas kinetic model from the gas kinetic theory and applied the method of moments to derive macroscopic equations of cooperative traffic flow. It was shown through numerical simulations that equipped vehicles have this traffic flow stabilizing effect, having assumed a linear relation between the desired velocity and the information value.

At a microscopic level, an approach consists of using car following models to evaluate similar effects. The main idea is that vehicles update their speed depending on their perception of the more than one headways and relative velocities to neighboring vehicles. In this case, the car following law is referred to as a multi-anticipative car following. Work carried out by Wilson [7] and Ge et al. [8] state that a multi-anticipative car following law modifies the stability threshold. It actually increases the stability domain in the parameter space, *i.e.* the domain where a perturbation does propagate in time. In [9], it was applied to calibrated traffic parameters and shown that the appearances of stop and go waves are being reduced with a single hop broadcast communication, based on DSRC technology and close to the Cooperative Adaptive Cruise Control (CACC) framework [10]. Non linear techniques can help go further to assess the shock wave structure itself [11]. It was analytically proved that cooperation has a positive effect on solitary waves (solitons) [12]. Besides, important results came out in previous research stating that a synchronization of the traffic flow can result in a better capacity [13] and can help avoiding the capacity breakdown phenomenon assumed to be caused by local instabilities and disturbances [14]. Indeed, local instabilities tend to increase with traffic flow heterogeneity [4], as the heterogeneity itself generates perturbations such as aggressive lane changes and braking vehicles [3]. It can be observed that for a braking vehicle the perturbation does propagate in time only when the stability condition is not respected [9]. However, for spontaneous perturbations due to aggressive lane changes, perturbations can propagate even though the stability condition is verified. The distribution of free flow speed correlated to unexpected lane changes might cause local instabilities leading to perturbation propagation. As it seems to match real data observations [3], it is important to consider for a future control strategy: a traffic flow maintained in stable regime combined with a restrictive lane changing strategy would make disappear local instabilities likely to cause a capacity breakdown.

## **2.2 Multi-agents systems**

Local traffic flow properties can therefore be derived and their knowledge help the anticipation of congestion, enabling smoother transitions between traffic regimes. However, the determinism resulting from such approaches brings up limitations. It is clear that the multiple communication capabilities imply very complex interaction schemes as well as a certain flexibility in the modeling framework. A vehicle fleet with a mix of cooperative and non-cooperative vehicles might exhibit some chaotic behaviors that are difficult to assess with sparse real-world datasets [15, 16]. The multiple communication schemes, the unpredictability

of drivers' cooperation and traffic parameters estimates as well as the varying equipment rate of vehicles are major uncertainty sources. A multi-agent framework seems suitable for modeling these interactions [17]. Each vehicle has its own and specific perception of the local environment and can adjust its kinematic and behavior depending on its perception. This approach has been used to help the design of ad-hoc networks and peer to peer networks or to improve autonomic computing principles [18]. Notions such as emergence of structures, adaptivity and self-maintenance characterize self-organization. Most of existing approaches are providing mechanisms that dynamically alter the structural relations between agents either through bio-inspired mechanisms or through the use of some specified transformation rules. Recently, more attention was given to mutual influence between informational and behavioural levels [19, 20]. The approach we develop in this paper takes up this idea with the specificity of using a trust layer [21] which can be seen as the learning level. The collective task would be to make traffic evolve in the stability regime. The informational flow must be organized to effectively exploit the information and to ensure its reliability.

### 3 Cooperative traffic modeling

#### 3.1 Multi-anticipative microscopic models

The longitudinal behavior of vehicles is classically modelled through car following models, i.e. a vehicle updates its acceleration as a function of its perception of the leading vehicle dynamics. The most general form that takes into account all the possible sensed information is written as:

$$\ddot{x}_n = f(\dot{x}_n, \Delta x_n, \Delta \dot{x}_n), \quad (1)$$

$\ddot{x}_n$  and  $\dot{x}_n$  being respectively the acceleration and the speed of vehicle  $n$ ,  $\Delta x_n$  being the space headway and  $\Delta \dot{x}_n$  the relative velocity between vehicles  $n$  and its leader. For a multi-anticipative traffic, a similar law is used:

$$\ddot{x}_n = f(\dot{x}_n, \sum_{i=-m}^m a_i \Delta x_{n+i}, \sum_{i=-m}^m b_i \Delta \dot{x}_{n+i}) \quad (2)$$

where  $(a_i)_{0 \leq i \leq m}$  and  $(b_i)_{0 \leq i \leq m}$  are weighting coefficients supposed to define the importance of the interaction between a vehicle  $i$  and the vehicles ahead ( $i + 1$  to  $m + i$ ) within its communication range ( $m$  vehicles). For the sake of simplicity, here it will be assumed that  $(a_i)_{0 \leq i \leq m} = (b_i)_{0 \leq i \leq m}$ . Well-known models are the Intelligent Driver Model (IDM) [22] and the Optimal Velocity with Relative Velocity (OVRV) [9,23]. Both models have exhibited interesting features [24]. Indeed it has been demonstrated that these two models represent traffic features accurately [24, 25], such as the stop and go wave phenomenon. In this work, we will focus on the OVRV model, which is derived from the Optimal Velocity Model proposed by Bando *et al.* [26].

Lateral movement in traffic is usually modelled via lane changing models. They are often defined as conditions vs. probability for determining whether a lane change could occur. Gap

acceptance models [27] are the first class of models: the driver evaluates if the perceived gap is large enough to proceed to a lane change. The MOBIL (Minimizing Overall Braking Decelerations Induced by Lane Changes) model [28] goes a step further as it directly deals with the perception of the acceleration of surrounding vehicles. As it deals with acceleration it is therefore directly linked to car following models. Thus a MOBIL strategy coupled with the OVM model (OVRV model without the relative velocity term) is a simple gap acceptance model. Finally, the explicit target lane choice model [29] is the ultimate level in the lane changing decision models as the driver takes into consideration different utilities such as the surrounding vehicles, the path plan and the lane attributes. The lane changing probability is then computed based on the utility function. This latter class is the one selected in this paper under an adapted form.

