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**Traffic congestion and road safety: statistical physics and new
cellular automata model**

JURY

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Dedication

To my beloved mother, my inspiration,

To my beloved father, my support,

*To my adored husband and my well-cherished future baby girl, my
strength and my motivation,*

To my favourite brother, my protection,

To my best aunt and cousins,

To all my lovely family and in laws,

To all my supportive friends,

This thesis is wholeheartedly dedicated to you. . .

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Résumé

Dans cette thèse, nous avons essayé d'aborder plusieurs volets relevant de la physique et l'ingénierie du trafic routier touchant aussi bien la sécurité que le confort des conducteurs.

En premier lieu, nous avons essayé de mettre en évidence les caractéristiques de la corrélation entre les lignes d'une route à deux voies, générée par l'entrée de cette infrastructure et où aucun changement de voie n'est autorisé.

En utilisant un modèle d'automate cellulaire (modèle de NaSch), Notre étude a confirmé la grandeur de l'impact d'un nœud. Nous avons décelé que si nous créons une perturbation dans une voie, une rupture spontanée de symétrie est générée dans l'ensemble du système. En effet, une auto-anisotropie se produit au niveau du nœud, à laquelle le système répond via un mécanisme d'auto-organisation. Ces résultats nous ont poussés à étudier l'anisotropie en tant que paramètre extrinsèque. En privilégiant une voie sur l'autre au niveau du nœud (convergeant ou divergeant), nous avons montré des comportements atypiques du système et nous avons pu confirmer que le système peut toujours s'auto-organiser et que trois phases peuvent être établies: la phase symétrique haute densité, la phase asymétrique basse densité et la phase asymétrique de transition basse densité/haute densité. Enfin, nous avons trouvé que le système est fortement corrélé lorsqu'il est en phase symétrique, et ne l'est pas lorsqu'il est en phase asymétrique. Ce résultat nous a amené à supposer que la corrélation croisée des observables d'un système quasi-unidimensionnel peut être considérée comme un paramètre d'ordre qui définit les transitions des phases.

En bref, compte tenu de la non-linéarité du trafic, ces résultats, c'est-à-dire la corrélation, peut être un premier pas très modeste dans le décortiquage et la compréhension du comportement des réseaux routiers.

En second lieu, nous avons essayé la relation de causalité entre la congestion et la sûreté de circulation.

A cet effet, grâce à des enquêtes de terrain réalisées par une caméra embarquée, et par les outils de la physique statistique, nous avons développé un modèle AC qui permet d'enquêter sur les collisions arrières et qui prend en compte le processus psychologique cognitif d'anticipation. Nous avons défini cette dernière comme la tendance des conducteurs à accélérer en fonction de l'historique de leur prédécesseur. En considérant deux types de conducteurs : conservateurs qui respectent les informations apprises sur les manœuvres sûres mais commettent des erreurs ou agressifs qui violent ces processus sécurisés, nous avons prouvé la complexité de la relation entre les états du trafic et les comportements des conducteurs. En effet, nous avons montré que les collisions arrières sont le résultat de l'anticipation comme réponse des conducteurs aux conditions de circulation : la congestion. Par ailleurs, nous avons également mis en évidence une amélioration du flux en état congestionné jusqu'à 11% en raison de l'anticipation. Enfin, nous avons constaté que les perturbations du trafic, qui génèrent les points noirs et peuvent être responsables de collisions, sont plus susceptibles d'être localisées en aval. La distance entre les deux emplacements dépend de la densité du trafic.

En résumé, l'importance de ces résultats devrait être prise en compte, mais seraient surtout mis en valeur s'ils étaient intégrés dans la communication de véhicule à véhicule.

Mots clés : Physique du flux trafic ; anisotropie ; nœud ; corrélation ; collisions arrières ; psychologie cognitive ; modèle d'automates cellulaires ; anticipation ; conducteurs conservateurs/agressifs.

Abstract

In this thesis, we have attempted to not only focus on one matter related to the issues of the road traffic but to two main problems compromising the safety and the comfort of drivers.

Firstly, we investigated a quasi-one dimensional system connected by a node and highlighted a correlation of the two roads, where no-lane changing was allowed. Our aim was to understand the reason behind the propagation of the congestion in big scale networks.

Indeed, by the mean of a cellular automata Model (NaSch model), we highlighted the strong effect of a node. We have found that if we create a disturbance in one lane, a spontaneous symmetry breaking occurs in the whole system. In fact, a self-anisotropy is produced at the node, to which the system responds via a self-organization mechanism. Subsequently, we investigated the anisotropy as an extrinsic parameter. By privileging one lane over the other at the node (merge or diverge), we have displayed unusual traffic behaviors, and have been able to confirm that the system can always get self-organized. We have found that three phase can be established: the symmetric high-density phase, the asymmetric low-density phase and the asymmetric phase of transition low-density/high-density. Finally, we have found that the system is strongly correlated when it is in a symmetric phase, and is not when in an asymmetric phase. This finding brought us to the assumption that the cross-correlation of the observables of a quasi-one-dimensional system connected by a node can be considered as an order parameter that defines the phases' transitions.

In brief, keeping in mind the non-linearity of the traffic, those findings, i.e. the correlation, can be a very humble first step in the decortication and the understanding of the behaviour of road networks.

Secondly, we studied the causality relationship between the congestion and the accidents occurrence.

In this respect, through field experiments performed by an embedded camera, and by the tools of the physics of traffic, we have developed a cognitive psychology based CA-model that explores the reasons behind the occurrence of rear-end collisions and that take into consideration psychological cognitive process of anticipation. Indeed, we have defined the latter as the tendency of drivers to accelerate based on the history of their predecessor. By considering two types of drivers: conservative who respect the learned information about the safe manoeuvres but make mistakes or aggressive who violate those secure processes, we have proved the complexity of the relationship between the states of the traffic flow and the drivers' behaviours. In fact, we have shown that rear-end collisions are a result of the anticipation as a response of the drivers to the traffic conditions: the congestion. Moreover, we have also highlighted an improvement of the flow in the congested state up to 11% due to the anticipation. Finally, we have found that the traffic perturbations, that generate hot spots and that can be responsible of collisions, are more likely to be located away in the downstream direction. The distance between the two locations depends on the traffic density.

To sum up, the importance of those results is to be considered, but would mostly be showcased if embedded into vehicle-to-vehicle communication.

Key words: Physics of traffic flow; anisotropy; node; correlation; Rear-end collisions; cognitive psychology; cellular automaton model; anticipation; conservative driver; and aggressive driver.

Résumé détaillé

Dans ce travail, nous avons essayé d'aborder plusieurs volets relevant de la physique et l'ingénierie du trafic routier. Usant des outils de la physique statistique, nous avons réussi à dévoiler certaines caractéristiques du trafic comme résumé par la suite.

En premier lieu, nous avons essayé de mettre en évidence les caractéristiques de la corrélation entre les lignes d'une route à deux voies, générée par l'entrée de cette infrastructure.

Pour cela, nous avons adopté un système quasi-unidimensionnel composé d'un nœud divergent reliant deux routes et où aucun changement de voie n'est autorisé. Notre étude a confirmé la grandeur de l'impact d'un nœud. Nous avons décelé que si nous créons une perturbation dans une voie, une rupture spontanée de symétrie est générée dans l'ensemble du système. En effet, une auto-anisotropie se produit au niveau du nœud, à laquelle le système répond via un mécanisme d'auto-organisation.

Ces résultats nous ont poussés à étudier l'anisotropie en tant que paramètre extrinsèque. En privilégiant une voie sur l'autre au niveau du nœud, nous avons pu confirmer que le système peut toujours s'auto-organiser et que trois phases peuvent être établies: la phase symétrique haute densité, la phase asymétrique basse densité et la phase asymétrique de transition basse densité/haute densité.

Enfin, nous avons trouvé que le système est fortement corrélé lorsqu'il est en phase symétrique, et ne l'est pas lorsqu'il est en phase asymétrique. Ce résultat nous a amené à supposer que la corrélation croisée des observables d'un système quasi-unidimensionnel peut être considérée comme un paramètre d'ordre qui définit les transitions des phases

Gardant à l'esprit les nombreuses différences entre la dynamique d'un nœud convergent et celle d'un nœud divergent, et à l'aide du même modèle d'automate cellulaire, nous avons étudié la réponse d'un système quasi-unidimensionnel composé de deux voies identiques, sans changement de voie, à un nœud convergent anisotrope. Notre principal enjeu était de confirmer qu'un nœud anisotrope, malgré son type, crée une corrélation entre les deux routes qu'il lie.

Les simulations ont montré des comportements atypiques. En effet, alors que la route privilégiée a conservé le comportement usuel d'un système unidimensionnel, la route non privilégiée subit une transition discontinue de la phase de basse densité à la phase de congestion puis continue à la phase de blocage.

De plus, nous avons mis en évidence un nouveau type de réentrance de phase de blocage à la phase de congestion.

En suivant les scénarios d'extraction des véhicules, nous avons constaté que les sorties des deux voies sont corrélées et qu'un processus d'auto-organisation régule l'extraction au niveau du nœud. Cette auto-organisation crée des différences de comportements entre les deux voies, générant une brisure spontanée de symétrie se manifestant par l'établissement de trois phases : une symétrique basse densité, une asymétrique haute densité et une phase asymétrique de transition haute densité/basse densité.

Enfin, un test de cross corrélation a prouvé que les flux des deux voies sont interdépendants dans la phase symétrique.

Par conséquence, nous avons suggéré que cette corrélation croisée peut être considérée comme un paramètre d'ordre qui caractérise la transition d'un système de trafic quasi-unidimensionnel avec un nœud quel que soit son type.

En second lieu, nous avons essayé de décortiquer la corrélation entre les phases du trafic et la sûreté de circulation.

Nous avons étudié les statistiques d'accidents en Europe et en Amérique du Nord fournies par l'ONU. Notre enquête a montré que les accidents dus à la circulation représentent environ 50 % du nombre total d'accidents chaque année. Parmi ces derniers, les collisions arrières détiennent une part de 20%. Ces chiffres dévoilent que les interactions entre les conducteurs peuvent être tenues comme source de ces incidents.

A cet effet, nous avons enquêté sur des situations conflictuelles pouvant être responsables des collisions arrières à l'aide d'un modèle d'automate cellulaire basé sur la psychologie cognitive.

En effet, grâce à des enquêtes de terrain réalisées par une caméra embarquée, nous avons soutiré un processus psychologique cognitif d'anticipation. Nous avons défini cette dernière comme la tendance des conducteurs à accélérer en fonction de l'historique de leur prédécesseur. Ensuite, nous avons exploité les outils de la physique du trafic pour développer un modèle AC qui prend en compte ce processus. En conséquence, nous avons pu reproduire ces incidents.

En considérant deux types de conducteurs : conservateurs qui respectent les informations apprises sur les manœuvres sûres mais commettent des erreurs ou agressifs qui violent ces processus sécurisés, nous avons prouvé la complexité de la relation entre les états du trafic et les comportements des conducteurs.

En effet, nous avons montré que les collisions arrières sont le résultat de l'anticipation comme réponse des conducteurs aux conditions de circulation : la congestion. Par ailleurs, nous avons également mis en évidence une amélioration du flux en état congestionné jusqu'à 11% en raison de l'anticipation, mais qui ne peut être obtenue que grâce à la communication de véhicule à véhicule (V2V).

Enfin, nous avons étudié les points noirs. Nous avons constaté que les perturbations du trafic, qui génèrent ces points noirs et peuvent être responsables de collisions, sont plus susceptibles d'être localisées en aval. La distance entre les deux emplacements dépend de la densité du trafic. Cette différence entre les positions de la perturbation du trafic et du point noir a encore prouvé la complexité, dans le temps et dans l'espace, de la transmission et de la réception des informations de décélération par les conducteurs.

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List of publications and presentations

List of publications

K. Jetto, Z. Tahiri, A. Benyoussef, and A. El Kenz, ‘Cognitive anticipation cellular automata model: An attempt to understand the relation between the traffic states and rear-end collisions’, *Accident Analysis & Prevention*, vol. 142, p. 105507, Jul. 2020, doi: 10.1016/j.aap.2020.105507.

Z. Tahiri, K. Jetto, M. Bouadi, A. Benyoussef, and A. El Kenz, ‘The effect of anisotropy on the traffic flow behavior: Investigation of the correlation created by a single node on two-lane roads’, *Int. J. Mod. Phys. C*, vol. 31, p. 2050060, Jan. 2020, doi: 10.1142/S0129183120500606.

Articles in the process of publication

Z. Tahiri, K. Jetto, A. Benyoussef, and A. El Kenz ‘Behavior of the two lanes of a quasi-one-dimensional system connected by an anisotropic node: Study of a merging node’

Contributed presentations

Z. Tahiri, K. Jetto, A. Benyoussef, and A. El Kenz, ‘The investigation of the correlation created by single anisotropic node on two-lane roads’ Poster presentation at 45th Conference of the Middle-European Cooperation in Statistical Physics from 14 to 16 September 2020 in Cluj-Napoca, Romania.

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Introduction

Do people really need to travel?

There is only one obvious answer to this question: YES!

A person needs to travel from a point A to a point B, for various reasons (economic, social, entertainment ...)

The means of transport have known an important development throughout the time, from animal driven coaches to mechanical and automatic vehicles.

Starting from the mid of the last century, the use of mechanical land mean of transport (cars, buses, motorbike...) has drastically increased. People are using driven vehicles for the speed, the commodity, the luxury ...

Subsequently, the stress on traffic facilities is more important. There is an urge to construct ~~at the~~ facilities to support this evolution.

The traffic conditions in those facilities are usually the results of interactions among vehicles ~~or~~ between vehicles and their surrounding environment [1]

Indeed, the more vehicles are present on the roads, the greater are these interactions. The roads are operating at different levels (LOS). At a point, a fallout of the roads system is observed. This is “congestion”.

The congestion, or more commonly known as Jam when a total blockage occur, has major negative impacts. A part from the waste of time, individuals and countries suffers from huge economic losses [2]–[8] . Indeed, a strong transportation system is known for being one of the pillars of the economic growth of a country and of the prosperity of its citizens. The nature of the fleet, its cost and its speed affect significantly the capacity of a region to fully exploit its resources, thus directly influence its economic vitality.

However, developing such efficient transportation system cannot be without any flaws. Indeed, encouraging more road using may put the drivers at the risk of having an accident, either consciously or unconsciously

Subsequently, authorities, scientists and other stakeholders are facing the dilemma of improving the fluidity of the road facilities while maintaining a safety threshold.

Actually, since the 30's, many researches have been produced in the aim to make the driving experience more comfortable [9]. Later on, other journals have appeared that focus on the traffic accidents flea[10].

Unfortunately, no clear answer has been brought to the following question: *how can we ameliorate the mobility on roads while assuring the highest level of security?*

Analysing the scientific literature has shown that there may be a disconnection when treating the relationship between the road safety and the traffic [10]. On the one hand, we can state that the security aspect of the road traffic has usually been studied all by itself, without, considering the fluidity. On the other hand, the evaluation and the studying of the traffic performances as far as the fluidity is concerned, were established on safe basis, no accidents were predicted.

In the attempt to remedy this situation, researchers have tapped into the traffic theory. Studies have shown that the risk of accidents depends on different traffic observables and is related to the traffic states [11] [12][13].

Nevertheless, the majority of those studies were based on real data that are provided by the countries authorities. However, these data can present many shortcomings[14]–[18]. Thus, relying solely on statistics may bring major difficulties when in the need of resolving current problems[19].

Subsequently, the exploitation of simulation models that would help study predefined collisions situations appears to be most convenient. Indeed, those models are strong in the measure where they can evaluate the safeness of the adopted measures before their application by traffic managers based on microscopic traffic parameters such as vehicle speed, acceleration, time headway, and space headway [20].

According to all the above, huge efforts are made in the aim to preserve the human lives that are lost on roads. Traffic accidents are behind the death over a million human every year and more than 40 fatal casualties.

Regardless of their types, they are found to be caused by human error or behavior in over 90% of total cases. Actually, traffic conditions, i.e. congestion, are generally translated into a frustration known as road rage. In fact, drivers only want to know how and when they will leave the jam [21] [22]. Some of them may adopt an aggressive driving, compromising then the safety of the whole system. Thus, the traffic safety should, more likely, be considered in the light of

the social sciences.

Hence, treating the issues related to the road safety requires the intervention of both the traffic theory and the social sciences, such as psychology or psychosociology.

Nevertheless, some roads are more affected by fluidity and safety problems than others. The tendency is usually to attempt to remedy to this problem punctually. However, traffic systems are complex. They always are connected with each other constituting traffic network.

Traffic networks are composed of links (roads) that are connected by nodes. The interactions ~~and~~ by the nodes cannot be overlooked when studying the driving conditions in a certain road. It is then crucial to understand those interactions and exhibit the responsible mechanisms.

In the real traffic, the complexity and the density of the conjunctions are what induce the difficulty of modelling the network as a whole, thus the hardness to figure the features of nodes and the outcomes of their existence on the global flow. Therefore, the investigation of a single node had proven to be interesting[23].

Numerous scientists have studied nodes by macroscopic models[23] [24], [25]. According to the number of links upstream and downstream, nodes have been sorted into:

- Merge: that contains two or more upstream flows and a unique downstream one.
- Diverge: that consists of one upstream link and two or more downstream flows.

Nodes have also been the subject of investigation by the mean of microscopic models for instance the cellular automata models. In fact, CA are microscopic models that model the traffic by discretizing the space and the time(see [26] and the references within). Various Cellular automata models have been proposed among which the totally asymmetric exclusion process (TASEP) model as the mother of the CA (see [26] and the references within).

An extended investigation of nodes in the light of the TASEP model has been realized through the years. However, there are other CA model that have shown many empirical observed phenomena for a wider range of V_{max} , for instance the NaSch model[27].

Indeed, the NaSch model has confirmed different results elaborated through the TASEP model, and have exhibited new observed traffic behaviors. On the one hand, when closed boundaries are considered, some researchers have proved the existence of the free flow phase,

the congested phase and the segregation phase[27]–[31]. They have also reproduced the phase transitions and the fundamental diagram. On the other hand, the open boundaries have brought to the evidence the existence of the low density phase, the high density phase [26], [30], the re-entrance [32] and the maximum flow phase[30], [33].

Accordingly, the investigation of the effect of nodes on the traffic behavior in the light of the NaSch model in the case of a $V_{max} > 1$ is appealing.

Nevertheless, despite being extensively investigated, nodes still present many challenges. Indeed, to exhaust the social, economic and urgent reasons behind routes choices as much as possible, scientists are faced by a multitude of priority schemes[34]. This brings more difficulty to node's modelling.

Consequently, studies usually differentiate between merge and diverge nodes. Despite being geometrically symmetric, the dynamics of diverge/merge nodes are different[35].

Furthermore, studies highlighted the existence of an interdependence between the upstream roads and the downstream roads[34]. However, to our knowledge, few if not none, deeply investigated the existence of a relationship between the downstream (upstream) links connected by the diverging (merging) node.

Therefore, carrying-on a standout investigation of diverging and merging nodes based on the fundamental differences between the nodes in addition to the lacking literature focusing on the relationship between the links connected by those would be appealing.

Chapter 1:
General context

1. The main observables of traffic flow

1.1. The demand

Demand is the primary measure of traffic using a particular facility. Therefore, the term demand refers to arriving vehicles and the term quantity refers to leaving vehicles.