### 3.2 Stability considerations

Stability analysis refers to the study of perturbations propagation [7]. In order to determine the stability conditions, we introduce a perturbation to the steady state traffic. Such state is reached when  $\Delta\dot{x} = 0$  and  $\ddot{x} = 0$ , i.e.:

$$f(\dot{x}_{eq}, \Delta x_{eq}, 0) = 0, \quad (3)$$

where  $\dot{x}_{eq}$  and  $\Delta x_{eq}$  are the steady state speed and headway. When introducing a perturbation  $y_n$  to the equilibrium flow the first order Taylors series development gives:

$$\ddot{y}_n = f(\dot{x}_{eq} + \dot{y}_n, \Delta x_{eq} + \Delta y_n, 0 + \Delta \dot{y}_n) = f_1 \dot{y}_n + f_2 \Delta y_n + f_3 \Delta \dot{y}_n \quad (4)$$

where  $(f_i)_{1 \leq i \leq 3}$  are the partial derivatives of  $f$  taken at the equilibrium point  $(\dot{x}_{eq}, \Delta x_{eq}, 0)$ . We then write the perturbation in Fourier mode and obtain the dispersion relation. After some straightforward development detailed in [7, 12] it turns out that the conditions over the partial derivatives that lead to an unstable dynamic system, *i.e.* when the perturbation does propagate in time, are:

$$f_1^2 - 2f_2 - 2f_1 f_3 < 0 \quad (5)$$

with  $f_1 < 0$ ,  $f_2 > 0$  and  $f_3 > 0$ . Those inequalities are introduced to be consistent with physical tendencies of acceleration and deceleration, see [9]. For a multi-anticipative car following model, the sufficient conditions leading to an unstable dynamical system are written:

$$f_1^2 \left( \frac{1}{2} + \sum_{j=0}^m j a_j \right) - f_2 - f_1 f_3 < 0 \quad (6)$$

Finally, the stability domain is being increased with the multi-anticipative law, as exhibited on figure 1 for realistic partial derivative values and for coefficients  $(a_i)_{0 \leq i \leq m}$  chosen as in [9]. The upper part of the 3D surfaces is the instable one, and it is visible that this domain is greater in the non-cooperative case (lower surface). As the unstable domain in the parameters space is smaller for the multi-anticipative case, it means that a multi-anticipative traffic have fewer traffic configurations that are likely to trigger congestion.

### 3.3 Formulation of the multi-agent framework

The goal of each agent -vehicle- is to cooperatively evolve with the global target to reach stable traffic conditions. To achieve this goal, a three layer architecture is proposed with physical, communication and trust layers. The communication and trust layers interact with the physical layer by managing information and using this information to control the vehicles dynamics described at the physical layer. At a control level, the purpose is to optimize the dynamical system with regard to a specific target criterion (here stability) derived from equation (5), and hence to homogenize traffic flow.

Figure 2 presents the interaction between the three layers. The physical layer concerns the vehicle dynamics rules and estimates on its dynamics. The communication layer governs the information exchanges through proximity, reliability, information renewal and lane changing rules. These rules are traduced into probabilities. The trust layer models the quality of the exchanged information and then influences the physical layer through communication. The definition of the information quality is twofold. First, each agent measures the confidence made in the received information as well as the confidence it has in itself. A cooperative agent is able to sense all its surrounding vehicles via sensing devices, *e.g.* radars, lasers, cameras. It compares this sensed information with comparable information coming from others agents such as speeds and positions, and then is able to share it with others agents, allowing the computation of a reliability value. Secondly, each cooperative agent can estimate its car following parameters based on its trajectory data. Another reliability value can therefore be computed depending on the variability of the estimates and on the quantity of available information to perform the estimates. The knowledge of such parameters is relevant for traffic flow stabilization.

#### 3.3.1 Physical layer

At each time step, each vehicle gets information through in-vehicle sensors or wireless communication. Wireless communication depends on communication probabilities (see communication layer, section 3.3.3). Let us call  $N_n(t)$  the set of neighbors for agent  $n$  at a time  $t$ , for simplicity purposes we will write  $N_n(t) = N_n$ . This set can be divided into two sets, a set for downstream communicant agents  $N_{nd}$  and a set for upstream communicant agents  $N_{nu}$ . On figure 3, the dashed ellipse gives an idea on the potential communicant agents for a connected vehicle.

##### a. Multi-anticipative car following law

The main objective of the physical layer is to accurately describe traffic dynamics. As discussed in section 3.2, we use the multi-anticipative OVRV car-following model:

$$\ddot{x}_n = -\frac{1}{\tau}\dot{x}_n + \frac{1}{\tau}V(\sum_{i=0}^m a_i \Delta x_{n+i}) + \frac{\eta}{\tau}\sum_{i=0}^m a_i \Delta \dot{x}_{n+i} + a_c \quad (7)$$



where  $\tau$  is the reaction time,  $\eta$  models the sensitivity of the driver's perception of the relative velocity and  $V$  is a non linear function that constrains the speed as a function of the headway.  $(a_i)_{0 \leq i \leq m}$  are weighting coefficients that depend on the proximity and reliability values computed at the communication and trust levels, and  $m + 1 = |N_{nd}|$ . We choose  $V$  as in [?, ?]:

$$V(\Delta x_n) = \frac{V_{\max}}{2} (\tanh(s \cdot h_c) + \tanh(s \cdot (\Delta x_n - h_c))) \quad (8)$$

where  $V_{\max}$  is a free flow speed,  $s$  is a smoothing coefficient and  $h_c$  is the critical headway for which we have the most unstable traffic. Besides,  $a_c$  is an added proportional cooperative control term which is chosen to be written as, at time  $t$  and for vehicle  $n$ :

$$a_c = k_1(\dot{x}_n - \dot{\bar{x}}) + k_2(\Delta x_n - \Delta \bar{x}), \quad (9)$$

with  $k_1 < 0$ ,  $k_2 > 0$ , and where

$$\begin{aligned} \dot{\bar{x}} &= \frac{1}{N_n} \sum_{i=-|N_{nu}|}^{|N_{nd}|} \dot{x}_{n+i}, \\ \Delta \bar{x} &= \frac{1}{N_n} \sum_{i=-|N_{nu}|}^{|N_{nd}|} \Delta x_{n+i}. \end{aligned} \quad (10)$$

The two added control terms are integrated in order to make the traffic converge towards more homogeneous conditions, *i.e.* neighboring average values of headways and relative velocities. Both terms aim at reducing the disorder between vehicles, based on the available information and its reliability.  $k_1$  and  $k_2$  terms are gain factors for the estimated terms (10).

Note that instead of using average values  $(\bar{x}, \Delta \bar{x})$ , a desired couple  $(\dot{x}_s, \Delta x_s)$  corresponding to a stable equilibrium regime could be chosen. The stability term would therefore depend on the parameters of the car following model plus the estimate of the local density.

### **b. Lane-changing law**

The lane changing probability law used in this paper is derived from the Target Lane Choice Model [29], where the probability of a lane change is computed according to utility functions. Besides to the reaction to immediate surrounding vehicles, lane changing strategies have to make fast vehicles using fast lanes, fill in the low density areas and avoid perturbation propagation in traffic. Our model is chosen to be relatively simple as we choose the utility of a lane change to be the sum of two utility terms. Its contribution consists of integrating into the utility terms the MOBIL strategy under a probabilistic form and an added term which can be seen as a control one. More generally, the utility of lane  $l$  as target lane for vehicle  $n$  at time  $t$  is written:

$$U_{lnt} = u_{lnt}^c \cdot \beta_c \quad (11)$$

where  $u_{lnt}^c$  is a vector of length  $c$ , which contains the  $c$  different utilities, and  $\beta_c$  a vector characterizing the weight assigned to each utility. The utility of a lane change should reflect the following considerations:

- Drivers react to surrounding conditions. The MOBIL strategy was intended to model such behaviors as vehicles sense the potential acceleration of surrounding vehicles in case a lane change would occur. Given that there was no lane change in a previous time frame  $T$ , a lane change is possible if

$$\bar{\ddot{x}}_n - \ddot{x}_n + p(\bar{\ddot{x}}_c - \ddot{x}_c + \bar{\ddot{x}}_o - \ddot{x}_o) > \delta a_{th} \quad (12)$$

$$\bar{\ddot{x}}_c > a_{saf}. \quad (13)$$

where  $\bar{\ddot{x}}$  denotes the potential acceleration of a vehicle on the targeted lane -acceleration if the lane change occurs- and the subscripts  $c$  and  $o$  refer to the following vehicles in the target and current lanes respectively.  $\delta a_{th}$  and  $a_{saf}$  are respectively the criterion for lane changing that denotes the permissiveness threshold of a lane change and the safe potential deceleration limit of the following vehicle  $c$ .  $p$  is a politeness (or aggressiveness) factor, which weights the acceleration gain or loss of the potential old and new followers. The vehicle is actually estimating an acceleration gain before proceeding to a lane change. If both conditions are satisfied, it changes his lane. Then, we transform this model into a probabilistic quantity. By writing  $\gamma = \bar{\ddot{x}}_n - \ddot{x}_n + p(\bar{\ddot{x}}_c - \ddot{x}_c + \bar{\ddot{x}}_o - \ddot{x}_o) - \delta a_{th}$ , we get the first component  $u_{lnt}^c(1)$  of vector  $U_{lnt}$ :

$$u_{lnt}^c(1) = \begin{cases} 0 & \text{if } \gamma < \gamma_{min} \\ 1 & \text{if } \gamma > \gamma_{max} \\ (\gamma - \gamma_{min}) / (\gamma_{max} - \gamma_{min}) & \text{otherwise.} \end{cases} \quad (14)$$

The condition is used *a posteriori* as a binary one.

- Vehicles tend to move towards vehicles that have the same behavioral parameters. The fast vehicles move to faster lanes and slow vehicles to slower lanes. By receiving speed of current and neighboring lanes the driver adjust the corresponding utility. The second component of  $U_{lnt}$  is written:

$$u_{lnt}^c(2) = \frac{V_{max,n} - V_{max,eq}}{V_{max,n}} \quad (15)$$

where  $V_{max}$  is the estimated maximum speed of vehicle  $n$  and  $V_{max,eq}$  is the estimated average maximum speed of surrounding vehicles. Note that this utility could rely on other parameters of the car following law.

Note that only the deterministic form of the MOBIL model has been calibrated. The probability of a lane change (lane  $l$  as target lane  $TL$ ) is then given by a logit model (see [29]):

$$P(TL_{nt}^l) = \frac{\exp(U_{lnt}^{TL})}{\sum_{m \in TL} \exp(U_{mnt}^{TL})} \quad (16)$$

where  $TL$  is the set of target lanes (current or the two adjacents). The global acceleration loss of vehicles in the targeted lane could be more important than the acceleration gain of the vehicle. Utilities such as lane disorder (inhomogeneity of speeds) and path plan could also be added.

### 3.3.2 Trust layer

In a distributed communication framework, information can be altered by unreliable agents. There is a need to remove the spread of erroneous information due to these agents. Each cooperative agent receive information from others cooperative agents and provides its information to other agents based on its own sensing device capabilities (*e.g.* lidars and lasers). Deceitful sensors or high sensitivity to particular exogeneous factors (*i.e.* weather conditions) could be sources of error. It is therefore important to dynamically assess which agent sends reliable information and which does not.

As shown in figure 3, each cooperative vehicle senses the two leaders and the follower on its lane, plus the immediate neighbors on adjacent lanes (leader and follower). This information can then be shared and compared with other agents, enabling the computation of a reliability value. A trust network (see [21]) was chosen for modeling agents reliability.

In such a framework, agents measure their confidence between them and in themselves using trust sets, composed of a trust graph and a trust table (which is kept confidential by each agent). The trustgraph of agent  $i$  is denoted  $TG_i$ , each arc corresponding to the existence of a past communication. Let  $i$  and  $j$  be cooperative agents -connected vehicles-, meaning that they have exchanged information at a time  $t$ . The direct trust of agent  $i$  towards agent  $j$   $DT_{ij}$  is computed if there is comparable data between the two agents. Besides, the trust of  $j$  in agent  $k$  is communicated by  $j$  to  $i$ : it is the indirect trust denoted  $IT_{jk_i}$ . The intrinsic trust  $T_{ij}$  is computed by considering both direct and indirect trusts.