1.2. The capacity

Capacity is the maximum flow rate that can be accommodated by a given traffic facility under normal conditions. The determination of capacity involves the observation of highways of various types operating under high-volume conditions

1.3. The flow

The traffic flow or the flux, usually given by (veh/h) or (veh/s), denotes the number of vehicles N that have passed through a detector at a given position during a time interval ΔT .

$$Q(x, t) = \frac{N}{\Delta T} \quad (1.1)$$

1.4. The occupancy

The occupancy measures the aggregation time interval during which a given detector is occupied by a vehicle.

$$O(x, t) = \frac{1}{\Delta t} \sum_{\alpha=\alpha_0}^{\alpha_0+N-1} (t_{\alpha}^1 - t_{\alpha}^0) \quad (1.2)$$

Where $t_{\alpha}^1 - t_{\alpha}^0$ denotes the time elapsed on a detector at a given position.

1.5. The traffic density

The traffic density is the number of vehicles occupying a given portion of the road with a length L .

$$\rho = \frac{N}{L} \quad (1.3)$$

1.6. The time mean velocity

The time mean velocity is the average velocity of vehicles passing across a detector at a given position during a given time interval.

$$V(x, t) = \langle v_\alpha \rangle = \frac{1}{N} \sum_{\alpha=\alpha_0}^{\alpha_0+N-1} v_\alpha \quad (1.4)$$

1.7. The space mean velocity

The space mean velocity is called usually the harmonic mean velocity. Basically, it is an average performed over the number of vehicles on a road of length L at a given time t . The formula is given by the following:

$$V_H(x, t) = \frac{1}{\langle \frac{1}{v_\alpha} \rangle} = \frac{N}{\sum_{\alpha=\alpha_0}^{\alpha_0+N-1} \frac{1}{v_\alpha}} \quad (1.5)$$

1.8. The cross-correlation function

The cross-correlation function quantifies the interdependence or the coupling between two observables. Those variables are characterized by a mean and a variance.

Thus, the correlation function is given by:

$$cc_{X,Y}(\tau) = \frac{\langle X(t)Y(t+\tau) \rangle - \langle X(t) \rangle \langle Y(t+\tau) \rangle}{\sqrt{(\langle X(t)^2 \rangle - \langle X(t) \rangle^2)(\langle Y(t)^2 \rangle - \langle Y(t) \rangle^2)}} \quad (1.6)$$

When the observables X and Y are weakly correlated, $cc_{X,Y}(\tau) \approx 0$. In contrast, when the variables X and Y are strongly correlated $cc_{X,Y}(\tau) \approx 1$.

2. Statistical mechanics

Statistical mechanics is a branch of physics that combines the principles and procedures of statistics with the laws of both classical and quantum mechanics, particularly with respect to the field of thermodynamics[30], [36], [37].

The aim of statistical mechanics is to estimate and explain the measurable properties of a macroscopic system based on the properties and behaviour of its microscopic constituents.

In other words, It explains the macroscopic behavior of a complex system from the behavior of the ensembles.

Historically, statistical mechanics was developed as the molecular kinetic theory of matter. Later on, the applications of statistical mechanics have opened up new horizons of interdisciplinary research and of system far from or non-equilibrium.

A class of non-equilibrium systems that has received much attention in recent years consists of interacting particles driven by an external field. Indeed, this non-equilibrium system can settle into a non-equilibrium steady state. This can in principle be far from the equilibrium state that can be reached without an external field.

Over the last decades, many physical systems have been successfully studied using techniques developed for models of such field-driven interacting particles.

Recently, nonequilibrium statistical mechanics has found even more unusual applications in the study of traffic flow of various types of objects, for instance **road traffic flow**.

3. Monte Carlo simulations

Even though some problems in statistical physics can be solved analytically using approximations and expansions, most current research exploits the computational power of modern computers to simulate or approximate solutions.

In this respect, a common approach is to use Monte Carlo simulations to understand the properties of complex systems.

Monte Carlo methods are a wide class of computational algorithms that rely on repeated random sampling to obtain numerical results.

The main concept of Monte Carlo method is to use randomness to solve problems that might be deterministic in principle.

In physics-related problems, Monte Carlo methods are useful for simulating systems with many coupled degrees of freedom, such as fluids, disordered materials, strongly coupled solids, cellular structures and interacting particle systems[30], [38].

Indeed, the most natural approach to stochastic systems is generally Monte Carlo simulation. In this case, the stochastic process is realized through computer by generating transitions with appropriate probabilities. Therefore, each Monte Carlo simulation generates one specific realization of the stochastic process. Since normally one is interested in averages

of certain quantities, one has to repeat such a simulation run sufficiently often and then average over the different runs, which correspond to different realizations of the process.

4. The models classification

In order to elucidate the traffic flow behavior, researchers have developed numerous classes of models.

In this context, from the different fields, they have suggested approximately 100 different traffic models, from engineering, mathematics, operational researches to physics.

In this thesis, we will focus on three main classes of traffic modeling:

- The microscopic models
- The macroscopic models
- The mesoscopic models

4.1. The microscopic models

The microscopic models follow the individual particles with high level of aggregation, namely, each particle is described apart. Hence, the whole system progresses according to the interactions between the particles.

The first proposed microscopic model is the car following model. In this context, each vehicle interacts with its predecessor to follow the leader principle.

4.2. The macroscopic models

In the macroscopic models, the whole traffic is considered as a compressible fluid [39]. The first and the basic model was proposed by Lighthill-Whitham [24]. In this context, the traffic flow on a given one dimensional road with the absence of ramps (sources and sinks) follows the continuity equation:

$$\frac{\partial \rho(x,t)}{\partial t} + \frac{\partial Q(x,t)}{\partial x} = 0 \quad (1.7)$$

Where $Q(x, t)$ is the product of the density and the average velocity

$$Q(x, t) = \rho(x, t)V_e(x, t) \quad (1.8)$$

The equation (1.7) reflects the conservation of vehicles number and it is a part any macroscopic model. By inserting the Equation (1.8) into the equation (1.7), we obtain:

$$\frac{\partial \rho}{\partial t} + C(\rho) \frac{\partial \rho}{\partial x} = 0 \quad (1.9)$$

Where:

$$C(\rho) = \frac{dQ_e}{d\rho} = V_e(\rho) + \rho \cdot \frac{dV_e}{d\rho} \quad (1.10)$$

The Eq. 22 has the form of a non linear wave equation where $C(\rho)$ denotes the propagation of the kinematic waves velocity. As exhibited in the Equation (1.10), the propagation velocity depends on the gradient of the steady state flow-density relation (fundamental diagram). Hence, the density variation may propagate either in the driving direction of traffic (Free flow) or in the opposite direction (congested flow)[39].

It is worth mentioning that $C(\rho)$ is the velocity of the characteristic lines, i.e., the local information propagation. Hence, The velocity $C(\rho)$ is a density dependent. Nevertheless, in contrast to the linear waves, the characteristic lines or the trajectories intersect. Indeed, their corresponding velocities in the congested areas are lower. This gives rise to changes of the wave profile, that is, to the formation of shock fronts.

In this context, the shock front is characterized by the upstream value ρ^- and the downstream value ρ^+ of the density. The difference between the flow Q^- upstream and the flow Q^+ downstream causes an abrupt density jump $\rho_1 - \rho_2$. Consequently, and because of the conservation law, the corresponding shock velocity would be the following:

$$S = \frac{Q_1 - Q_2}{\rho_1 - \rho_2} \quad (1.11)$$

The Lighthill-Whitham model allowed us to understand the concept of shock waves. However, this model suffers from major a shortcoming, namely, the unbounded acceleration and deceleration rates. In order to circumvent this problem, the burger equation has been elaborated. Accordingly, a diffusion term is added to the mean velocity to make the wave front smoother[39]:

$$V(x, t) = V_e(\rho(x, t)) - \frac{D}{\rho(x, t)} \frac{\partial \rho(x, t)}{\partial x} \quad (1.12)$$

The Equation (1.12) reflects the fact that the conductors tend to reduce their velocity when they saw an increasing density on the road.

4.3. The mesoscopic models

The mesoscopic models are generally based on the gaz kinetics. More precisely, the traffic flow is described by the phase space density:

$$\rho'(x, v, t) = \rho(x, t)P(x, v, t) \quad (1.13)$$

$\rho(x, t)$ is the vehicles density and $P(x, v, t)$ the probability distribution of the vehicles localized at the position x with the velocity v at time t .

The first gaz kinetic traffic flow model was elaborated by Prigogine et al[40]. Hence, the gaz kinetic traffic model follows the following continuity equations.

$$\frac{d\rho'}{dt} = \frac{\partial \rho'}{\partial t} + v \frac{\partial \rho'}{\partial t} = \frac{d\rho'}{dt}_{rel} + \frac{d\rho'}{dt}_{int} \quad (1.14)$$

The first term in the right hand of the equation denotes the relaxation term which reflects the tendency of vehicles to reach their maximal velocity. The second term takes into account the interactions between the vehicles.

5. Cellular automata models

Cellular automata models are one of the most exploited methods of traffic modelling.

A CA is a microscopic model that is discrete in all variables. They are an idealization of physical systems in which position, speed, acceleration and time are all discrete variables.

The dynamics of a cellular automata model are ruled-based and stochastic. Here, the road is represented by a lattice of a definite number of cells. Each cell can be either occupied by a single vehicle or empty at every instant. In addition, all the concerned variables can only have a definite number of discrete states.

By a CA model, vehicles are moved according to a certain number of rules. Indeed, at each discrete time step t , the system is updated according to a well-defined prescription.

There are two types of vehicles updated:

- Parallel (synchronous) update: where all particles (vehicles) are moved simultaneously.
- Random- sequential update: where the particles that are to be moved are chosen

randomly. This type of updated is more suited for continuous time dynamics.

In brief, Traffic cellular automata models are more efficient than car-following and coupled-map lattice approaches as far as computational requirements are concerned.

Several TCA models have seen the lights during the last 3 decades[30], [41].

5.1. The TASEP model

The ASEP (asymmetric simple exclusion process) model is known as the mother of all the cellular automata models.

The ASEP model is a model of interacting random walk where particles hop to the right or to the left with a predefined probability.

Indeed, N random walkers are placed on a one-dimensional lattice. Those particles are then moved to the right with a probability p or to the left with a rate q , if and only if the aimed target is empty.

There are many variant of the ASEP model, depending on the value or the ratio of the allowed direction of movement.

However, the most exploited variant is the TASEP (totally asymmetric simple exclusion process) model.

The TASEP model is the from of the model where only one direction of motion is allowed[30], [42], [43].

5.2. The KKW model

The KKW model is a discretization of the space-continuous microscopic model developed by Kerner and Klenov[44], [45].

This model combines elements of car-following model with the standard distant dependent interactions.

The KKW model is usually known as the three-phases theory:

- The free-flow phase.
- The synchronized flow phase.
- The wide moving jam.

The KKW model is a cellular automaton model that generalizes the NaSch model to take

into account the following aspects:

- The slow to start rule in order to reproduce the hysteresis effect.
- The presence of a synchronized distance in which vehicles tend to synchronize their velocities regardless the value of the gap.

From the three phase theory perspective, the transition $F \rightarrow J$ which characterizes the fundamental diagram approach is inexistent and inconsistent with the real traffic flow. Instead, the traffic state should undergo the transition $F \rightarrow S$ before getting to the jamming phase (J). Those transitions are known to be as first order transition.

In addition to the aforementioned findings, Kerner argues that in order to describe the real traffic flow behavior, we should consider the spatiotemporal evolution of the different traffic observables (flow, mean velocity, density).

5.3. The NaSch Cellular automata model

In the NaSch cellular automaton model, the space, the time and the velocity are discretized variables[27].

The road is a one dimensional chain represented by cells. Each cell can be either empty or occupied by one vehicle. Thus, the one cell length is given by inverse of the blockage density, which is approximately 7.5 m.

Subsequently, each vehicle hopes to attain its maximal velocity under two constrains:

- The gap between two successive vehicles,
- And the driver nature which is quantified by a probability of spontaneous deceleration.

In traffic flow, the dynamics discussed above are parallel, namely, the velocities corresponding to each vehicle are updated simultaneously at a time t .

Hence, the vehicular motion according to the NaSch model is given by the following at a given time t :

- Acceleration: $v_n = \min(V_{\max}, v_n + 1)$, $V_{\max}$ is the vehicles maximum velocity which takes discrete values.
- Deceleration: $v_n = \min(v_n, d_n)$, where $d_n = x_{n+1} - x_n - 1$ is the gap between the leading and the preceding vehicle.

- Randomization: If $v_n > 0$, $v_n \rightarrow \max(v_n - 1, 0)$ with probability P .
- This rule quantifies the spontaneous deceleration of a given driver, $P=0$ corresponds to aggressive or commuter drivers.
- Vehicle motion: $x_n \rightarrow x_n + v_n$

x_n and v_n will denote respectively, position and velocity of the vehicle n .

After the vehicular motion, the time is increased by 1.

It is worth mentioning that the $V_{\max}$ which is the maximal velocity value is discrete.

Chapter 2:
The effect of anisotropy
on the traffic flow
behaviour: investigation
of a single node

1.Introduction: Traffic networks

1.1. Definition

The road traffic network is a typical spatial network due to its geographical factors.

Road network model is built by:

- nodes that mean the intersections
- edges that mean the road sections by which the two intersections can be connected directly[46].

Similarly, According to HCM[1], traffic networks are composed of:

- Links: We speak of a link when a length between two nodes keeps the same characteristics.
- Nodes: We speak of a node when it is the place of interaction between different flows, a single flow controlled by a control system or the place of a significant change in capacity (reduction of the number of channels ...)

1.2. Traffic networks in literature

Research of road traffic network, based on the relation between the structure and function, is of great significance.

In this respect, many studies, based on different approaches, have been conducted in the attempt of analysing a traffic network.

i. statistical

Some papers have chosen to adopt statistical and probabilistic tools and approaches to address the efficiency of a traffic network. On the one hand, Moore has attempted to define the fastest path among a network routes with travel time and flowrate constraints [47]. By considering the natural presence and the interdependence of those two restrictions, he has developed two algorithms that help with the matter. On the other hand, Chen et al have focused on the capacity of a traffic network through probabilistic treatment. With taking into account the variability of links' capacities, they have defined the potential response of a network to a certain demand[48]. Finally, Yuan et al have raised the issue of the important amount of data that need to be collected when studying a network. In fact, they have developed a cross-correlation based method for spatial-temporal traffic analysis that aims to minimize this data

[49].

However, due to the shortcomings and limitations any statistical approach, this kind of study cannot truly reflect the characteristics of real traffic network.

ii. Macroscopic

Other researches have adopted macroscopic modelling approaches to characterize a traffic network as a whole. Herman et al have defined a two-fluid model that would describe the overall network[50]. In fact, they have proved that the mean speed of moving vehicles is proportional to the fraction of moving vehicles raised to a power and that the stopping time is proportional to the travel time. Those two assumptions have then been investigated and validated experimentally [51], [52]. Based on those results, many works have been able to reproduce the macroscopic fundamental diagram of a traffic network[53], [54]. Later, Gerolimini and Daganzo have proved, experimentally and analytically its existence[55], [56], while Xie et al have developed it for an inhomogeneous and instable traffic network[57].

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Nonetheless, the macroscopic models are incapable to capture the details of the traffic. Thus, other scientists have opted for mesoscopic or hybrid approaches. Burghout et al, for instance, have proposed a mesoscopic model which would be able to integrate with microscopic ones so as to bring the sufficient degree of details needed in network analyses[58], [59].

All those studies have proven that the different observables of a traffic network are correlated but more importantly have pointed out the difficulties of processing, microscopically, the large amount of data characterizing it. Actually, an urban network is a system composed of an important number of nodes and connected roads; each node represents a junction of at least two segments while each segment is connected to two nodes[1, Ch. 10]. The complexity and the density of those conjunctions are what induce those difficulties, thus the difficulty of modelling the network as a whole.

Subsequently, we think that reducing the size of the network to the minimal, namely, two roads and a single node may be benefic.

1.3. Reduced Networks: nodes investigation

1.3.1. Definition

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exhaust the social, economic and urgent reasons behind routes choices as much as possible, scientists are faced by a multitude of priority schemes[34]. This brings more difficulty to node's modelling.

Accordingly, studies usually differentiate between merge and diverge nodes. Despite being geometrically symmetric, the dynamics of diverge/merge nodes are different[35].

On the one hand, a diverge node models an incoming road splitting into two outgoing segments[34]. The moving flow depends on the volume of the traffic coming from the upstream link, on the capacity of the diverging segments and is strongly affected by the vehicles destinations (road choices). Then, in certain circumstances where a vehicle cannot take its chosen path, a blockage is created upstream the node. In this case, no other vehicle can leave the upstream link until the blocked vehicle does. Subsequently, the dynamics of the diverging node are insured by a FIFO (first in first out) behavior[60].

On the other hand, a merge node connects two upcoming flows to one outgoing link[34]. Being a reverse of the diverge[61], the moving flow in a merge is majorly defined by the capacity of the downstream segment and the traffic volume from the upstream roads. Nevertheless, the dynamics here are dictated by the priority given to each road, thus by the interactions and the conflicts of the merging streams[35].

1.3.2. Node's modelling

Many papers adopted macroscopic models to define the distribution of the flow in downstream and upstream links(roads), connected by the node[23]. Meanwhile, other studies opted for microscopic models, for instance the Totally Asymmetric Exclusion Process (TASEP)[62]–[68].

1.3.2.1. Macroscopic

Numerous scientists have studied nodes by macroscopic models. Daganzo has been among the first scientists to tackle this issue[23]. According to the number of links upstream and downstream, he sorted nodes into:

- Merge: that contains two upstream flows $\{q_1, q_2\}$ and a unique downstream one $\{q\}$.
- Diverge: that consists of one upstream link $\{q\}$ and two downstream flows $\{q_1, q_2\}$.

His aim was to estimate the evolution of the flow in a network $\{q, q_1, q_2\}$ while

Introduction

Do people really need to travel?

There is only one obvious answer to this question: YES!

A person needs to travel from a point A to a point B, for various reasons (economic, social, entertainment ...)

The means of transport have known an important development throughout the time, from animal driven coaches to mechanical and automatic vehicles.

Starting from the mid of the last century, the use of mechanical land mean of transport (cars, buses, motorbike...) has drastically increased. People are using driven vehicles for the speed, the commodity, the luxury ...

Subsequently, the stress on traffic facilities is more important. There is an urge to construct ~~at the~~ facilities to support this evolution.

The traffic conditions in those facilities are usually the results of interactions among vehicles ~~or~~ between vehicles and their surrounding environment [1]

Indeed, the more vehicles are present on the roads, the greater are these interactions. The roads are operating at different levels (LOS). At a point, a fallout of the roads system is observed. This is “congestion”.

The congestion, or more commonly known as Jam when a total blockage occur, has major negative impacts. A part from the waste of time, individuals and countries suffers from huge economic losses [2]–[8] . Indeed, a strong transportation system is known for being one of the pillars of the economic growth of a country and of the prosperity of its citizens. The nature of the fleet, its cost and its speed affect significantly the capacity of a region to fully exploit its resources, thus directly influence its economic vitality.