The trust set dynamics consists of the following steps (see [30] for further details). Each agent computes direct trust by comparing information. To compute trust in  $j$ , agent  $i$  compare its own direct data  $D_{ij}$ , of cardinal  $\beta$  (number of comparable informations). An inconsistency level is being computed:

$$I_l = \frac{\sum_{i \in \{1, \dots, \beta\}} \delta(x_i, y_i)}{\beta \cdot \delta_{max}} \quad (17)$$

where  $x_{i \in \{1, \dots, \beta\}}$  is the information sensed by agent  $i$ ,  $y_{i \in \{1, \dots, \beta\}}$  the information sensed by agent  $j$ ,  $\delta(x_i, y_i)$  the measure of discrepancy between informations, and  $\delta_{max}$  the maximum distance between incoherent informations. We have

$$DT_{ij} = \begin{cases} DT_{ij} + \tau^+ & \text{if } I_l > \mu \\ DT_{ij} - \tau^+ & \text{if } I_l < \mu, \end{cases} \quad (18)$$

where the threshold  $\mu$  determines if the agent increases or decreases its trust in  $j$  by a factor  $\tau^+$ . Once a upper threshold ( $\varepsilon_{up}$ ) or lower threshold ( $\varepsilon_{lw}$ ) is reached the agent is said to be reliable or unreliable, with  $0 < \varepsilon_{lw} < \varepsilon_{up} < 1$ .

We then merge the trustgraphs, associating  $DT_{ij}$  the trust agent  $i$  has in  $j$  to the arc  $ij$ , and being careful with the trust incoherence when computing the indirect trust. Indeed, information can be received at different time steps, producing that the trust agent  $k$  has in  $l$

communicated to  $i$  is different to the trust agent  $k$  has in  $l$  communicated to  $j$ , i.e.  $IT_{kl,i} \neq IT_{kl,j}$  for  $(k,l) \in TG_i \cup TG_j$ . The global indirect trust  $IT_{kl,ij}$  is then computed:

$$IT_{kl,ij} = \frac{\sum_{x \in Path_i} (T_{ix} IT_{xl,i}) + \sum_{y \in Path_j} (T_{iy} IT_{ky,j})}{\sum_{x \in Path_i} T_{ix} + \sum_{y \in Path_j} T_{iy}}, \quad (19)$$

where  $Path_i$  and  $Path_j$  are the shortest paths in  $TG_i$  and  $TG_j$  containing arc  $(k,l)$ , and where we initialize the intrinsic trust as the direct trust. The intrinsic trust of an agent  $i$  in an agent  $x$  in  $TG_i$  is written

$$T_{ix} = \frac{T_{ii} DT_{ix} + \sum_{k \in \mathcal{A}} (T_{ik} IT_{kx})}{T_{ii} + \sum_{k \in \mathcal{A}} T_{ik}}, \quad (20)$$

where  $T_{ii}$  is initialized to 1, and  $\mathcal{A}$  is the set of all past communicant agents with agent  $i$ .

### 3.3.3 Communication layer

The communication layer describes the exchange of information between vehicles. Rules aim at describing physical constraints as well as filtering choices such as dependence on reliability values, as it has a direct impact on the physical layer. For the sake of simplicity, two rules were judged to be important for the dissemination of information. At each simulation step (0.5 s), a probability to receive updated information from its neighbors is associated to each vehicle. Those two rules are described as follows.

- The proximity rule. The communication range when broadcasting information is assumed to be around 250 - 300 m. These values are consistent with the DRSC range. Information from downstream should be more important than information from upstream. Facing the complexity of modelling communication channels [16], we choose a gamma approximation of successful propagation, as described in [31]. The proximity probability that a vehicle  $i$  receives information for a vehicle  $j$  at a time step  $T$  is written

$$p_{prox}(i,j) = \exp(-\lambda|x_j - x_i|), \quad (21)$$

where we assume bidirectional propagation.

- The reliability rule. The probability is simply given by the trust agent  $i$  has in agent  $j$ .

$$p_{rel}(i,j) = T_{ij} \quad (22)$$

Note that here we did not model indirect communication. Indirect communication refers to an exchange of information between vehicles out of their communication range. It happens because vehicles forward the information they receive to upstream vehicles, for example in

some special traffic circumstances. Certain abnormal conditions likely to benefit from indirect communication could be an average speed lower than a critical threshold on a lane or group disagreement value higher than a threshold.

We choose to weight the importance of each specific communication rule, and the global probability of an exchange of information between agent  $i$  and agent  $j$ , given that agent  $i$  sends the information, is written:

$$p(i, j) = \omega \cdot p_{prox}(i, j) + (1 - \omega) \cdot p_{rel}(i, j). \quad (23)$$

Note that the weights are not chosen dynamically in this paper, as we are trying to first assess the importance of each communication rule. This importance may have to vary depending on the environment context and conditions (road section and traffic conditions). These parameters would ideally be learnt and dynamically modified via an endogeneous control.

Finally,  $p(i, j)$  represents the probability of an exchange of information, but only if vehicle  $j$  is willing to communicate its information. This only depends on the trust an agent has in itself. A probability of sending acceptance is therefore defined. For each vehicle  $i$ , the probability of sending acceptance is written:

$$p(i) = T_{ii} \quad (24)$$

which means that unreliable agents tend not to communicate at all. The trust an agent has in itself is computed via equation (20).

### 3.3.4 Multi-anticipative coefficients

This allows writing the multi-anticipative law coefficients (equation 2). Coefficients  $a_i$  should take into account the distance between interacting vehicles as well as reliability values, as they are supposed to weight the importance of each downstream information in order to help the anticipation of perturbations. In the scope of this paper they will be chosen such as:

$$a_i = \begin{cases} \frac{1}{2} [1 + \cos(\pi(\frac{x_{n+i} - x_n}{r}))] & \text{if } n + i \in N_{nd} \text{ and } \max_{j \in \mathcal{J}_{n+i}} T_{nj} > \varepsilon_{up}, \\ 0 & \text{otherwise.} \end{cases} \quad (25)$$

where  $\mathcal{J}_{n+i}$  is the set of agents sensing the position and speed of agent  $n + i$ ,  $T_{nj}$  is the average trust agent  $n$  has in agent  $j$ ,  $r$  the maximum distance between agent  $n$  and downstream communicant agents belonging to  $N_{nd}$ .

## 3.4 Experimental set-up

In order to be in realistic traffic conditions, the OVRV and MOBIL model were calibrated. The used dataset is a NGSIM 15 minutes observation frame (7:50 am to 8:05 am) on a stretch of the Hollywood Freeway (US 101) located in Los Angeles, California and collected on June 15, 2005. The two most left lanes were considered.

## 4 Simulation results

### 4.1 Simulation set-up and calibration

A two-lane freeway traffic was therefore simulated, with an entrance flow distribution taken from the US 101 sample data. The mean flow were respectively  $0.48\text{veh/s}$  and  $0.50\text{veh/s}$  for the two lanes. The parameters were chosen as calibrated, with a lognormal distribution for  $V_{max}$  of standard deviation  $2\text{feet/s}$ , which is roughly fitting observations. For a more accurate representation of the microscopic parameters and their distributions, see previous work [32, 33].

The calibration process is related to previous work by Kesting *et al.* [24]. A particular objective function is designed and optimized through a genetics algorithm. For more details, see [3]. For the OVRV model, the five parameters to be calibrated are  $(V_{max}, \tau, \eta, h_c, s)$ , being respectively the maximum speed, the perception reaction time of the driver, the sensitivity to the relative velocity, the non-constraining headway, and a smoothing coefficient. The coefficients were found to be  $(30.9, 1.98, 0.54, 45.3, 0.28)$ , units being in *feet* and *seconds*. For the MOBIL model, the parameters to be calibrated are  $(a_{saf}, p, \Delta a_{th})$ , being respectively the safe deceleration limit, the aggressiveness factor and the acceleration gain permissiveness threshold of a lane change. Coefficients were found to be  $(8.0, 0.5, 0.9)$ , accelerations being in  $\text{feet/s}^2$ .

Other parameters were fixed:  $\gamma_{min} = -0.1$ ,  $\gamma_{max} = 0.1$ ,  $\beta_c = (1, 0)$ ,  $\lambda_1 = 0.003$ .  $\lambda_1$  was chosen to be representative of the communication possibilities. The communication parameter was selected as  $\omega = 0.6$ , and the agents all set to be reliable. From a computational perspective, the same seed was associated to each uniform distribution to allow comparisons between successive simulations (the randomness is caused by the percentage of cooperative drivers and aggressive lane changes, the computation of the adjacency matrix based on probabilities and the free flow distribution).

A critical question is the one regarding the performance indicators. It was discussed in [4] that the group disagreement value is a relevant indicator for traffic homogeneity, and therefore of the likelihood to enter into congestion. Indeed, homogenization in a stable regime helps reduce the emergence of local perturbations and their propagation. The group disagreement value is actually the sum of the variance of the speed within a communication group, meaning between vehicles within their communication range. It was defined and used as indicator in [4, 34].

### 4.2 First results

The mechanism of stop and go waves is observed via simulation by triggering perturbations, either by making a vehicle brake or by forcing an aggressive lane change. Note that for the car following model, the calibrated set of parameters does not mathematically correspond to an unstable traffic (equation 5), however perturbations can still appear and propagate due to the heterogeneity of traffic.

The global group disagreement value is computed in order to assess the effectiveness of control strategies and of communication schemes. It is defined as the sum of the disagreement values for every time step during the whole simulation, which lasted 10 minutes. Perturbations

were introduced through aggressive lane changing behaviors, as a percentage of the drivers were picked to have a negative politeness factor such as  $p = -1$ . Drivers with a negative  $p$  are actually changing their lanes even if they perceive a loss in this action, acting as clear traffic troublemakers. Such random perturbations could introduce high disturbances in traffic. Table 1 provides the global group disagreement value depending on the equipped vehicles' penetration rate and the percentage of aggressive lane changing behaviors, and shows how cooperative traffic tends to decrease the variance of speeds and therefore the likeliness to fall into local congestion phenomena. This fact can be verified with a time space diagram. Indeed, it is visible on figure 1 that cooperation prevents the appearance of perturbations, see figure 1. This figure shows that the stabilizing effect of cooperative traffic can be relevant and can help limitate the impact of aggressive drivers (which go against a gain of acceleration when making a lane change). An increasing penetration rate reduces the impact of aggressive lane changing behaviors, as it increases the stability domains and homogenize traffic: there is less propagation of perturbations.

Let us examine the control and communication parameters  $(k_i)_{0 \leq i \leq 2}$  and  $\omega$ . With a cooperative penetration rate of 80% and a percentage of aggressive lane changing behaviors set to 20%, first results show the impact of ponderation in communication. An effort consisted of investigating the effect of the longitudinal control law (equation 7). Control terms have positive effects to some extent. The positive effect of the control persists until a parameter threshold is reached, again corresponding to an unstable domain. This happens when the gain of the control terms is too high and increases disturbances instead of reducing them. Besides, a too high gain can lead to collision, so the implemented emergency braking is then a source of instabilities. Sensitivity analyses of these parameters values are under investigation in order to better understand their interactions and cumulative effects.

### 4.3 Discussion

Real-time traffic evolves in very sensitive traffic situations. Here, we have chosen to fix the traffic situation (*i.e.* the traffic model's parameters) to evaluate the effect of cooperativeness on a perturbed traffic. The study of the effects of communication and control is then performed. This can be seen as the conditional effect assessment for a given traffic situation. This is clearly a first step, as there is a dependence between the traffic situation and the optimal set of control and communication parameters. The conditional sensitivity analysis is prior to a more general analysis under investigation.

In this respect, the presented model can be seen as parameter-dependent. The physics part (traffic model parameters) can be calibrated but some data are needed to more accurately evaluate the possible reaction of non-cooperative drivers in a mixed traffic. However, we believe that the interaction between traffic physics and the communication and trust layers exhibit very promising results, and that future implementations would provide data that would help reduce uncertainties.

## 5 Conclusion

We have proposed a multi-agents framework to deal with the complexity of information exchanges. Stability results were put in evidence as they condition the development of perturbations in traffic. A combination of car following and lane changing models was chosen to model microscopic traffic. These two elements form the core of a physical layer directly linked to the environment and describing the agents' dynamics. The perception of each vehicle was computed through communication rules, which are supposed to include physical constraints as well as communication preferences. Such preferences are based on logical considerations but also interact with a trust layer. The trust layer models information's reliability. Based on received information, each vehicle adapts its behavior. First simulations results have exhibited promising applications for the proposed framework. A distributed control based on local stability conditions and traffic homogeneity for car following behavior discloses some interesting results. Finally, the built-in trust layer for detection of unreliable on-board sensors would provide a better information management and avoid some dangerous situations created by such perturbations.