However, developing such efficient transportation system cannot be without any flaws. Indeed, encouraging more road using may put the drivers at the risk of having an accident, either consciously or unconsciously

Subsequently, authorities, scientists and other stakeholders are facing the dilemma of improving the fluidity of the road facilities while maintaining a safety threshold.

Actually, since the 30's, many researches have been produced in the aim to make the driving experience more comfortable [9]. Later on, other journals have appeared that focus on the traffic accidents flea[10].

Unfortunately, no clear answer has been brought to the following question: *how can we ameliorate the mobility on roads while assuring the highest level of security?*

Analysing the scientific literature has shown that there may be a disconnection when treating the relationship between the road safety and the traffic [10]. On the one hand, we can state that the security aspect of the road traffic has usually been studied all by itself, without, considering the fluidity. On the other hand, the evaluation and the studying of the traffic performances as far as the fluidity is concerned, were established on safe basis, no accidents were predicted.

In the attempt to remedy this situation, researchers have tapped into the traffic theory. Studies have shown that the risk of accidents depends on different traffic observables and is related to the traffic states [11] [12][13].

Nevertheless, the majority of those studies were based on real data that are provided by the countries authorities. However, these data can present many shortcomings[14]–[18]. Thus, relying solely on statistics may bring major difficulties when in the need of resolving current problems[19].

Subsequently, the exploitation of simulation models that would help study predefined collisions situations appears to be most convenient. Indeed, those models are strong in the measure where they can evaluate the safeness of the adopted measures before their application by traffic managers based on microscopic traffic parameters such as vehicle speed, acceleration, time headway, and space headway [20].

According to all the above, huge efforts are made in the aim to preserve the human lives that are lost on roads. Traffic accidents are behind the death over a million human every year and more than 40 fatal casualties.

Regardless of their types, they are found to be caused by human error or behavior in over 90% of total cases. Actually, traffic conditions, i.e. congestion, are generally translated into a frustration known as road rage. In fact, drivers only want to know how and when they will leave the jam [21] [22]. Some of them may adopt an aggressive driving, compromising then the safety of the whole system. Thus, the traffic safety should, more likely, be considered in the light of

the social sciences.

Hence, treating the issues related to the road safety requires the intervention of both the traffic theory and the social sciences, such as psychology or psychosociology.

Nevertheless, some roads are more affected by fluidity and safety problems than others. The tendency is usually to attempt to remedy to this problem punctually. However, traffic systems are complex. They always are connected with each other constituting traffic network.

Traffic networks are composed of links (roads) that are connected by nodes. The interactions ~~and~~ by the nodes cannot be overlooked when studying the driving conditions in a certain road. It is then crucial to understand those interactions and exhibit the responsible mechanisms.

In the real traffic, the complexity and the density of the conjunctions are what induce the difficulty of modelling the network as a whole, thus the hardness to figure the features of nodes and the outcomes of their existence on the global flow. Therefore, the investigation of a single node had proven to be interesting[23].

Numerous scientists have studied nodes by macroscopic models[23] [24], [25]. According to the number of links upstream and downstream, nodes have been sorted into:

- Merge: that contains two or more upstream flows and a unique downstream one.
- Diverge: that consists of one upstream link and two or more downstream flows.

Nodes have also been the subject of investigation by the mean of microscopic models for instance the cellular automata models. In fact, CA are microscopic models that model the traffic by discretizing the space and the time(see [26] and the references within). Various Cellular automata models have been proposed among which the totally asymmetric exclusion process (TASEP) model as the mother of the CA (see [26] and the references within).

An extended investigation of nodes in the light of the TASEP model has been realized through the years. However, there are other CA model that have shown many empirical observed phenomena for a wider range of V_{max} , for instance the NaSch model[27].

Indeed, the NaSch model has confirmed different results elaborated through the TASEP model, and have exhibited new observed traffic behaviors. On the one hand, when closed boundaries are considered, some researchers have proved the existence of the free flow phase,

the congested phase and the segregation phase[27]–[31]. They have also reproduced the phase transitions and the fundamental diagram. On the other hand, the open boundaries have brought to the evidence the existence of the low density phase, the high density phase [26], [30], the re-entrance [32] and the maximum flow phase[30], [33].

Accordingly, the investigation of the effect of nodes on the traffic behavior in the light of the NaSch model in the case of a $V_{max} > 1$ is appealing.

Nevertheless, despite being extensively investigated, nodes still present many challenges. Indeed, to exhaust the social, economic and urgent reasons behind routes choices as much as possible, scientists are faced by a multitude of priority schemes[34]. This brings more difficulty to node's modelling.

Consequently, studies usually differentiate between merge and diverge nodes. Despite being geometrically symmetric, the dynamics of diverge/merge nodes are different[35].

Furthermore, studies highlighted the existence of an interdependence between the upstream roads and the downstream roads[34]. However, to our knowledge, few if not none, deeply investigated the existence of a relationship between the downstream (upstream) links connected by the diverging (merging) node.

Therefore, carrying-on a standout investigation of diverging and merging nodes based on the fundamental differences between the nodes in addition to the lacking literature focusing on the relationship between the links connected by those would be appealing.

Chapter 1:
General context

1. The main observables of traffic flow

1.1. The demand

Demand is the primary measure of traffic using a particular facility. Therefore, the term demand refers to arriving vehicles and the term quantity refers to leaving vehicles.

1.2. The capacity

Capacity is the maximum flow rate that can be accommodated by a given traffic facility under normal conditions. The determination of capacity involves the observation of highways of various types operating under high-volume conditions

1.3. The flow

The traffic flow or the flux, usually given by (veh/h) or (veh/s), denotes the number of vehicles N that have passed through a detector at a given position during a time interval ΔT .

$$Q(x, t) = \frac{N}{\Delta T} \quad (1.1)$$

1.4. The occupancy

The occupancy measures the aggregation time interval during which a given detector is occupied by a vehicle.

$$O(x, t) = \frac{1}{\Delta t} \sum_{\alpha=\alpha_0}^{\alpha_0+N-1} (t_{\alpha}^1 - t_{\alpha}^0) \quad (1.2)$$

Where $t_{\alpha}^1 - t_{\alpha}^0$ denotes the time elapsed on a detector at a given position.

1.5. The traffic density

The traffic density is the number of vehicles occupying a given portion of the road with a length L .

$$\rho = \frac{N}{L} \quad (1.3)$$

1.6. The time mean velocity

The time mean velocity is the average velocity of vehicles passing across a detector at a given position during a given time interval.

$$V(x, t) = \langle v_\alpha \rangle = \frac{1}{N} \sum_{\alpha=\alpha_0}^{\alpha_0+N-1} v_\alpha \quad (1.4)$$

1.7. The space mean velocity

The space mean velocity is called usually the harmonic mean velocity. Basically, it is an average performed over the number of vehicles on a road of length L at a given time t. The formula is given by the following:

$$V_H(x, t) = \frac{1}{\langle \frac{1}{v_\alpha} \rangle} = \frac{N}{\sum_{\alpha=\alpha_0}^{\alpha_0+N-1} \frac{1}{v_\alpha}} \quad (1.5)$$

1.8. The cross-correlation function

The cross-correlation function quantifies the interdependence or the coupling between two observables. Those variables are characterized by a mean and a variance.

Thus, the correlation function is given by:

$$cc_{X,Y}(\tau) = \frac{\langle X(t)Y(t+\tau) \rangle - \langle X(t) \rangle \langle Y(t+\tau) \rangle}{\sqrt{(\langle X(t)^2 \rangle - \langle X(t) \rangle^2)(\langle Y(t)^2 \rangle - \langle Y(t) \rangle^2)}} \quad (1.6)$$

When the observables X and Y are weakly correlated, $cc_{X,Y}(\tau) \approx 0$. In contrast, when the variables X and Y are strongly correlated $cc_{X,Y}(\tau) \approx 1$.

2. Statistical mechanics

Statistical mechanics is a branch of physics that combines the principles and procedures of statistics with the laws of both classical and quantum mechanics, particularly with respect to the field of thermodynamics[30], [36], [37].

The aim of statistical mechanics is to estimate and explain the measurable properties of a macroscopic system based on the properties and behaviour of its microscopic constituents.

In other words, It explains the macroscopic behavior of a complex system from the behavior of the ensembles.

Historically, statistical mechanics was developed as the molecular kinetic theory of matter. Later on, the applications of statistical mechanics have opened up new horizons of interdisciplinary research and of system far from or non-equilibrium.

A class of non-equilibrium systems that has received much attention in recent years consists of interacting particles driven by an external field. Indeed, this non-equilibrium system can settle into a non-equilibrium steady state. This can in principle be far from the equilibrium state that can be reached without an external field.

Over the last decades, many physical systems have been successfully studied using techniques developed for models of such field-driven interacting particles.

Recently, nonequilibrium statistical mechanics has found even more unusual applications in the study of traffic flow of various types of objects, for instance **road traffic flow**.

3. Monte Carlo simulations

Even though some problems in statistical physics can be solved analytically using approximations and expansions, most current research exploits the computational power of modern computers to simulate or approximate solutions.

In this respect, a common approach is to use Monte Carlo simulations to understand the properties of complex systems.

Monte Carlo methods are a wide class of computational algorithms that rely on repeated random sampling to obtain numerical results.

The main concept of Monte Carlo method is to use randomness to solve problems that might be deterministic in principle.

In physics-related problems, Monte Carlo methods are useful for simulating systems with many coupled degrees of freedom, such as fluids, disordered materials, strongly coupled solids, cellular structures and interacting particle systems[30], [38].

Indeed, the most natural approach to stochastic systems is generally Monte Carlo simulation. In this case, the stochastic process is realized through computer by generating transitions with appropriate probabilities. Therefore, each Monte Carlo simulation generates one specific realization of the stochastic process. Since normally one is interested in averages

of certain quantities, one has to repeat such a simulation run sufficiently often and then average over the different runs, which correspond to different realizations of the process.

4. The models classification

In order to elucidate the traffic flow behavior, researchers have developed numerous classes of models.

In this context, from the different fields, they have suggested approximately 100 different traffic models, from engineering, mathematics, operational researches to physics.

In this thesis, we will focus on three main classes of traffic modeling:

- The microscopic models
- The macroscopic models
- The mesoscopic models

4.1. The microscopic models

The microscopic models follow the individual particles with high level of aggregation, namely, each particle is described apart. Hence, the whole system progresses according to the interactions between the particles.

The first proposed microscopic model is the car following model. In this context, each vehicle interacts with its predecessor to follow the leader principle.

4.2. The macroscopic models

In the macroscopic models, the whole traffic is considered as a compressible fluid [39]. The first and the basic model was proposed by Lighthill-Whitham [24]. In this context, the traffic flow on a given one dimensional road with the absence of ramps (sources and sinks) follows the continuity equation:

$$\frac{\partial \rho(x,t)}{\partial t} + \frac{\partial Q(x,t)}{\partial x} = 0 \quad (1.7)$$

Where $Q(x, t)$ is the product of the density and the average velocity

$$Q(x, t) = \rho(x, t)V_e(x, t) \quad (1.8)$$

The equation (1.7) reflects the conservation of vehicles number and it is a part any macroscopic model. By inserting the Equation (1.8) into the equation (1.7), we obtain:

$$\frac{\partial \rho}{\partial t} + C(\rho) \frac{\partial \rho}{\partial x} = 0 \quad (1.9)$$

Where:

$$C(\rho) = \frac{dQ_e}{d\rho} = V_e(\rho) + \rho \cdot \frac{dV_e}{d\rho} \quad (1.10)$$

The Eq. 22 has the form of a non linear wave equation where $C(\rho)$ denotes the propagation of the kinematic waves velocity. As exhibited in the Equation (1.10), the propagation velocity depends on the gradient of the steady state flow-density relation (fundamental diagram). Hence, the density variation may propagate either in the driving direction of traffic (Free flow) or in the opposite direction (congested flow)[39].

It is worth mentioning that $C(\rho)$ is the velocity of the characteristic lines, i.e., the local information propagation. Hence, The velocity $C(\rho)$ is a density dependent. Nevertheless, in contrast to the linear waves, the characteristic lines or the trajectories intersect. Indeed, their corresponding velocities in the congested areas are lower. This gives rise to changes of the wave profile, that is, to the formation of shock fronts.

In this context, the shock front is characterized by the upstream value ρ^- and the downstream value ρ^+ of the density. The difference between the flow Q^- upstream and the flow Q^+ downstream causes an abrupt density jump $\rho_1 - \rho_2$. Consequently, and because of the conservation law, the corresponding shock velocity would be the following:

$$S = \frac{Q_1 - Q_2}{\rho_1 - \rho_2} \quad (1.11)$$

The Lighthill-Whitham model allowed us to understand the concept of shock waves. However, this model suffers from major a shortcoming, namely, the unbounded acceleration and deceleration rates. In order to circumvent this problem, the burger equation has been elaborated. Accordingly, a diffusion term is added to the mean velocity to make the wave front smoother[39]:

$$V(x, t) = V_e(\rho(x, t)) - \frac{D}{\rho(x, t)} \frac{\partial \rho(x, t)}{\partial x} \quad (1.12)$$

The Equation (1.12) reflects the fact that the conductors tend to reduce their velocity when they saw an increasing density on the road.

4.3. The mesoscopic models

The mesoscopic models are generally based on the gaz kinetics. More precisely, the traffic flow is described by the phase space density:

$$\rho'(x, v, t) = \rho(x, t)P(x, v, t) \quad (1.13)$$

$\rho(x, t)$ is the vehicles density and $P(x, v, t)$ the probability distribution of the vehicles localized at the position x with the velocity v at time t .

The first gaz kinetic traffic flow model was elaborated by Prigogine et al[40]. Hence, the gaz kinetic traffic model follows the following continuity equations.

$$\frac{d\rho'}{dt} = \frac{\partial \rho'}{\partial t} + v \frac{\partial \rho'}{\partial t} = \frac{d\rho'}{dt}_{rel} + \frac{d\rho'}{dt}_{int} \quad (1.14)$$

The first term in the right hand of the equation denotes the relaxation term which reflects the tendency of vehicles to reach their maximal velocity. The second term takes into account the interactions between the vehicles.

5. Cellular automata models

Cellular automata models are one of the most exploited methods of traffic modelling.

A CA is a microscopic model that is discrete in all variables. They are an idealization of physical systems in which position, speed, acceleration and time are all discrete variables.

The dynamics of a cellular automata model are ruled-based and stochastic. Here, the road is represented by a lattice of a definite number of cells. Each cell can be either occupied by a single vehicle or empty at every instant. In addition, all the concerned variables can only have a definite number of discrete states.

By a CA model, vehicles are moved according to a certain number of rules. Indeed, at each discrete time step t , the system is updated according to a well-defined prescription.

There are two types of vehicles updated:

- Parallel (synchronous) update: where all particles (vehicles) are moved simultaneously.
- Random- sequential update: where the particles that are to be moved are chosen

randomly. This type of updated is more suited for continuous time dynamics.

In brief, Traffic cellular automata models are more efficient than car-following and coupled-map lattice approaches as far as computational requirements are concerned.

Several TCA models have seen the lights during the last 3 decades[30], [41].

5.1. The TASEP model

The ASEP (asymmetric simple exclusion process) model is known as the mother of all the cellular automata models.

The ASEP model is a model of interacting random walk where particles hop to the right or to the left with a predefined probability.

Indeed, N random walkers are placed on a one-dimensional lattice. Those particles are then moved to the right with a probability p or to the left with a rate q , if and only if the aimed target is empty.

There are many variant of the ASEP model, depending on the value or the ratio of the allowed direction of movement.

However, the most exploited variant is the TASEP (totally asymmetric simple exclusion process) model.

The TASEP model is the from of the model where only one direction of motion is allowed[30], [42], [43].

5.2. The KKW model

The KKW model is a discretization of the space-continuous microscopic model developed by Kerner and Klenov[44], [45].

This model combines elements of car-following model with the standard distant dependent interactions.

The KKW model is usually known as the three-phases theory:

- The free-flow phase.
- The synchronized flow phase.
- The wide moving jam.

The KKW model is a cellular automaton model that generalizes the NaSch model to take

into account the following aspects:

- The slow to start rule in order to reproduce the hysteresis effect.
- The presence of a synchronized distance in which vehicles tend to synchronize their velocities regardless the value of the gap.

From the three phase theory perspective, the transition $F \rightarrow J$ which characterizes the fundamental diagram approach is inexistent and inconsistent with the real traffic flow. Instead, the traffic state should undergo the transition $F \rightarrow S$ before getting to the jamming phase (J). Those transitions are known to be as first order transition.

In addition to the aforementioned findings, Kerner argues that in order to describe the real traffic flow behavior, we should consider the spatiotemporal evolution of the different traffic observables (flow, mean velocity, density).

5.3. The NaSch Cellular automata model

In the NaSch cellular automaton model, the space, the time and the velocity are discretized variables[27].

The road is a one dimensional chain represented by cells. Each cell can be either empty or occupied by one vehicle. Thus, the one cell length is given by inverse of the blockage density, which is approximately 7.5 m.

Subsequently, each vehicle hopes to attain its maximal velocity under two constrains:

- The gap between two successive vehicles,
- And the driver nature which is quantified by a probability of spontaneous deceleration.

In traffic flow, the dynamics discussed above are parallel, namely, the velocities corresponding to each vehicle are updated simultaneously at a time t .

Hence, the vehicular motion according to the NaSch model is given by the following at a given time t :

- Acceleration: $v_n = \min(V_{\max}, v_n + 1)$, $V_{\max}$ is the vehicles maximum velocity which takes discrete values.
- Deceleration: $v_n = \min(v_n, d_n)$, where $d_n = x_{n+1} - x_n - 1$ is the gap between the leading and the preceding vehicle.

- Randomization: If $v_n > 0$, $v_n \rightarrow \max(v_n - 1, 0)$ with probability P .
- This rule quantifies the spontaneous deceleration of a given driver, $P=0$ corresponds to aggressive or commuter drivers.
- Vehicle motion: $x_n \rightarrow x_n + v_n$

x_n and v_n will denote respectively, position and velocity of the vehicle n .

After the vehicular motion, the time is increased by 1.

It is worth mentioning that the $V_{\max}$ which is the maximal velocity value is discrete.

Chapter 2:
The effect of anisotropy
on the traffic flow
behaviour: investigation
of a single node

1.Introduction: Traffic networks

1.1. Definition

The road traffic network is a typical spatial network due to its geographical factors.

Road network model is built by:

- nodes that mean the intersections
- edges that mean the road sections by which the two intersections can be connected directly[46].

Similarly, According to HCM[1], traffic networks are composed of:

- Links: We speak of a link when a length between two nodes keeps the same characteristics.
- Nodes: We speak of a node when it is the place of interaction between different flows, a single flow controlled by a control system or the place of a significant change in capacity (reduction of the number of channels ...)

1.2. Traffic networks in literature

Research of road traffic network, based on the relation between the structure and function, is of great significance.

In this respect, many studies, based on different approaches, have been conducted in the attempt of analysing a traffic network.

i. statistical

Some papers have chosen to adopt statistical and probabilistic tools and approaches to address the efficiency of a traffic network. On the one hand, Moore has attempted to define the fastest path among a network routes with travel time and flowrate constraints [47]. By considering the natural presence and the interdependence of those two restrictions, he has developed two algorithms that help with the matter. On the other hand, Chen et al have focused on the capacity of a traffic network through probabilistic treatment. With taking into account the variability of links' capacities, they have defined the potential response of a network to a certain demand[48]. Finally, Yuan et al have raised the issue of the important amount of data that need to be collected when studying a network. In fact, they have developed a cross-correlation based method for spatial-temporal traffic analysis that aims to minimize this data

[49].

However, due to the shortcomings and limitations any statistical approach, this kind of study cannot truly reflect the characteristics of real traffic network.

ii. Macroscopic

Other researches have adopted macroscopic modelling approaches to characterize a traffic network as a whole. Herman et al have defined a two-fluid model that would describe the overall network[50]. In fact, they have proved that the mean speed of moving vehicles is proportional to the fraction of moving vehicles raised to a power and that the stopping time is proportional to the travel time. Those two assumptions have then been investigated and validated experimentally [51], [52]. Based on those results, many works have been able to reproduce the macroscopic fundamental diagram of a traffic network[53], [54]. Later, Gerolimini and Daganzo have proved, experimentally and analytically its existence[55], [56], while Xie et al have developed it for an inhomogeneous and instable traffic network[57].

iii. Mesoscopic

Nonetheless, the macroscopic models are incapable to capture the details of the traffic. Thus, other scientists have opted for mesoscopic or hybrid approaches. Burghout et al, for instance, have proposed a mesoscopic model which would be able to integrate with microscopic ones so as to bring the sufficient degree of details needed in network analyses[58], [59].

All those studies have proven that the different observables of a traffic network are correlated but more importantly have pointed out the difficulties of processing, microscopically, the large amount of data characterizing it. Actually, an urban network is a system composed of an important number of nodes and connected roads; each node represents a junction of at least two segments while each segment is connected to two nodes[1, Ch. 10]. The complexity and the density of those conjunctions are what induce those difficulties, thus the difficulty of modelling the network as a whole.

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Accordingly, studies usually differentiate between merge and diverge nodes. Despite being geometrically symmetric, the dynamics of diverge/merge nodes are different[35].

On the one hand, a diverge node models an incoming road splitting into two outgoing segments[34]. The moving flow depends on the volume of the traffic coming from the upstream link, on the capacity of the diverging segments and is strongly affected by the vehicles destinations (road choices). Then, in certain circumstances where a vehicle cannot take its chosen path, a blockage is created upstream the node. In this case, no other vehicle can leave the upstream link until the blocked vehicle does. Subsequently, the dynamics of the diverging node are insured by a FIFO (first in first out) behavior[60].

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- Merge: that contains two upstream flows $\{q_1, q_2\}$ and a unique downstream one $\{q\}$.
- Diverge: that consists of one upstream link $\{q\}$ and two downstream flows $\{q_1, q_2\}$.

His aim was to estimate the evolution of the flow in a network $\{q, q_1, q_2\}$ while

maximizing the flow $\{q\}$. For this purpose, he adopted the macroscopic kinematic wave model of Lighthill and Whitham and Richards (the LWR model) [24], [25] and he defined routes choice patterns. Indeed, especially when diverge nodes are considered, the biggest question that prevails is the distribution of the upcoming flow to the two downstream links at the node. He proposed then two distribution schemes:

- When the turning proportions are predefined
- When the turning proportions are not specified but are derived from the destination of the vehicles.

Similarly, Lebacque has investigated diverge and converge nodes but while maximizing the flow in links $\{q_1, q_2\}$ [69], [70]. He also introduced the supply demand diagram that will constitute the framework of many future works[69]. Indeed, Jin and Jiang have studied merging nodes in the light of supply demand diagram[61]. Jin has also studied the asymptotic traffic states of diverge-merge networks in the same framework[71]. However, the complexity of defining turning proportions imposed the use of analytical methods to quantify the traffic behaviors in different links[72], for instance the Riemann Problem. In fact, Jin has determined the Riemann problem for different distribution schemes and solved it by defining the stationary flow and traffic states in the different links connected by the node[73].

1.3.2.2. Microscopic

Nodes have also been the subject of investigation by the mean of microscopic models for instance the cellular automata models. In fact, CA are microscopic models that model the traffic by discretizing the space and the time(see [26] and the references within) . The particularity of those models is that they can be easily computed so as to perform simulations, under periodic boundaries where roads are considered as a closed loop, or under open boundaries where vehicles can enter or leave the road. Various Cellular automata models have been proposed among which the totally asymmetric exclusion process (TASEP) model as the mother of the CA (see [26] and the references within).

In the respect of the latter, Pronina et al have been among the first to tackle the three branches model with a junction positioned in the middle[65]. Their objective was to reproduce the fundamental diagram through mean field approximations and simulations. In this paper, the system is alimented from the left according to a probability α and vehicles are extracted from the right with a rate β . At the merging point, vehicles hop randomly from one lane or the other to the third chain. They are extracted from the upstream half of the system with an effective extraction rate β_{eff} and injected into the downstream half with an effective injection rate α_{eff} . The overall flow in the system is then equal to the sum of the flows in the upstream links or to the flow in the downstream link. Thus, by considering all the above-mentioned injection and extraction rates and knowing that all the branches have equal length L and can behave as one-dimensional road when isolated, Pronina et al have defined five possible phases along with the transitions and boundaries.

Later on, those same results have been reproduced or generalized by different papers:

- By considering different injection rates[68].
- By considering a junction connecting M -input to 1-ouput or m -input to n -output[63], [66].

In the same way, diverge nodes have also been investigated in this same framework. In fact, by introducing a new hopping parameter that simulates the waiting time or the obstruction at the junction, Wang et al have defined the phase diagram of the whole branching system[67]. A generalization of this study to a 1-input m -output model has then been proposed by Lui et al[62].

Nodes have also been studied as part of more specific facilities, in occurrence tollbooths[74]–[77]. Indeed, Jiang et al have proven that the existence of a node brings the upstream flow to experience a capacity drop by the effect of the hindrance created at the tollbooth[74]. Nagatani, instead, by fixing a probability for choosing one lane over the other, has established that traffic state in each lane strongly depends on the state of the other lane when lane changing is allowed and that this impact fades away in the opposite case[77].

2. Problematics

In brief, an extended investigation of nodes in the light of the TASEP model has been realized through the years. However, there are other CA model that have shown many empirical observed phenomena for a wider range of V_{max} , for instance the NaSch model[27]. Subsequently, how would a system react under the circumstances of a node, in the light of the NaSch Model?

Furthermore, some studies have showcased a correlation between the lanes of two-lane roads [37], [78]. However, those works have been conducted under periodic boundaries, which limits the sources of this correlation to the lane changing possibilities. But, can the conflicts present at the node be source of another correlation between the different lanes?

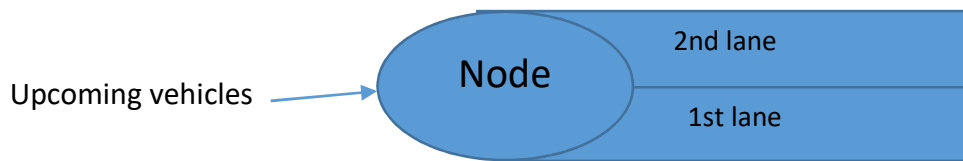
Nevertheless, the fundamental differences between the nodes in addition to the lacking literature focusing on the relation between the links connected by those bring an important question: How will the differences between merge and diverge affect the global results?

3. Model definition

3.1. Diverge model

In the aim to study the features of a diverge node connecting the entry of a two-lane road with no lane changing, we will adopt a cellular automaton model to simulate the behavior of our system.

For simplification purposes, we will consider the following schema where no restriction is applied to the upcoming vehicles in the node:



Schema: when a vehicle is present at the node (the entry of the two lane) according to a demand, it can be injected either into the first lane or in the second lane.

3.1.1. The injection through the node

The demand represents the number of vehicles arriving to the entry of a specific facility desiring to use it[79].

To quantify this demand, an injection parameter α has been introduced. α define the probability of having a vehicle aiming to enter the road.

However, to determine how this vehicle would be injected, many strategies have been proposed. We can list three main strategies:

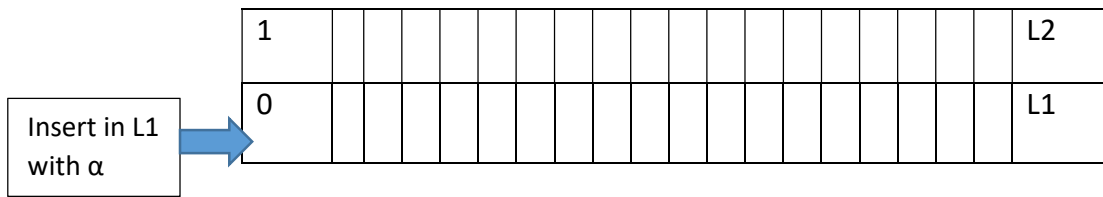
- The standard injection strategy where an additional site is created at the beginning of the system[80]. With a probability α , a new vehicle is injected in this site with a velocity that depends on the gap to the first vehicle on the road. If this velocity is equal to 0, this vehicle is deleted.
- The expended injection strategy where $(V_{\max}+1)$ cells are created at the beginning of the system[81]. At each iteration, with a probability α , a new vehicle is injected into this mini-system with a velocity $V_{\max}$ and with at least a distance $V_{\max}$ to the first vehicle in the road.
- The strategy proposed by Bouadi et al where a new vehicle is injected directly into the lattice with a velocity $V_{\max}$ and a probability α [32]. The velocity and the position of this vehicle are then updated according to the NaSch rules.

In this investigation, we adopt the latest injection strategy. Indeed, since there is no constraint at the node, the vehicles will be arriving into it with their desired velocity.

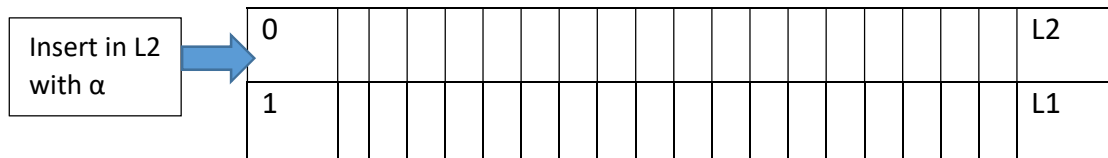
Nonetheless, in the previous investigations of diverge nodes, the route choosing is generally defined previous to the study: vehicles either choose their path randomly or they arrive at the node knowing their future path, if they cannot take it, they imperatively wait. This may create a delay in the upstream link. However, some drivers could take the decision to change their direction if the entry of the link they initially considered is blocked. Then, the following questions arise: how can we capture the scenario where drivers adapt their destination to the traffic states?

In this respect, vehicles will be injected into one of the two lanes with the same velocity with respect to one of the following distribution schemes that we will call scenarios: S_i :

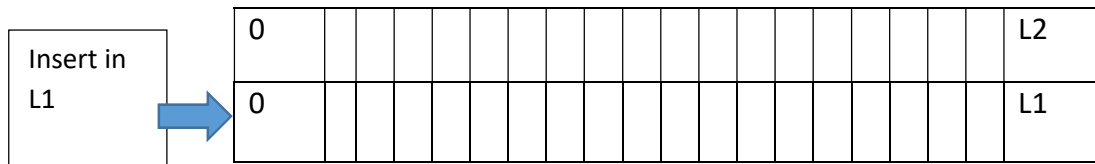
- S_1 : when the first cell of the first lane is empty and second one is occupied: the vehicle is inserted in the first lane.



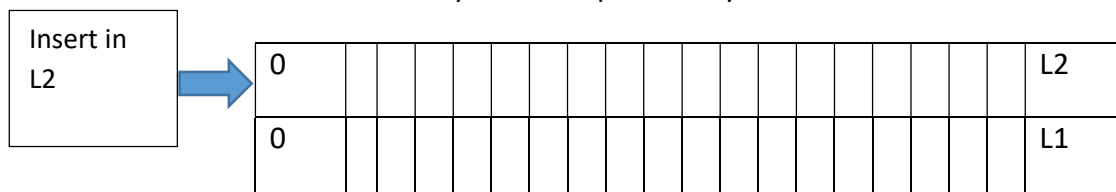
- S2: when the first cell of the second lane is empty and first one is occupied: the vehicle is inserted in the second lane.



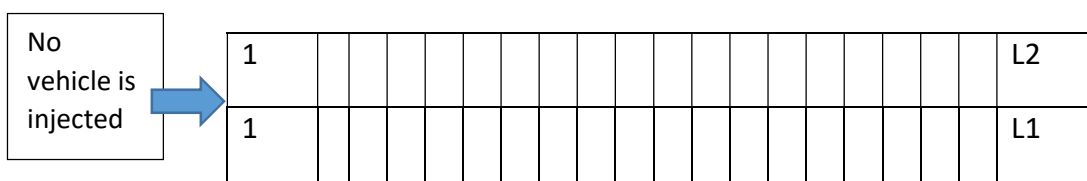
- S3: when both first cells of the two lanes are empty and the vehicle is inserted in the first lane randomly or with a probability P_i .



- S4: when both first cells of the two lanes are empty and the vehicle is inserted in the second lane randomly or with a probability $1-P_i$.



- S5: when both first cells of the two lanes are occupied: the vehicle is eliminated.



3.1.2. The extraction strategy

The flow of a road can be measured through the volume of vehicles discharging [79]. This volume can be quantified by an extraction rate β that is inversely proportional to the service time.

When there is no restriction at the exit of the road, $\beta=1$. This is the case when there is no signalization.

However, when $\beta<1$, a signalization controls the number of vehicles that can exit the road.

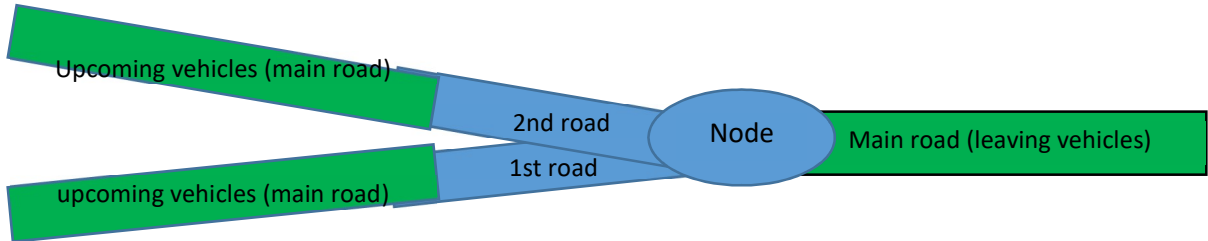
To simplify the analyses, we consider that the two lanes have the same extraction rate: both can be freed at the same time with the same extraction rate.

It is worth to mention that, in a traffic network, this rate β can represent the demand to another node.

3.2. Merge model

In the merge study, we consider a quasi-one-dimensional system composed of two separated roads connected by a merging node. We mirror the global schema of the diverge system. Here, the roads are located upstream the node.

We adopt the following schema where vehicles leave the roads through the node:



In each road, a vehicle is injected with a probability α and a velocity corresponding to the gap available[32].

3.2.1. Extraction strategy

When vehicles arrive at the exits, they are extracted by probability β .

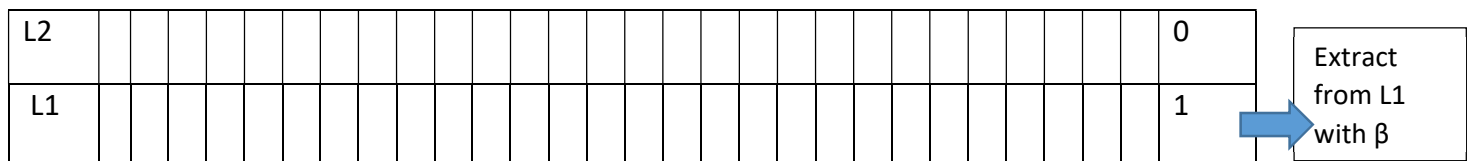
However, with the existence of a merge, an extra restriction is applied to the right boundaries since the node can only deserve one vehicle at a time. Thus, the choice of the prioritized road need to be made.

Many priority schemes were previously proposed. To name a few[34]:

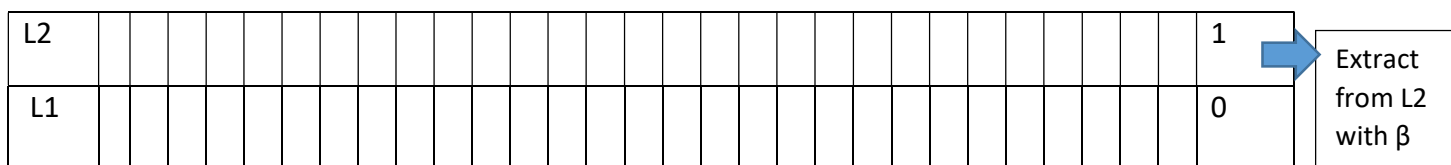
- Optimal merge model[23]
- Fairness model[61]
- Fractional off-merge model[69]

Few other papers estimated a priority scheme empirically[35], [82].

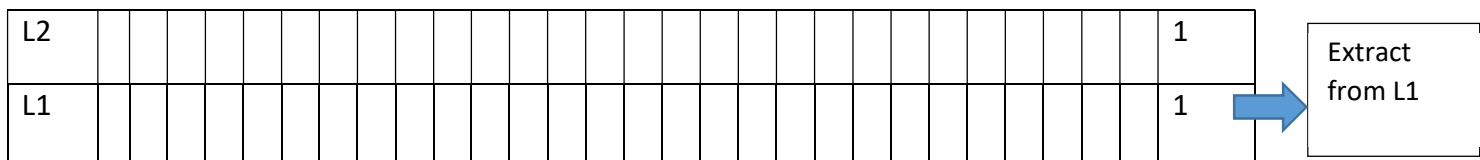
Vehicles are extracted following one of the scenarios below:



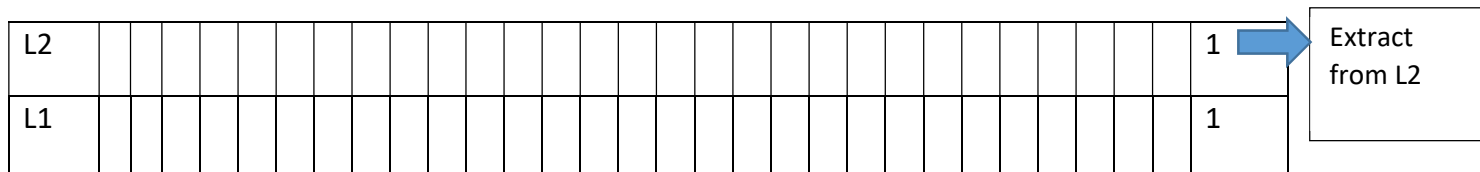
Se₁: when the last cell of the first lane is occupied and second one is empty: the vehicle is extracted from the first lane



Se₂: when the last cell of the second lane is occupied and first one is empty: the vehicle is extracted from the second lane.



Se₃: when both last cells of the two lanes are occupied and the vehicle is extracted from the first lane randomly or with P_e



Se₄: when both last cells of the two lanes are occupied and the vehicle is extracted from the second lane randomly or with 1-Pe

3.2.2. The injection strategy

In the merge study section, we will adopt the Bouadi et al injection strategy [32].

3.3. The motion model

The NaSch Cellular Automaton Model[27], where space, time and velocity are discretized, aims to simulate the traffic.