Among the perspectives of the proposed work, first, the stability and collision-free motion of vehicles should be guaranteed. The possibility of getting a stable and collision-free motion depends on the distribution of parameters and on the initial heterogeneity value between the actual traffic configuration and the desired one. The multi-anticipative and control strategies should be applied in a safe domain of parameters and homogeneous enough traffic state with the aim of achieving a linearly stable traffic. Then, infrastructure communication capabilities should be integrated. Road Side Units (RSU) shall act as a second type of agent that will help to estimate local traffic conditions at a mesoscopic scale, typically the scale of a road section it controls. In this work, we have assumed that the car following and lane changing models parameters were given, *i.e.* known by each agent. In future work, RSU could be part of an estimation process: the online parameters identification and its integration into the trust layer are a critical step towards a more consistent framework. Moreover, RSU can be a key element within indirect communication modeling as they can help detect abnormal traffic conditions and forward it to upstream vehicles as well as to upstream RSU. One could imagine two-step incident detections processes where RSU detect and signal specific situations that are then verified by targeted vehicles themselves. Learning processes by agents or emergence phenomena will of course be analyzed, especially in the case of a mixed traffic (connected/non-connected vehicles, reliable/unreliable information, different class of vehicles). Besides, emergence of drivers behaviors and drivers' reaction to a specific control may depend on the road site and its geometry, which strengthens the need of static learning agents like RSU. This last aspect raises the issue of the nature and frequency of the information that has to be sent to drivers, as well as the criteria that have to be controlled.

Although connected vehicles are still seldom implemented, this work underlines the potential of a multi-agent framework for modeling a connected road network and ultimately aims at providing a cooperative decision support tool for both vehicles and road managers [35]. By *a priori* analyzing the potential impacts of these future technologies, the effects of the penetration rate, the importance of information reliability as well as the communication and management strategies to be undertaken, this paper aims to contribute to a better anticipation of the future large-scale deployment issues.



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## References

- [1] Andreas Tapani. Traffic Simulation Modelling of Rural Roads and Driver Assistance Systems. PhD thesis, Linköping University, Department of Science and Technology, The Institute of Technology, 2008.
- [2] Car 2 Car communication consortium, 2008.
- [3] J. Monteil, A. Nantes, R. Billot, and N-E. El Faouzi. Microscopic cooperative tra\_c based on ng-sim data. ITS World Congress, Vienna, 2012.
- [4] J. Monteil, R. Billot, and N-E. El Faouzi. Des vehicules cooperatifs pour une gestion dynamique du trafic: approche theorique et simulation. To appear in Recherche Transport Securite (RTS), 2012.
- [5] Perry Y. Li, Roberto Horowitz, Luis Alvarez, Jonathan Frankel, and Anne M. Robertson. Traffic flow stabilization, 1995.
- [6] D. Ngoduy, S.P. Hoogendoorn, and R. Liu. Continuum modeling of cooperative traffic flow dynamics. *Physica A: Statistical Mechanics and its Applications*, 388(13):2705-2716, 2009.
- [7] R. E. Wilson and J. A. Ward. Car-following models: fifty years of linear stability analysis - a mathematical perspective. *Transportation Planning and Technology*, 34(1):3-18, 2011.
- [8] H.X. Ge, S.Q. Dai, and L.Y. Dong. An extended car-following model based on intelligent transportation system application. *Physica A: Statistical Mechanics and its Applications*, 365(2):543-548, 2006.
- [9] J. Monteil, R. Billot, D. Rey, and N-E. El Faouzi. Distributed and centralized approaches for cooperative road traffic. *Procedia - Social and Behavioral Sciences*, 48:3198-3208, 2012.
- [10] S. Shladover. Effects of cooperative adaptive cruise control on traffic flow: testing drivers' choices of following distances. Berkeley, Calif, California PATH Program, Institute of Transportation Studies, University of California at Berkeley.
- [11] E. Wilson. Mechanisms for spatio-temporal pattern formation in highway traffic models. *Phil. Trans. R. Soc. A*, 366(1872):2017-2032, 2008.
- [12] J. Monteil, R. Billot, J. Sau, and N-E. El Faouzi. Stability techniques for evaluating cooperative road traffic. Technical report IFSTTAR, 2012.
- [13] C.F Daganzo, M.J Cassidy, and R.L Bertini. Possible explanations of phase transitions in highway traffic. *Transportation Research Part A: Policy and Practice*, 33(5):365 { 379, 1999.
- [14] Hwasoo Yeo and Alexander Skabardonis. Understanding stop-and-go tra\_c in view of asymmetric traffic theory. In William H. K. Lam, S. C. Wong, and Hong K. Lo, editors, *Transportation and Traffic Theory 2009: Golden Jubilee*, pages 99-115. Springer US, 2009.
- [15] Miguel Sepulcre and Javier Gozalvez. Experimental evaluation of cooperative active safety applications based on v2v communications. In *Proceedings of the ninth ACM international*

workshop on Vehicular inter-networking, systems, and applications, VANET '12, pages 13-20, New York, NY, USA, 2012. ACM.

[16] Andreas F. Molisch, Fredrik Tufvesson, Johan Karedal, and Christoph Mecklenbrauker. Propagation aspects of vehicle-to-vehicle communications - an overview. In Proceedings of the 4<sup>th</sup> international conference on Radio and wireless symposium, RWS'09, pages 171-174, Piscataway, NJ, USA, 2009. IEEE Press.

[17] Kutluhan Erol, Renato Levy, and James Wentworth. Application of Agent Technology to Traffic Simulation.

[18] Richard Holzer, Hermann Meer, and Christian Bettstetter. On autonomy and emergence in self-organizing systems. In Proceedings of the 3rd International Workshop on Self-Organizing Systems, IWSOS '08, pages 157-169, Berlin, Heidelberg, 2008. Springer-Verlag.

[19] Olivier Lefevre, Frederic Armetta, Gael Clair, and Salima Hassas. Mana: A new multi-agent approach for complex assignment problems. In Proceedings of the 2009 Computation World: Future Computing, Service Computation, Cognitive, Adaptive, Content, Patterns, COMPUTATIONWORLD '09, pages 167-172, Washington, DC, USA, 2009. IEEE Computer Society.

[20] Sherief Abdallah and Victor Lesser. Multiagent reinforcement learning and self-organization in a network of agents. In Proceedings of the 6th international joint conference on Autonomous agents and multiagent systems, AAMAS '07, pages 39:1-39:8, New York, NY, USA, 2007. ACM.

[21] S. Marsh. Formalising Trust as a Computational Concept, 1994.