In this model, when injected, the vehicle can only move forward. Thus, the system is updated according to the following rules:

- Acceleration: $v_n = \min(v_{\max}, v_n + 1)$, where $v_{\max}$ is the maximal velocity.
- Deceleration: $v_n = \min(v_n, d_n)$, where $d_n = x_{n+1} - x_n - 1$ is the gap between the leading and the following vehicle.
- Randomization: $v_n = \max(v_n - 1, 0)$, with a probability Pr .
- Vehicle motion: $x_n = x_n + v_n$, where x_n and v_n are respectively the position and the velocity of the vehicle N .

In our system, each lane is an independent one-lane facility. It will then be treated as a standard one-dimensional system.

In this respect, we will adopt the NaSch CA to model the movement of the vehicles in each lane, thus in the entire system.

N.B.: in the following, since no lane changing is allowed, each lane of the considered two-lane road can be referred to either by lane or by road. Moreover, since the time is discretized, probability and rate refer to the same meaning.

4. The Effect of road's Traffic Conditions on the Node

4.1. Introduction

To tackle the investigation of nodes, we propose a quasi-one-dimensional system consisting of one diverge node relating the two separated lanes of a road at the entries, with open boundaries and where no lane changing will be allowed and we study the reaction of it to different injection rates (traffic demands) and extraction rates. We aim to shell the response of the node to the traffic states of each lane and to answer the following question: Could considering the road state while choosing the direction create any sort of connection between the different links of the network through the node?

Simulation Conditions:

To run the simulation, we consider a cellular automaton double lattice; each road is of $L=500$ cells.

In the aim to reach the steady state, we execute 50000 Monte Carlo iteration while we average 40 initial configurations to eliminate statistical fluctuations.

It is worth to mention that longer lattices have been considered to verify the effect of finite size effect, and no changes have been observed. Thus, for computing efficiencies, only $L=500$ have been adopted.

We consider that the two lanes are identical and have the same traffic conditions: both lanes have the same length, the same maximum velocity and the same randomization probability. In this case, both lanes have the same flow and the same global density (figure1) and a symmetric behavior is observed. (The explication of this diagram is the subject of the following section 5.1)

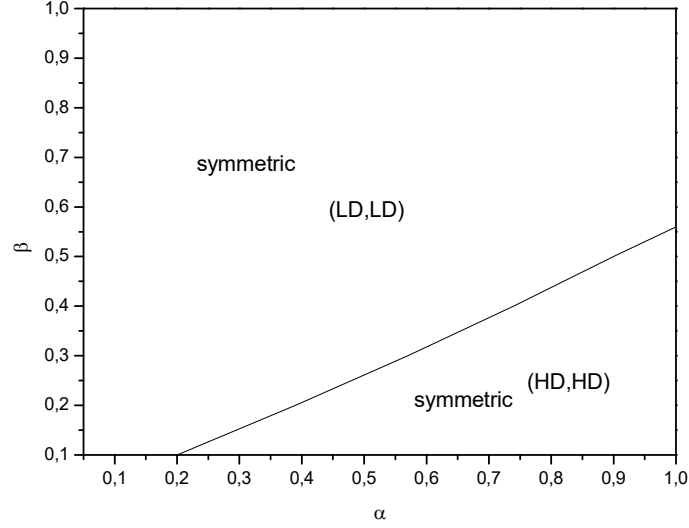


Figure 1: phase diagram exhibiting the different phases of the two lanes (L1,L2) for different values of α and β

In most multilane roads, some lanes are more exploited than others, for various reasons, namely work zones, limited speed, friction caused by opposed vehicles[31], [79]... This over-exploiting is believed to have a strong impact on the concerned lanes performances. Yet, could it also affect the behaviors of the non-affected lanes?

In order to answer this question, we will alter the circulation in one lane (that will refer to as the first lane) while maintaining the second lane as it is according to the following situations:

- Situation 1: Hanaura et al have proved the effect of a perturbed lane on a whole double-lane system with periodic boundaries and where lane changing is allowed [83]. In our case, we implement a perturbation zone into the first lane and we observe the global density. This perturbation zone is represented by a limited number of cells where each vehicle may decelerate with a probability P_d , while the rest of the vehicles will not [84]. We will adopt a perturbation zone that is 100 cells long starting at the cell 250 and going upstream, with a probability of deceleration $P_d = 0.5$
- Situation 2: In order to capture the effect of the behavior of drivers, we introduce a randomization probability $Pr = 0.3$ in one lane, and we follow the response of the two lanes.
- Situation 3: we limit the maximum velocity in one lane to $V_{max1} = 2$ while we maintain $V_{max2} = 5$ in the other lane, and we replot the densities of both lanes.

The global behavior of the altered lane under the different situations has already been treated and explained by numerous papers (see:[85], [30], [31])

The objective is to highlight any change in the behavior of the traffic flow in the non-altered lane while the traffic in the first lane is altered, despite only being connected at the node.

The figure 2 shows changes in the density and the velocity of the second lane for a fixed a value of the extraction rate $\beta=0.5$. Indeed, despite the fact that no lane changing is allowed and that the features of this lane are not altered, the behavior of the second lane varies when the first lane is altered.

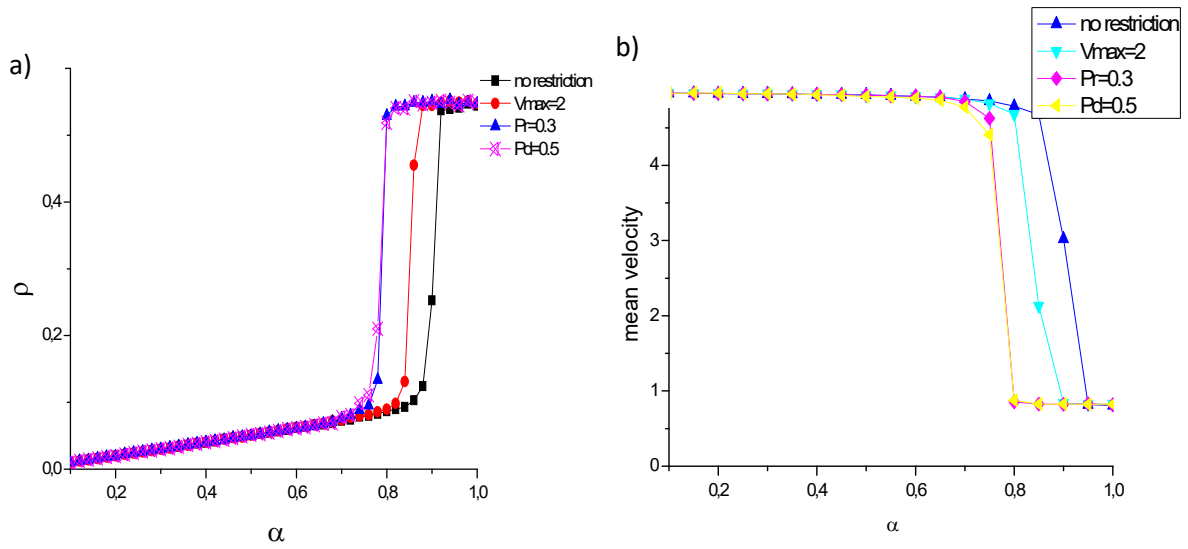


Figure 2: a) the density b) the velocity of the second lane versus the injection rate α for an extraction rate $\beta=0.5$: in the situation 1: $P_d=0.5$, the situation 2: $P_r=0.3$, the situation 3: $V_{max}=2$ and the situation when no alteration is applied on the first lane

4.2. The behavior of the flow and the density

To push this investigation further, we will focus on the situation 1 in the following.

We recall that we will adopt a perturbation zone that is 100 cells long starting at the cell 250 and going upstream, with a probability of deceleration $P_d=0.5$, no randomization is considered $P_r=0$.

The figures (3, 4) point out the differences in the behaviors of both lanes.

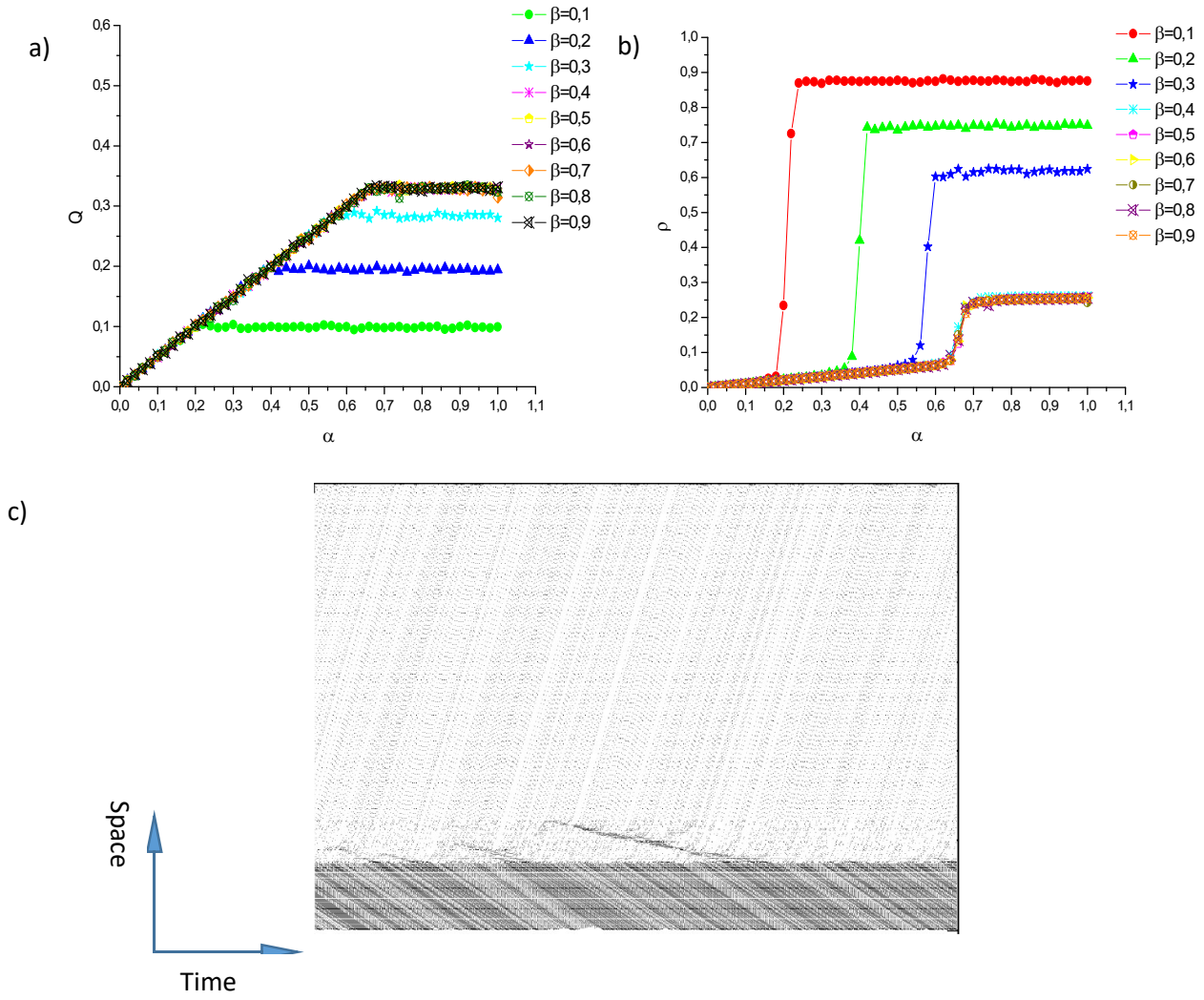


Figure 3: a) flow b) density of the first lane versus the injection rate α for different values of the extraction rate β when $Pd=0.5$; c) space-time diagram of the first road for $\alpha=1, \beta=0.55$ (500 cells over 500 time steps)

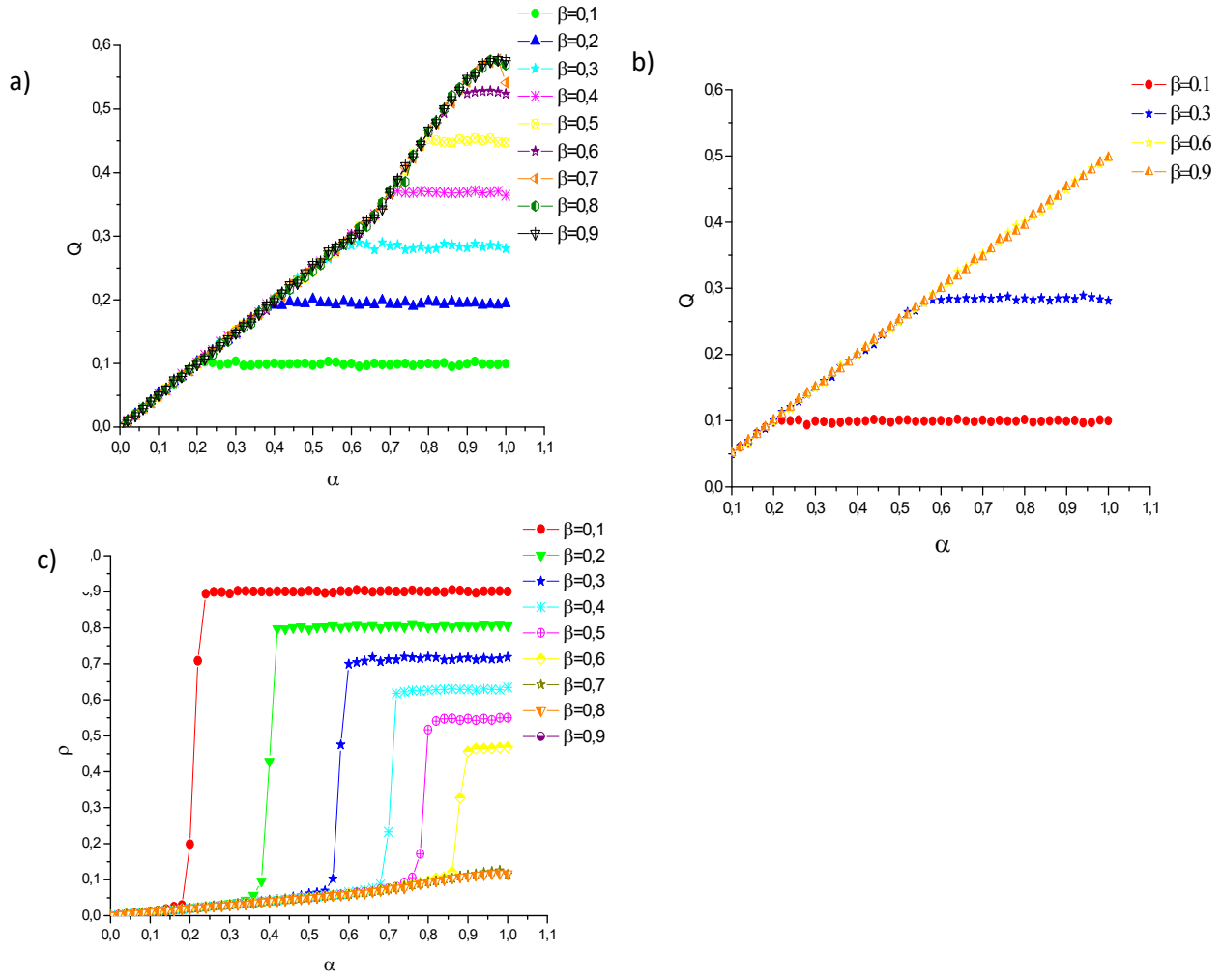


Figure 4: flow of the second lane versus the injection rate α for different values of the extraction rate β when a) $Pd=0.5$ b) $Pd=0$; c) density of the second lane versus the injection rate α for different values of the extraction rate β when $Pd=0.5$

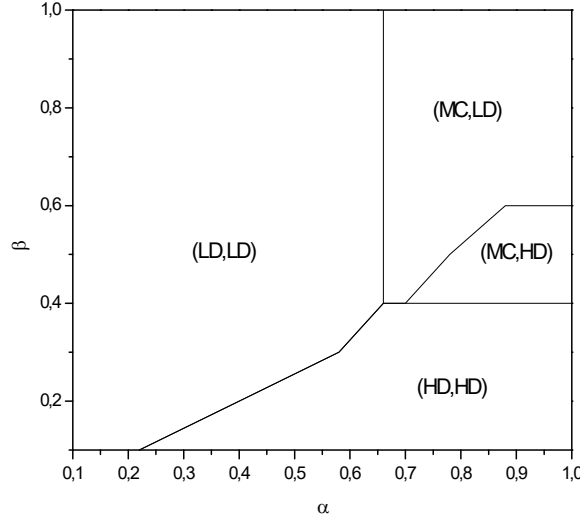


Figure 5: phase diagram exhibiting the different phases of the two lanes (L1,L2) for different values of α and β

The behavior of the first lane changes with respect to $\beta=0.4$.

When $\beta < 0.4$, the system undergoes a transition from the low-density phase to the high-density phase at $\alpha_{cl} > \beta$. However, **when $\beta \geq 0.4$,** the lane transits to the segregation phase instead at $\alpha_{cl}=0.65$ for all this range of β . In this phase, the maximum flow that can be reached is equal to 0.34 (figure3-a/b) and the traffic parameters do no longer depend on β and α . Those statements have been made previously by Bouadi et al while studying the effect of a compact distribution of defects on a one-dimensional system[31].

4.3. Spontaneous Symmetry Braking

Being the subject of the perturbation, only the first lane is predicted to behave differently, since the two lanes are only connected at the node. Knowing that no lane changing is allowed, the effect of the deceleration zone is expected to stay limited to the affected lane and to dissipate by the effect of the boundaries.

Nevertheless, the response of the second lane also changes. Indeed, when the first lane transits to the maximum flow phase, i.e. **when $\beta \geq 0.4$ and $\alpha \geq 0.65$,** the flow and the density of the 2nd lane are higher in comparison to the case when $P_d=0$ (figure 4-b). Moreover, the maximum value of the flow is improved (figure2).

This observation leads us to speculate the existence of a spontaneous symmetry breaking for **$\beta \geq 0.4$ and $\alpha \geq 0.65$** as observed in bridge models (figure 5).

Actually, in the case of the bridge model, two species of particles are driven in different

direction either in the same lattice[86]–[89] or in two separate symmetric chains[90]–[94]. At the boundaries, both particles are injected with the same injection probability α and extracted with the same extraction probability β . The two species are then expected to have symmetric and equal flows and densities, i.e. symmetric phases[87], [88]. However, in some specific ranges of (α, β) , this symmetry is broken. According to previous studies, the spontaneous symmetry breaking is due to a perturbation or a fluctuation at the boundaries. Those fluctuations could be a droplet variation of α or β at one boundary[87], [88]. This variation can generate a different state to the one governing the system, which propagates and causes a SSB. The fluctuations can also be a hindrance generated at the junctions or the gatherings of the two lanes at which two opposite flows (entering and exiting) are competing[91]–[94]. In all cases, a domain wall is formed and travels into the system, bringing along a difference into the states of the two species.

In our case, the two lanes are only connected at the left boundary. In addition, only one type of vehicles is injected into the system, all driving in the same direction (from left to right). Hence, the previously stated causes of SSB are not occurring. The question that arises at this point is: what is the deficiency that is responsible of this symmetry breaking? How does it occur?

Those interrogations bring us to the importance of studying the entries of each lane that are located in the node.

4.4. The injection scenarios: A self-organization Process

In the respect of the observations of the sub-section above (4.2), we investigate how every upcoming vehicle is injected into the system through the node. For this purpose, we consider the probability of the occurrence of each scenario ‘ S_i ’:

$$P(S_i) = \frac{\text{the number of the occurrences of the scenario } S_i}{\text{the total number of the occurrences of all the scenarios}} = \frac{N(S_i)}{\sum N(S_i)} \quad (2.1)$$

N.B: the probability $P(S_i)$ corresponds to the inflow injected to the lane according to the scenario S_i .

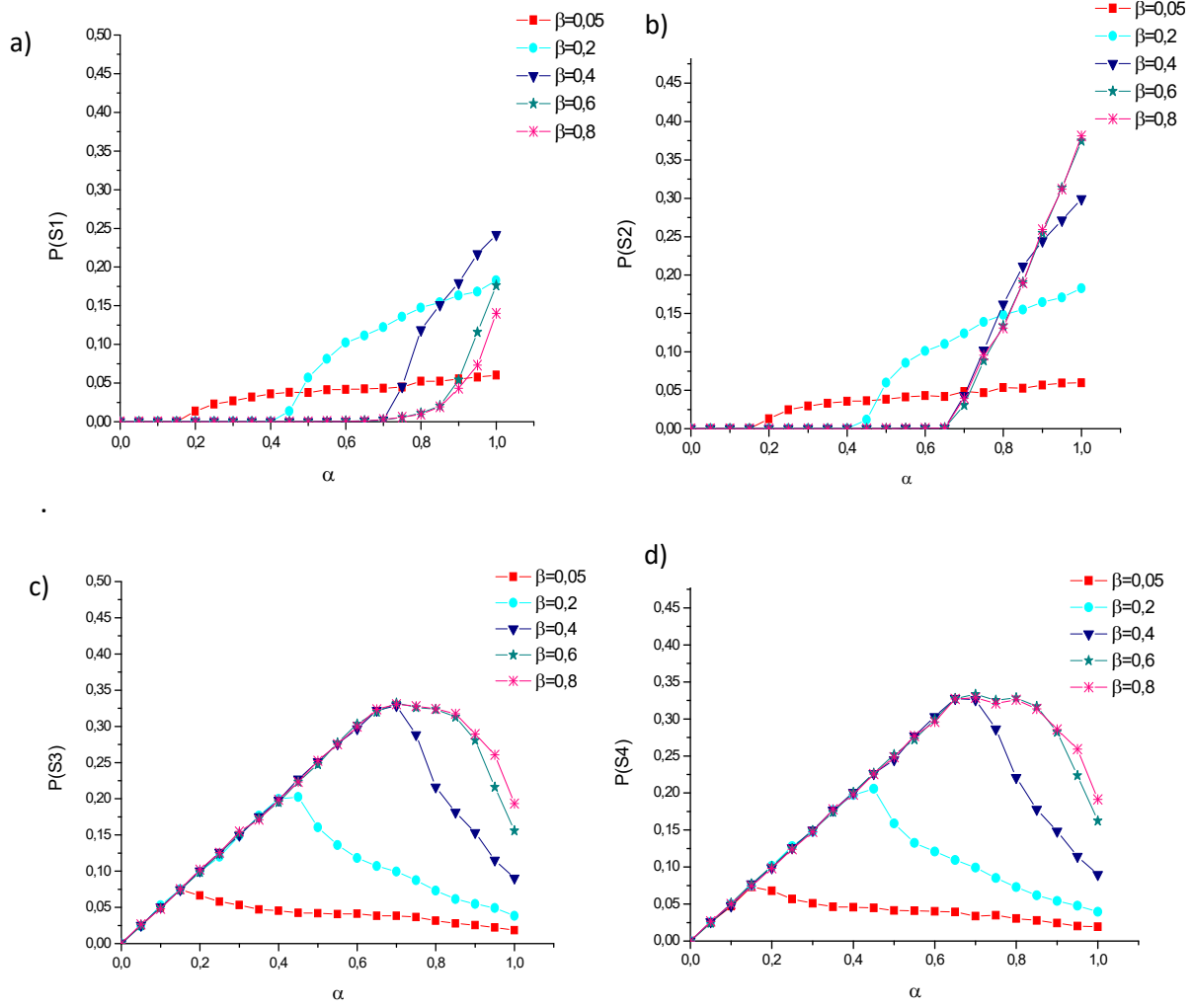


Figure 6: the probability of the occurrence of the scenarios a) S1, b) S2, c) S3 and d) S4 versus the injection rate α for different values of the extraction rate β , with $Pd=0.5$

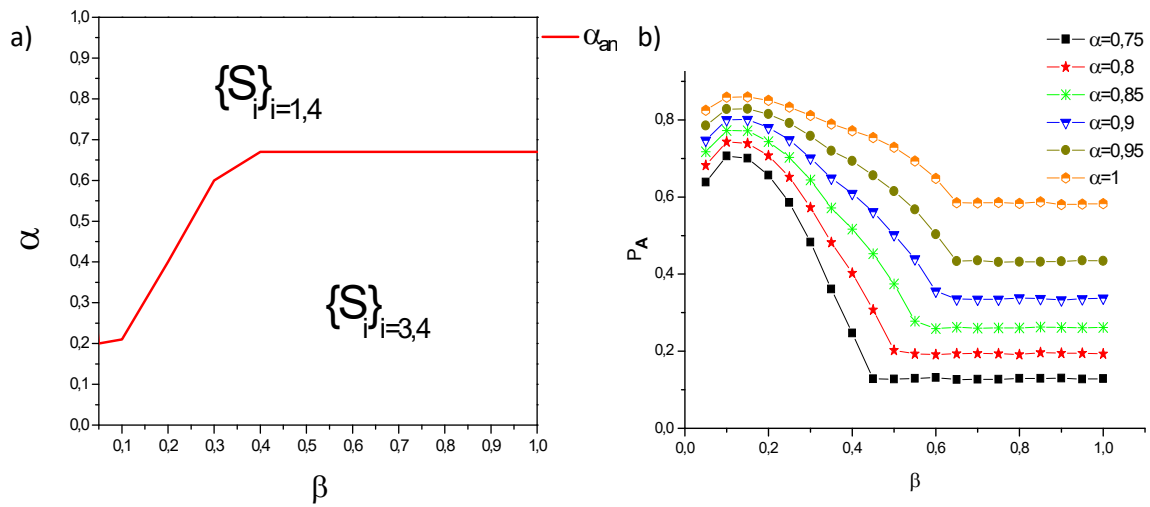


Figure 7: a) the spectrum of the occurrence of the 4 scenarios, b) the ratio of the occurrence of S1 and S2 combined to total scenarios : $P_A = \frac{N(S1)+N(S2)}{\sum N(Si)}$, with $Pd=0.5$

We plot the probability of occurrence of each scenario $P(S_i)$ for different values of (α, β) (figure 6) and we examine the different configuration of the system $\{S_i\}_{i=1,4}$ with respect to the traffic phases of the first lane (figure 3). The figure 7-a sums up the spectra of (α, β) where each scenario exists.

i. For $\beta < 0.4$:

When $\beta = 0.2$, only the scenarios S3 and S4 exist for $\alpha \leq \alpha_{th} = 0.4$. When $\alpha > \alpha_{th}$, the scenarios S1 and S2 appear and increase exponentially while the remaining scenarios start decreasing. This threshold value α_{th} corresponds to the α_{c1} at which the first lane transits from the low density phase to the high density phase.

ii. For $\beta \geq 0.4$:

When $\beta \geq 0.4$, the scenarios maintain the same behavior with respect to $\alpha_{th} = 0.65$. However, this threshold value α_{th} corresponds to the α_{c1} at which the first lane transits from the low density phase to the segregation phase and does not depend on the value of β .

In fact, when the first lane is in the low-density phase, this same phase is dominant in the second lane and the beginning of the system is more likely to be freed instantly due to the low demand. Only the two scenarios S3 and S4 can be present and increase when increasing α . However, when the first lane transits to the high or the segregation phase, the scenario S1 appears by the effect of the oppression at the beginning of the system and the probability of emptying the two first sites at a time decreases. Then, more vehicles are to be injected into the second lane creating the high density thus, a blockage at the entry of this lane: The scenario S2 appears.

Indeed, the configurations $\{S_i\}_{i=1,4}$ strongly depends on the states of the first lane. It is also worth to mention that the configurations $\{S_i\}_{i=1,4}$ can be brought down to one of two main configurations that are in an opposition of phases: $\{S1; S2\}$ and $\{S3; S4\}$. This opposition brings into the evidence the existence of a self-organization by which the whole system responds to both the boundaries and the volume of lanes.

Therefore, the self-organization at the boundary guarantees the establishment of the different phases in the two lanes. But, **what is the mechanism behind this self-organization?**

4.5. The anisotropy

In order to answer the previous question, we investigate deeply the configuration $\{S1; S2\}$.

4.5.1. In literature

In physical systems, the anisotropy represents the fact that each direction has different characteristics, which privilege one over the other. In The traffic flow theory, the anisotropy defines the fact that drivers react mainly with respect to their leaders and occasionally consider their followers [95], [96]. The anisotropy has also been investigated in the bi-dimensional case where it has been defined as the difference of the probabilities of the change of the motion directions of cars[97].

4.5.2. In our approach

However, as stated previously, in a specific interval of (α, β) (figure 7), the upcoming vehicle to the diverge node is injected imperatively in one lane because the first site of the other lane is occupied. This process does not only concern one vehicle, but represents the self-organization of the system as a response to the traffic condition. Indeed, this self-organization is what induces privileging one lane over the other. Thus, by analogy to physical systems, we refer to choosing one lane over the other as anisotropy. We believe that this anisotropy is the deficiency at the boundary that causes the SSB.

We represent the ratio that quantifies this anisotropy (figure 8):

$$A_s = N(S1) / (N(S1) + N(S2)) \quad (2.2)$$

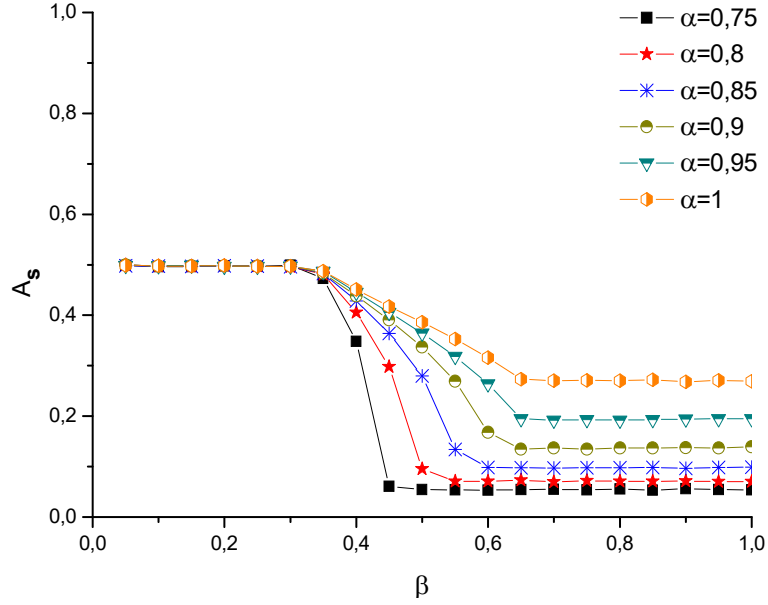


Figure 8: ratio A_s versus the extraction rate β for different values of the injection rate α , with $Pd=0.5$

Two phases are observed in this figure:

- When $\beta < 0.4$, the vehicles are equally injected in one of the lanes and the system is isotropic.
- When $\beta > 0.4$, the vehicles are more likely to enter the second lane by a probability $(1 - A_s)$ and the anisotropy is stronger.

✓ **Interpretation:**

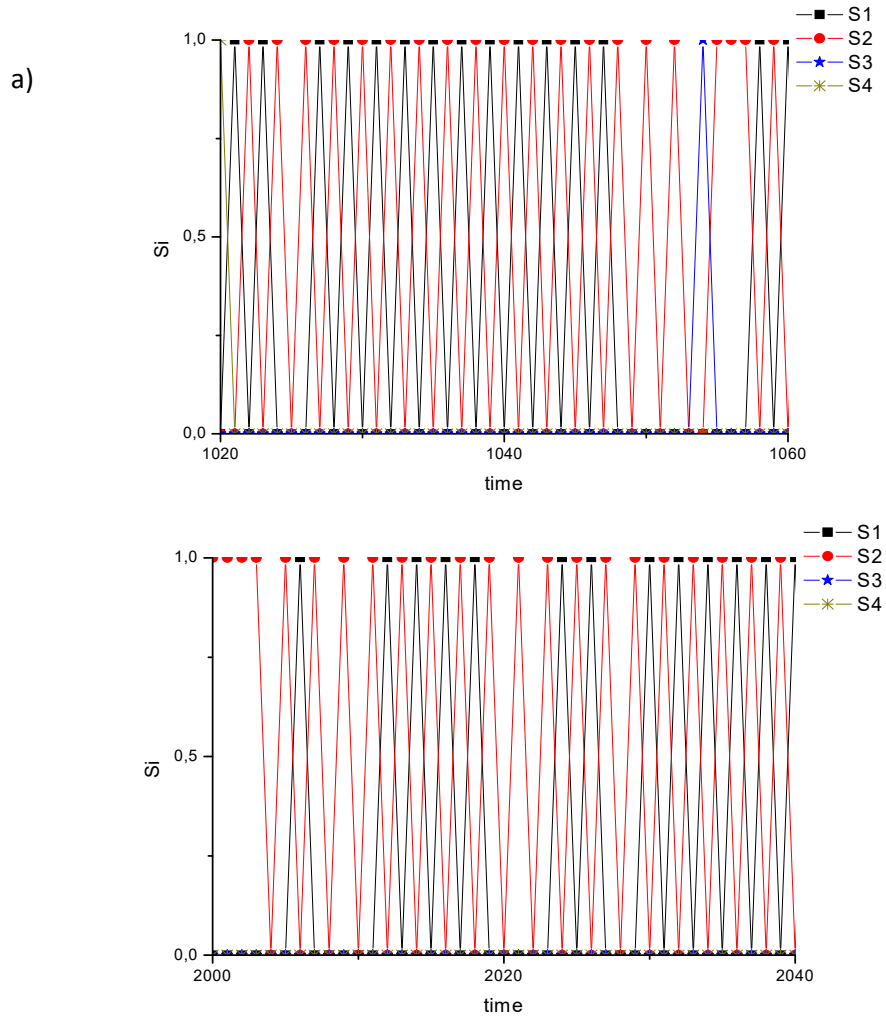


Figure 9: a) the occurrence of the different scenarios in time for $\alpha=1$ and $\beta=0.3$ with $Pd=0.5$: this occurrence is quantified by 0 if the scenario does not occur and 1 if it does

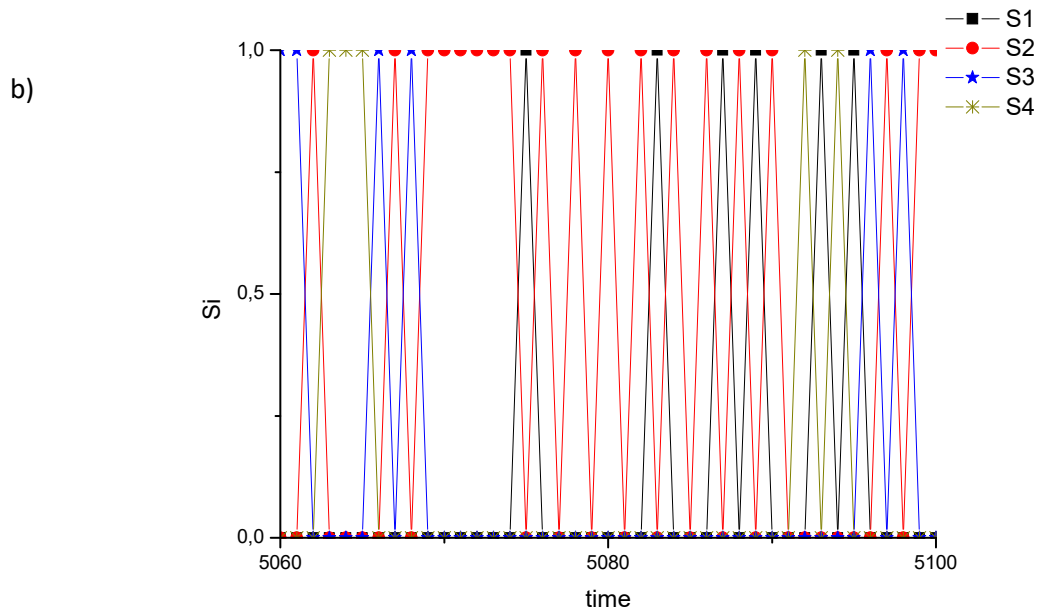


Figure 9: b) the occurrence of the different scenarios in time for $\alpha=1$ and $\beta=1$ with $Pd=0.5$: this

occurrence is quantified by 0 if the scenario does not occur and 1 if it does

Let us take $\alpha=1$

For $\beta < 0.4$, both lanes are in the high-density phase (figure3-4), the tendency of liberating two sites at a time decreases by the effect of this phase: mostly, only one site is available and the two scenarios S1 and S4 alternate (figure 9-a), thus, $A_s = 0.5$.

For $0.4 < \beta < 0.65$, the first lane is in the segregation phase: the beginning of the system is always dominated by the high density due to deceleration zone (figure3-c). The second lane, on the other hand, is still under a high density. However, by the effect of a greater β , more space can be freed in this lane, which allows more vehicles to be injected into it when they were eliminated when β was lower [32]. The scenario S2 increases then and the ratio A_s is decreasing when increasing β .

For $\beta > 0.65$, the second lane is in the low-density phase while the first lane still is in the segregation phase (figure3). At this stage, only the injection strategy can alter the injection into the second lane [32] while the first lane is, most of the time blocked at the entry: the vehicles mostly enters the second lane (figure 9-b). Since the extraction rate does no longer affect the system [32], the ratio A_s is constant.

4.6. Summary

In a two-lane road, when both lanes have the same characteristics, they act the same: they have the same flow and the same global density for all the values of (α, β) . However, if we alter the features of one lane, by a deceleration zone for instance, the two lanes are affected even if ***they are only related at the entries***. A spontaneous symmetry breaking is observed.

In fact, if a disturbance is generated in one lane, it is expected to dissipate by the effect of the boundaries. Nonetheless, the existence of the node translates the perturbation into a self-anisotropy within the system. This same anisotropy induces a behaviors' changing in both lanes, i.e. a spontaneous symmetry breaking. As a response, the whole system gets self-organized so as to satisfy the demand as in the normal case. Those results could only reflect the strong effect of a node.

By combining all those results, we can build a phase diagram that depicts the mechanism of injection imposed by this self-organization with regard to the phase diagram (figure 10). This diagram is believed to be decently helpful to the traffic engineers as far as nodes' designing is concerned.