[22] A. Kesting, M. Treiber, and D. Helbing. Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity. Philosophical Transactions of the Royal Society, A 368:4585-4605, 2010.

[23] Rui Jiang, Qingsong Wu, and Zuojin Zhu. Full velocity difference model for a car-following theory. Phys. Rev. E, 64:017101, Jun 2001.

[24] Arne Kesting and Martin Treiber. Calibrating car-following models using trajectory data: Methodological study. Journal of the transportation research Board, 2088:148, 2008.

[25] Martin Treiber and Arne Kesting. Validation of traffic flow models with respect to the spatiotemporal evolution of congested traffic patterns. Transportation Research Part C: Emerging Technologies, 21(1):31-41, 2012.

[26] M. Bando, K. Hasebe, A. Nakayama, A. Shibata, and Y. Sugiyama. Dynamical model of traffic congestion and numerical simulation. Phys. Rev. E, 51(2):1035-1042, Feb 1995.

[27] Kazi I. Ahmed, Moshe E. Ben-Akiva, Haris N. Koutsopoulos, and Rabi G. Mishalani. Models of Freeway Lane Changing And Gap Acceptance Behavior. In Proceedings of the 13th International Symposium on the Theory of Traffic Flow and Transportation, 1996.

[28] Arne Kesting, Martin Treiber, and Dirk Helbing. General lane-changing model mobil for car following models. Transportation Research Record: Journal of the Transportation Research Board, Volume 1999:86-94, 2005.

[29] Tomer Toledo, Charisma Choudhury, and Moshe E Ben-Akiva. Lane-changing model with explicit target lane choice. Transportation Research Record: Journal of the Transportation Research Board, Volume 1934:157-165, 2005.

[30] Quang-Anh Nguyen Vu, Richard Canal, Benoit Gaudou, Salima Hassas, and Frederic Armetta. Trustsets: using trust to detect deceitful agents in a distributed information collecting system. Journal of Ambient Intelligence and Humanized Computing, 3:251-263, 2012.

[31] Bruce (Xiubin) Wang, Teresa M. Adams, Wenlong Jin, and Qiang Meng. The process of

information propagation in a tra\_c stream with a general vehicle headway: A revisit. *Transportation Research Part C: Emerging Technologies*, 18(3):367- 375, 2010.

[32] K. Jiwon and H. Mahmassani. Correlated parameters in driving behavior models: Car following example and implications for tra\_c microsimulation. *Transportation Research Record: Journal of the Transportation Research Board*, pages 62-77, 2011.

[33] V. Punzo, B. Ciu\_o, and M. Montanino. May we trust results of car-following models calibration based on trajectory data? *Transportation Research Record: Journal of the Transportation Research Board*, pages 11-24, 2012.

[34] Jongeun Choi, Songhwai Oh, and Roberto Horowitz. Distributed learning and cooperative control for multi-agent systems. *Automatica*, 45(12):2802-2814, December 2009.

[35] CO-Drive project. <http://www.pole-moveo.org/pdf-projets-das/codrive-a.pdf>, 2012.

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Table 1: Group disagreement values ( $\times 10^6$ ) for different cooperative vehicles' penetration rates and different percentage of aggressive drivers

		Cooperative vehicles percentage rate					
		0%	20%	40%	60%	80%	100%
Aggressive behavior rate	0%	1,44	1,67	1,48	0,86	0,54	0,22
	10%	1,45	1,60	1,32	1,03	0,55	0,23
	20%	2,98	1,70	1,58	1,20	0,62	0,33

Figure 1: Stability domains

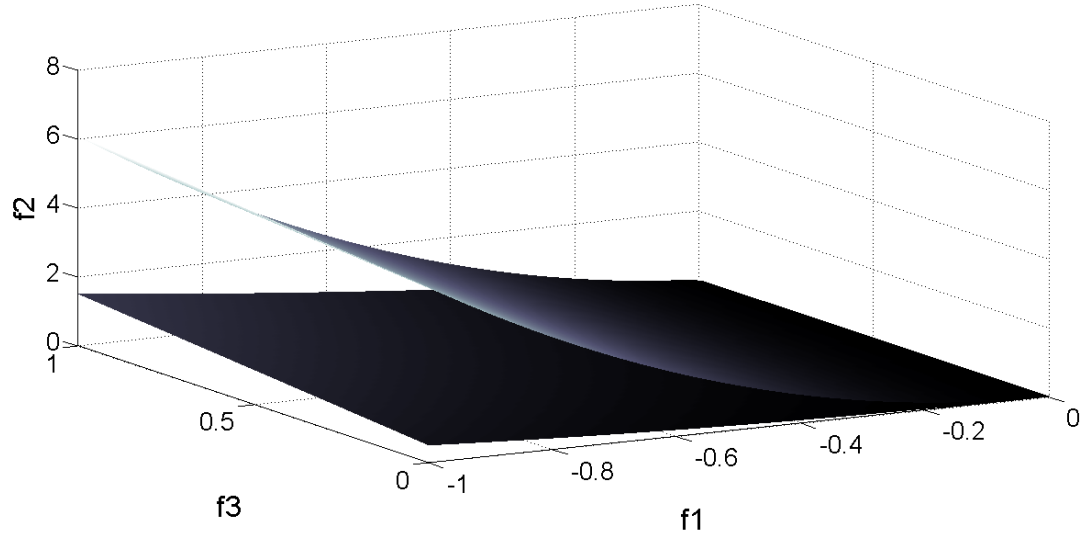


Figure 2: Interaction between layers

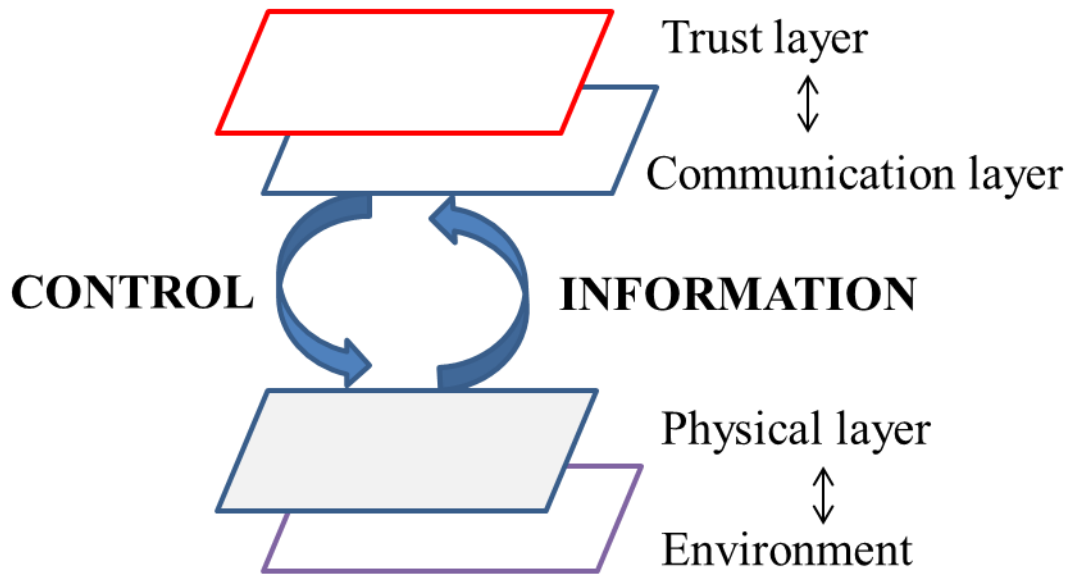


Figure 3: Interaction between agents

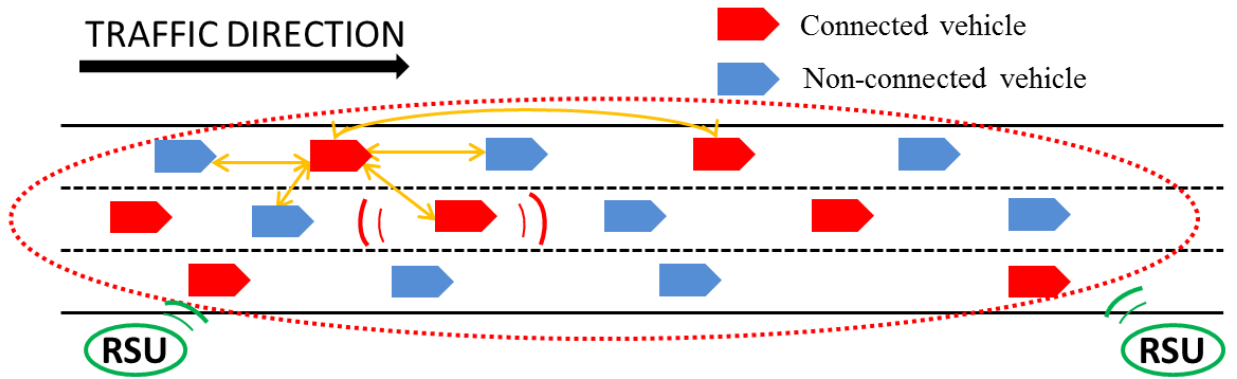
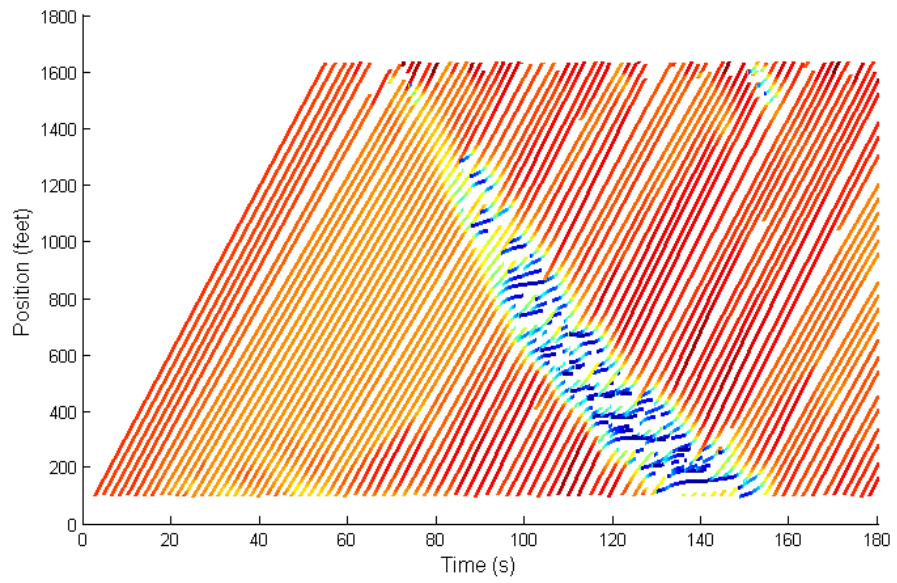
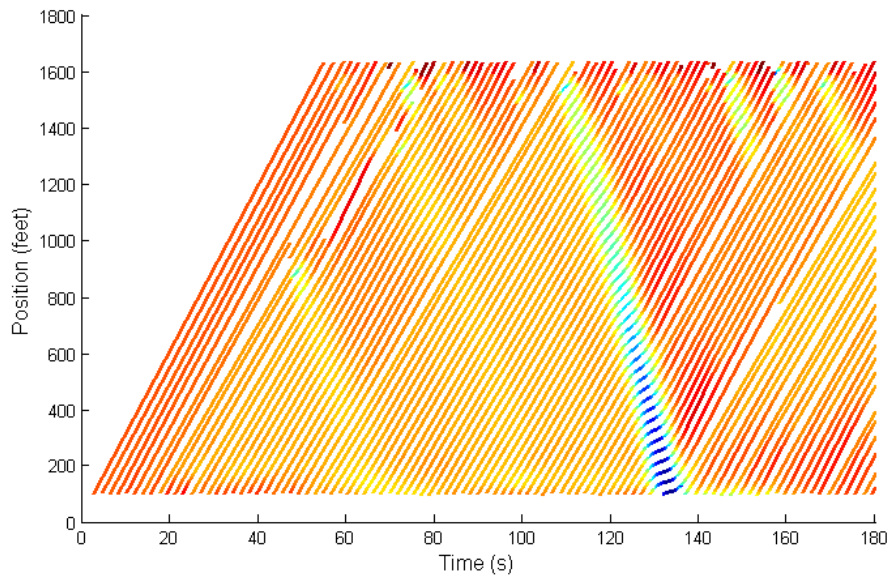




Figure 4 : Fast lane. Time-space diagram for different cooperative vehicles' penetration rate (a) 0 %, (b) 100 %



(a)



(b)