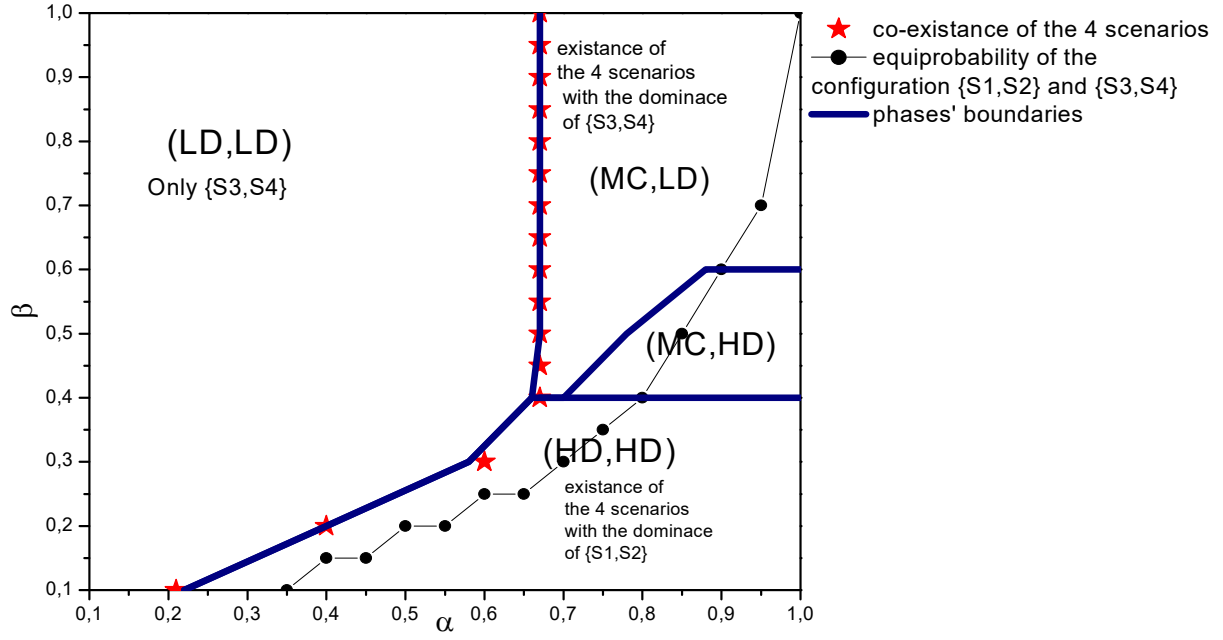


Figure 10: self-organization diagram that represents the spectrum (α, β) of the existence of the 4 scenarios $\{S_i\}_{1,4}$ along with the traffic phases of the system.

4.7. Correlation of the two roads

To push the investigation of the establishment of the SSB further, we will calculate the cross correlation of the observables of the two lanes.

The figure 11 represents the cross-correlation between the densities of the two roads. According to the figure 10, the two roads are correlated mainly when in symmetric phases.

In order to understand this behavior, we will study a diverge node with an extrinsic anisotropy in the following section.

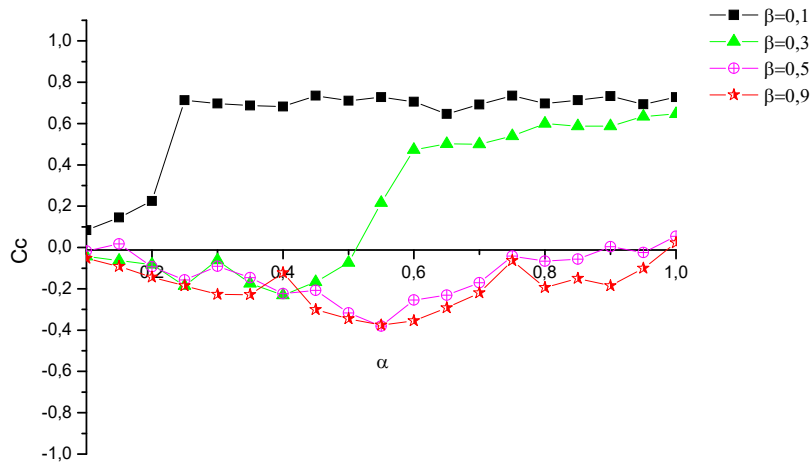


Figure 11: the cross-correlation between the different parameters of the traffic flow in both lanes versus the injection rate α for different extraction rates β .

5. The Effect of an Extrinsic Anisotropy

5.1. Diverge node

5.1.1. Introduction

In section 4, we have shown that a node can translate the effect of an irregularity in one lane into an intrinsic self-anisotropy that generates at spontaneous symmetry breaking. Different traffic phases are governing the two lanes through a self-organization process. Moreover, when in symmetric phases, the node creates a strong correlation between the two roads.

In this section, we aim to decorticate how this anisotropy affects the performances of the system and establishes the spontaneous symmetry breaking and the correlation.

For this purpose, we will change the features of the model so as the anisotropy parameter becomes extrinsic to the system. In this context, we will introduce a new parameter P_i that will interfere within the injection phase, with respect to the following:

Only one vehicle is going to be injected into the road. This vehicle will be introduced into one of the lanes if the first cell of the other lane is occupied or it will be deleted if the beginning of the system is full. If both first sites are free, the vehicle will be injected in the first lane with the probability P_i or in the second lane with $1-P_i$.

N.B: the connotation of the scenarios defined in the Model section 3 remains the same.

Simulation Conditions:

Similarly, To run the simulation, we consider a cellular automaton double lattice; each lane is of $L=500$ cells.

In the aim to reach the steady state, we execute 50000 Monte Carlo iteration while we average 40 initial configurations to minimize statistical fluctuations, focusing only on the deterministic case $Pr=0$ of $V_{max}=5$.

5.1.2. Phase diagram

To point out the behavior of the system, we consider, for instance, $P_i=0.1$. We run the simulation for various pairs (α, β) and we plot the inflow and the outflow of the two lanes.

5.1.2.1. The inflow

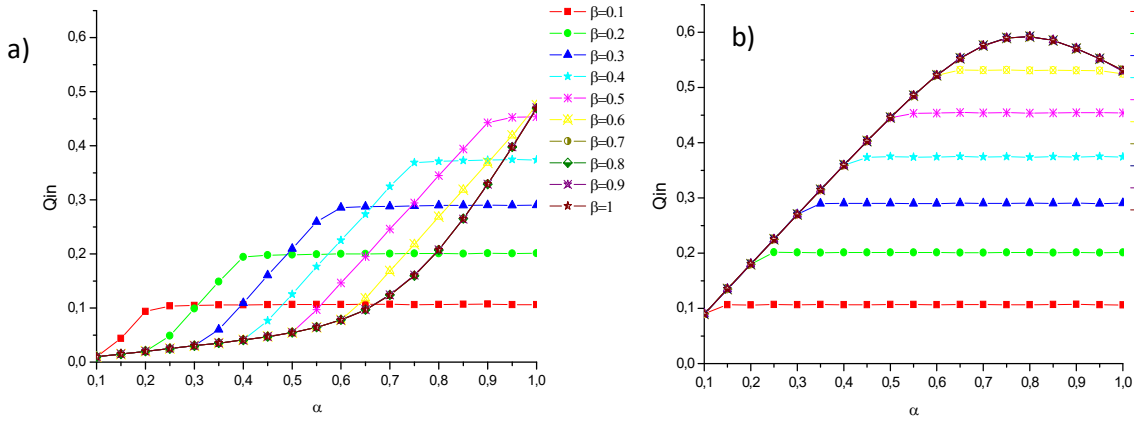


Figure 12: the inflow of the a) first lane b) second lane versus the injection rate α for different values of the extraction rate

The figure 12-a represents the inflow of the first lane, while the figure 12-b represents the inflow of the privileged (second) lane.

In the aim to interpreter these plots, we decided to compute the flow entering each lane according to each one of the four scenarios $Q_{in}(S_i)_{i=1,4}$, for the different values of α and β (figure 13).

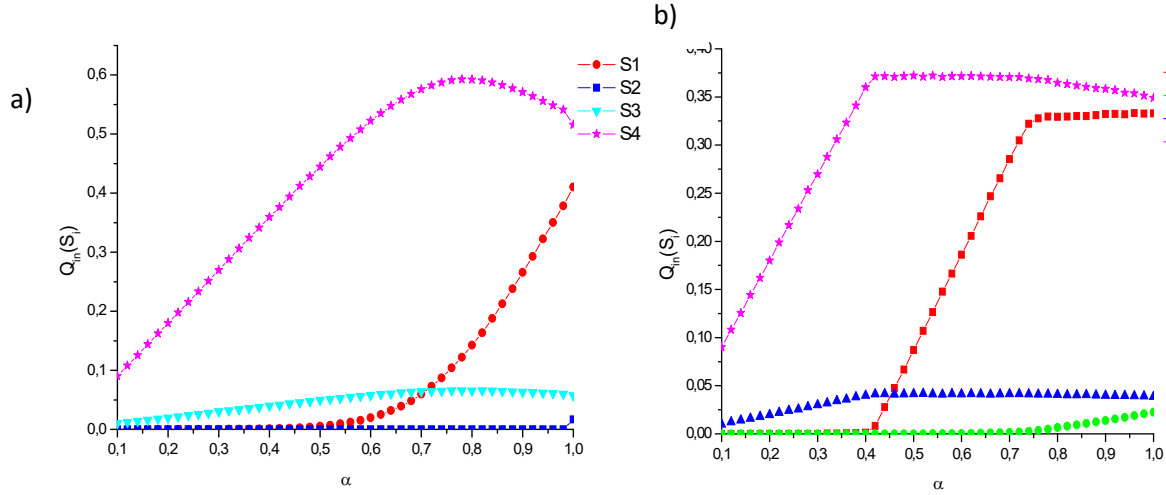


Figure 13: the inflow corresponding to each one of the scenarios S1, S2, S3 and S4 versus the injection rate α for different values of the extraction rate a) $\beta=1$, b) $\beta=0.4$, with $Pi=0.1$

The inflow in the first lane is generated by the two scenarios S1 and S3. The one in the second lane is generated by the two remaining, S2 and S4.

$$Q_{in} = Q_{in}(S_3) + Q_{in}(S_1) \quad (2.3)$$

$$Q_{in} = Q_{in}(S_4) + Q_{in}(S_2) \quad (2.4)$$

The behaviors of the inflows are different and mainly vary with respect to $\beta \geq 0.6$.

On the one hand, **when $\beta < 0.6$** , the inflows undergo a transition when varying the injection

rate α .

Let us consider **$\beta=0.4$** .

When $\alpha < 0.4$, the inflows are very low (figure 12) and are equal to:

$$Q_{in} = Q_{in}(S_3) = \alpha P_i \quad (2.5)$$

$$Q_{in2} = Q_{in}(S_4) = \alpha(1 - P_i) \quad (2.6)$$

However, when $\alpha=0.4$, $Q_{in2}=Q_{in}(S_4)$ becomes constant: more vehicles enter the first lane by the scenario S1.

Thus, an additional inflow is generated: $q_{in1}' = Q_{in}(S_1)$ (figure 13-b).

$$Q_{in} = Q_{in}(S_3) + Q_{in}(S_1) \quad (2.7)$$

This explains the great variation of the inflow.

Whereas when $\alpha=0.74$, the inflow according to the scenario S1 becomes constant bringing a transition of the inflow of the first lane.

On the other hand, **when $\beta \geq 0.6$** , the behavior of the inflows is independent of β . Same as the previous case, the variations of the latter are solely dictated by the variation of flows corresponding to the injection scenarios.

5.1.2.2. The outflow

The outflows of the two lanes also exhibit different behaviors from each other (figure 14).

The outflow of the 2nd lane only undergoes one transition at **$\beta=\beta_{c2}$** .

However, the outflow of the 1st lane, as a β 's function, undergoes, two transitions. In fact, for each single value of α , the outflow increases, at first, until reaching a maximum value at **$\beta=\beta'_{c1}$** . Then, it starts decreasing for **$\beta'_{c1} \leq \beta \leq \beta_{c1}$** . Lastly, when **$\beta=\beta_{c1}$** , the outflow gets saturated at a median value for the rest of β 's range.

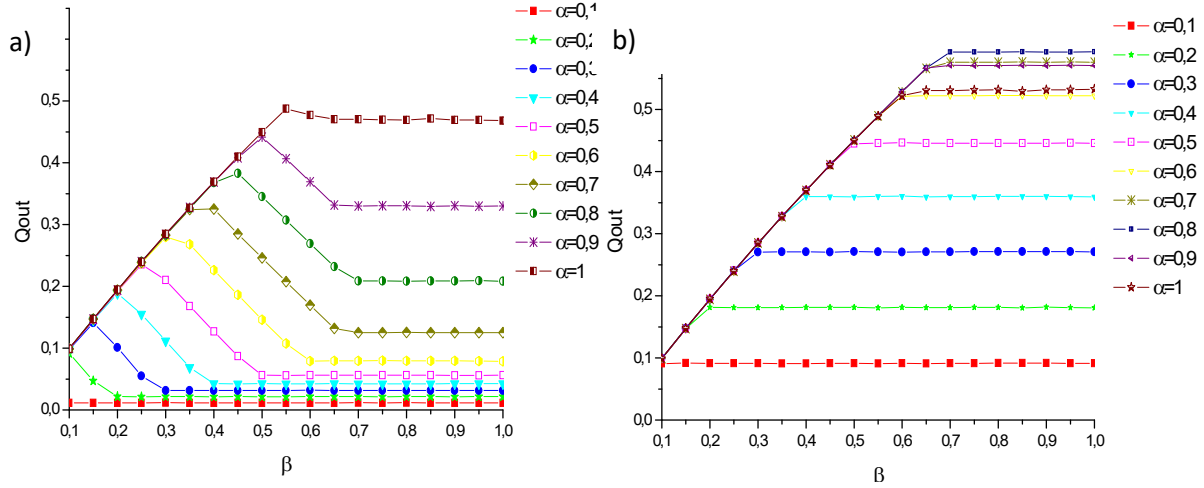


Figure 14: the outflow of a) the first lane b) the second lane versus the extraction rate β for different values of the injection rate α when $Pi=0.1$

5.1.2.3. The phase diagram

In order to define the different phases governing the system, we will compare the inflow and the outflow of each lane for the whole range of (α, β) .

We recall that:

- when $Q_{in} < Q_{out}$, the road is the low density phase
- when $Q_{in} > Q_{out}$, the road is the high density phase
- when $Q_{in} = Q_{out}$, the road transits from the low density to the high density phase.

In this respect, two phase diagrams are to be plotted, one for each lane. By superposing the two, we can define the global phases governing the system (two roads connected by node) and plot the global phase diagram of the whole system (figure 15).

We can state that a broken symmetry is definitely established in the system.

Indeed, the global phase diagram exhibits three separate regions or phases:

- a symmetric high density phase (HD-HD) where both lanes are in the high density phase and have the same flow and density
- an asymmetric low density phase (LD-LD) where both lanes are in the low density phase but have different flows and densities
- a total asymmetric phase (LD-HD) where the first lane is in the low density phase while the second lane is in the high density phase; this case can be considered as **Phase of transition** of the system from the HD phase to the LD phase

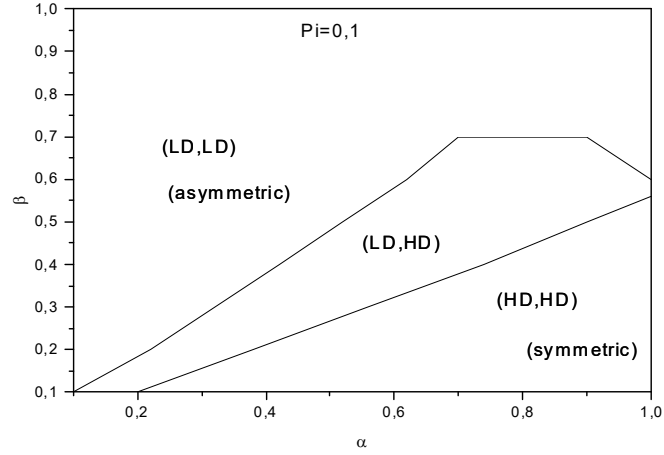


Figure 15: phase diagram exhibiting the different phases of the two lanes (L1-L2) for different values of α and β , $Pi=0.1$

5.1.2.3.1. The establishment of the asymmetric low density

When $\beta \geq 0.6$, both lanes are in the low density phase, but have different behaviors and different values of the flow and the density.

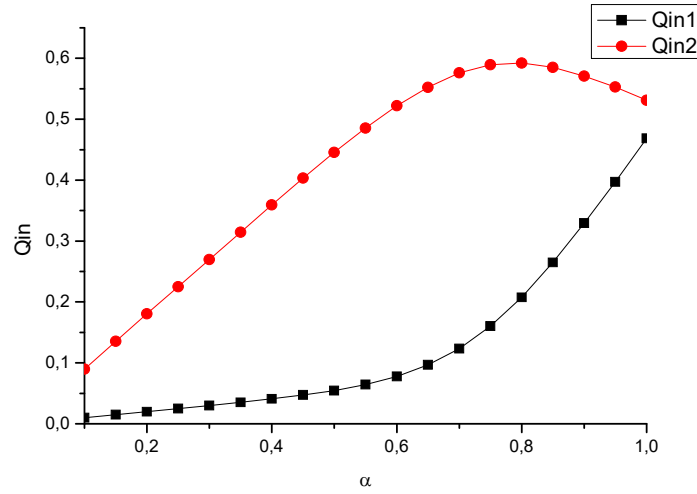


Figure 16: the comparison of the inflows of the first lane (black squares) and of the second lane (red circles) versus the injection rate α for $\beta=1$

Indeed, the inflow of the second lane has a parabolic behavior (figure 16- red circles). On the other hand, the inflow of the first lane has an exponential shape (figure 16- black squares) but its behavior changes with regard to $\alpha=0.5$.

In fact, according to figure 13-a, *when $\alpha \leq 0.5$* , the only existent inflows are corresponding to the scenarios S3 and S4. Thus, the inflow of the two lanes are:

$$Q_{in} = Q_{in}(S_3) = \alpha \cdot Pi \quad (2.5)$$

$$Q_{in2} = Q_{in}(S_4) = \alpha(1 - P_i) \quad (2.6)$$

α and P_i being very low, the flow in the first lane has then very low values (figure 16) generating an asymmetry between the two lanes.

Whereas, when $\alpha > 0.5$, the number of vehicles injected with respect to the first scenario S1 increases when increasing α (figure 13-a).

The flow in the first lane is then:

$$Q_{in} = Q_{in}(S_3) + Q_{in}(S_1) \quad (2.3)$$

Thus, the variation of $Q_{in}(S_1)$ and $Q_{in}(S_3)$ combined leads to the significant increase of the flow. The inflow of the second lane remains:

$$Q_{in2} = Q_{in}(S_4) \quad (2.6)$$

However, since $\alpha < 1$, vehicles are not aiming to enter the system at every time step, giving time to the system to free the entries: especially enabling the first lane to evacuate the first site from the vehicle injected by the scenario S1. More vehicles are then expected to enter the second lane according to the scenario S4 (figure 13-a).

Subsequently, the flow in the first lane remains lower than the one governing the second lane, generating a broken symmetry.

The same logic holds when $\beta < 0.6$ and both lanes are still in the low density phase.

Indeed, since vehicles are injected in the first lane by S3 and in the second lane by S4 (figure 13-b), the low value of P_i makes it in a way that: $Q_{in1} < Q_{in2}$. An asymmetric low density is established.

5.1.2.3.2. The asymmetric phase of transition: from the asymmetric low density phase to the symmetric high density phase

When $\beta < 0.6$, the two lanes can either be in the asymmetric phases (LD,LD) and (LD,HD) or in the symmetric phase (HD,HD), with respect to the injection rate α (figures 15-17).

Let us take the case of $\beta = 0.4$ (figure 17).

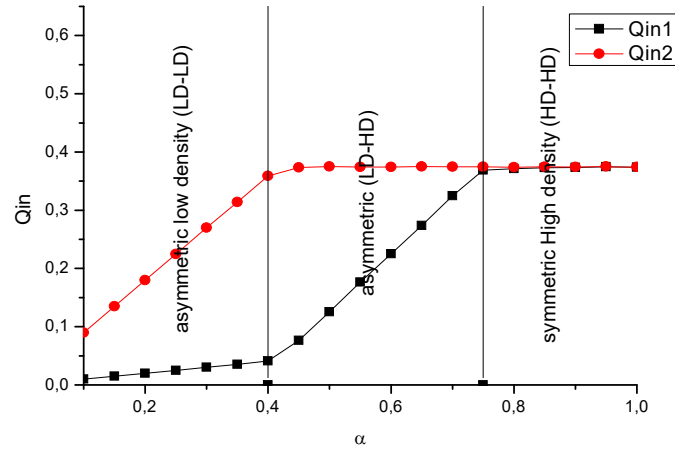


Figure 17: the comparison of the inflows of the first lane (black squares) and of the second lane (red circles) versus the injection rate α for $\beta=0.4$

When $\alpha < 0.4$, the system is dominated by the asymmetric low-density phase in both lanes (figure 17) by the effect of low P_i :

$$Q_{in1} = Q_{in}(S_3) = \alpha P_i \quad (2.5)$$

$$Q_{in2} = Q_{in}(S_4) = \alpha(1 - P_i) \quad (2.6)$$

When $\alpha = 0.4$, the second lane reaches the high-density phase (figures 17, 14-b).

$$Q_{in2} = Q_{in}(S_4) = \alpha(1 - P_i) = 0.36 = q_{out}$$

At this stage, the first site of the second lane is more likely to be occupied by the effect of the high density; more vehicles are then obliged to enter the first lane.

The scenario S1 appears and the inflow of the first lane becomes: (figure 13-b).

$$Q_{in1} = Q_{in}(S_3) + Q_{in}(S_1) \quad (2.3)$$

Thus, the Q_{in1} is more important. Yet, the first lane is still in the low density phase, creating an asymmetric (LD,HD) phase.

Whereas when $\alpha = 0.74$, the first lane reaches the HD phase (figures 17, 14-a):

$$Q_{in} = Q_{in}(S_3) + Q_{in}(S_1) = 0.36 = q_{out}$$

The two lanes reach the high density phase.

5.1.2.3.3. The establishment of the symmetric high density

When both lanes are in the high density phase, a symmetry is established.

Indeed, since the high density phase is strongly dependent of the extraction rate β , the one value of β considered for both lanes makes it impossible to have asymmetric phases[91].

5.1.3. The microscopic interpretation of the phase diagram

As mentioned in the previous sections, the anisotropy created at the entrance of the two roads generates a symmetry breaking. It is then crucial to investigate the features at the beginning of the system in the aim to understand *microscopically* the establishment of the different phases.

Let us take the case of $P_i=0.1$ and $\alpha=0.9$. In this case, there would be no restriction at the beginning of the system and a strong anisotropy will be created.

To start our analysis, we draw the probability of the occurrence of each scenario $P(S_i)$ as a β function (figure 18).

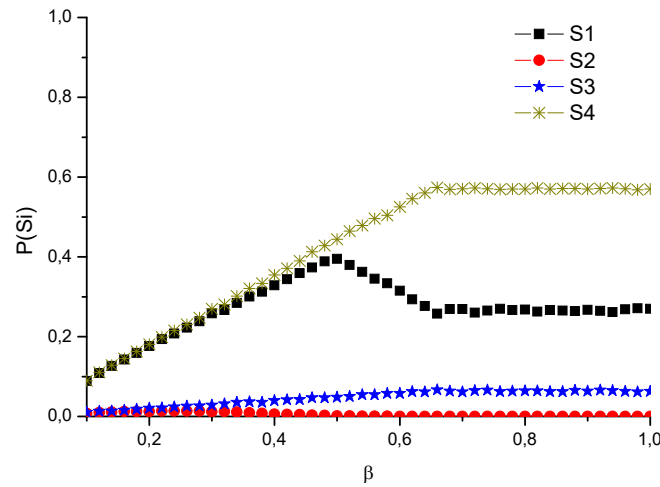


Figure 18: the probability of the occurrence of the different scenarios S_i for $P_i=0.1$, $\alpha=0.9$ and different values of β

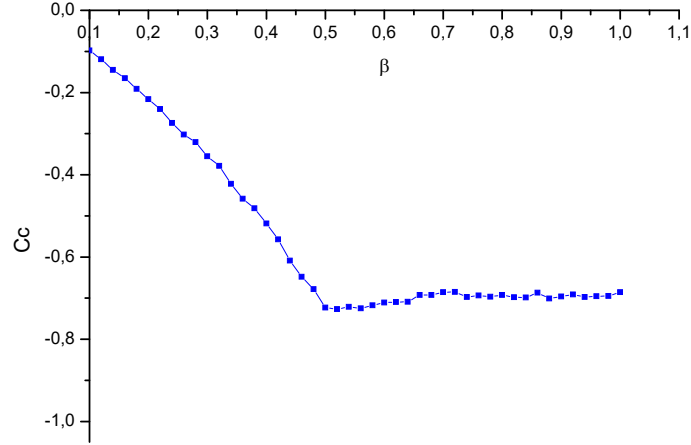


Figure 19: cross correlation between the probability of occurrence of the scenarios S1 and S4 for different values of β when $P_i=0.1$ and $\alpha=0.9$

We observe that the scenarios S1 and S4 are the dominant scenarios:

- When $\beta \leq 0.5$, both scenarios are increasing and are almost equal.
- When $0.5 \leq \beta \leq 0.65$, the scenario S4 keeps increasing while the scenario S1 decreases with respect to β .
- When $\beta > 0.65$, both scenarios are constant.

The system is then mainly controlled by those two scenarios (figure 18). However, **are they inter-dependent?**

In the purpose of answering this question, we calculate and plot the cross-correlation coefficient between the two preponderant scenarios: S1 and S4.

In the figure 19, the cross-correlation coefficient has three behaviors with respect of β .

When $\beta \leq 0.5$, this coefficient starts very weak and increases until $\beta=0.5$. At this point, it reaches a maximum value of -0.72.

When $0.5 \leq \beta \leq 0.65$, the cross correlation slightly decreases, which corresponds to the change of the behavior of the two scenarios (figure 18).

When $\beta > 0.65$, the cross correlation gets saturated at a maximum value -0.7 for the rest of β 's range.

Therefore, the occurrence of each scenario depends on the probability of the occurrence of the other one.

Nevertheless, since only one vehicle can be injected at every time step, only one scenario can occur at a time. Therefore, to understand the reason behind this correlation and in order to interpret the behaviours observed in the figure 18, we plot the behaviours of the scenarios in time for the previous ranges of β (figures 20).

i. When $\beta \leq 0.5$:

For this interval of β , the system is controlled by the exit and both lanes are in the high-density phase.

The figure 20-a shows the existence of two time intervals: injection interval and obstruction interval. Due to the high density phase, a blockage with a certain length is created at the beginning of the two lane. After few iterations, the system gets rid of the effect of β and the first scenario that occurs is S4. In fact, since both ends are synchronized (same β), both entries get freed at once, hence the appearance of S4 at first by the effect of P_i . An alternation of S4 and S1 will take place for few more iterations before giving way to a new blockage. The system will then alternate between these two phases. A competition between the blockage and the two scenarios is created and persists during the whole simulation (figure 20-a).

Moreover, the more we increase β , the more vehicles can enter the system, which justify the growth of the probability of occurrence of the two scenarios (S1,S4) (figure 18).

ii. When $0.5 \leq \beta \leq 0.65$:

At this range of β , the system is in the asymmetric transition's phase (LD-HD): the first lane is still in the low density phase while the second lane has already transited to the high density phase.

According to the figure 20-b, a pseudo-alternation of the two scenarios (S1,S4) occurs. Indeed, even though being in the high density phase, the important value of β makes it possible to free the entry of the second lane more often. The probability of having the entries emptied at the same time increases. Thus, by the effect of P_i , more vehicles are to enter the second lane according to S4 first and next by S1 into the first lane. A pseudo-alternation of (S1,S4) governs then the system.

However, the more β increases, the more the entry of the second lane is alleviated. In addition, since $\alpha=0.9$, vehicles are not always present at the entry of the system, which increases the probability of having both entries emptied at the same time. By the effect of P_i , more vehicles are to enter the second lane. The probability of having the scenarios S4 is greater than the one of having S1 (figure 18).

iii. When $\beta \geq 0.65$:

In this range of β , both lanes are in the low-density phase.

According to the figure 20-c, alternation of the scenarios S1 and S4 occurs. Indeed, due to effect of P_i , a vehicle is firstly injected into the second lane by S4. In the following time step, by the effect of the injection strategy, the upcoming vehicle cannot be injected in the same lane: it enters then the first lane according to S1 (figure 20-c). Since both lanes are in the low density phase, this alternation will persist, and the system manages to reach a self-organization to neutralize the effect of P_i .

Furthermore, as for the previous range of β , by the effects of $\alpha=0.9$ and $P_i=0.1$ combined, the probability of having the scenarios S4 is greater than the one of having S1. And since β has no impact on the system, these two probabilities remain constant.

In brief, this pseudo-alternation points out a self-organization of the system that ***guarantees the establishment of the different phases.***

Thereby, this bi-dimensional system is ***self-correlated through a self-organization.***

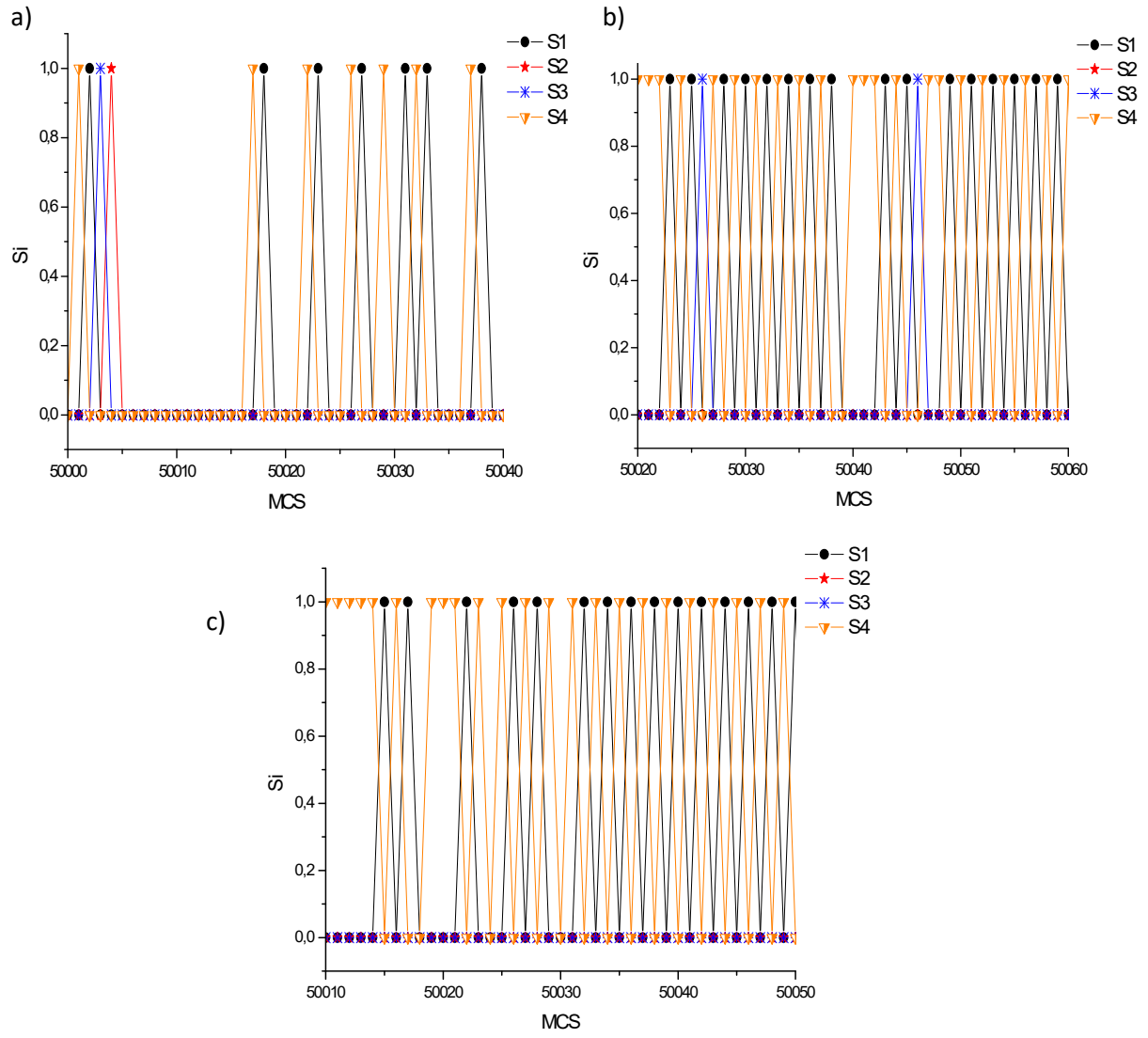


Figure 20: the occurrence in time of the different scenarios for $\alpha=0.9$ and $Pi=0.1$ and a) $\beta=0.2$ b) $\beta=0.6$ c) $\beta=0.8$: this occurrence is quantified by 0 if the scenario does not occur and 1 if it does

5.1.4. The effect of P_i on the phase diagram

In the section 4, we have plotted the phase diagram for an intrinsic anisotropy (figure 5). An important difference between the latter and the phase diagram of $P_i=0.1$ is observed (figure 15).

The investigation of the effect of the anisotropy on the phase diagram is interesting.

The figure 21 sums up the phase diagrams of the different values of $0 \leq P_i \leq 0.5$.

Accordingly, the spectrum of the asymmetric phase (LD,HD) shrinks when increasing P_i . Moreover, only the behavior of the second lane varies and control the width of this phase while the transitions of the first lane are not affected by the variation of P_i .

In brief, the anisotropy at the node brings a SSB into the system and the variation of its impact is non-linear.

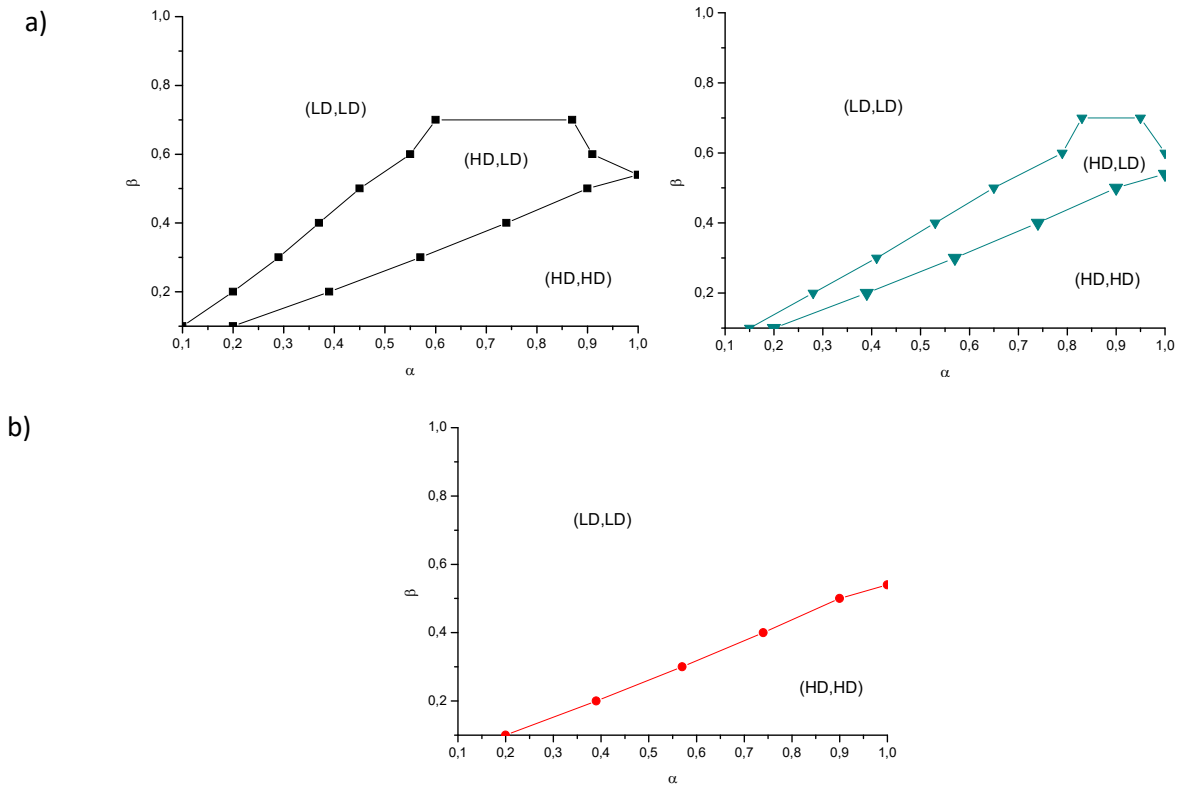


Figure 21: phase diagram exhibiting the different phases of the two lanes (L1,L2) for different values of α and β for $0 \leq P_i \leq 0.5$: a) $P_i=0$, b) $P_i=0.3$, c) $P_i=0.5$

5.1.5. The correlation of the traffic characteristics of the two roads

The above-mentioned results, especially those of the first lane, have shown few new behaviors, namely, a parabolic inflow with an additional transition. Furthermore, a broken symmetry has been highlighted.

According to the figure 11, we have found that the two roads are correlated, at least when in symmetric phase, when an intrinsic self-anisotropy is considered. To generalize this finding, we decided to investigate the correlation between the different parameters of the traffic flow with an extrinsic anisotropy.

When $\alpha=1$, the figure 22 confirms the strong correlation between both lanes, especially in the symmetric phases.

On the one hand, when $\beta < 0.55$, both lanes are under the symmetric high-density conditions, the flows of both lanes are much positively correlated: $C_c=1$.

On the other hand, when $\beta > 0.62$, both lanes are operating under the asymmetric low density phase and the correlation rate is near (-0.95).

Nevertheless, when $0.55 < \beta < 0.62$, the correlation rate is decreasing and is very low. In this β 's spectrum, the system is in the phase of transition: the first lane is in the low-density phase whereas the second lane is in the high density phase.

It is worth to mention that the more the symmetry braking is pronounced the more the cross-correlation is lower.

For instance, **when $\alpha=0.7$** , the system is in the asymmetric low density phase for $\beta > 0.7$. However, according to the figures 12, the difference between the two lanes' flows is more pronounced than for $\alpha=1$. The cross correlation in this case is then much lower.

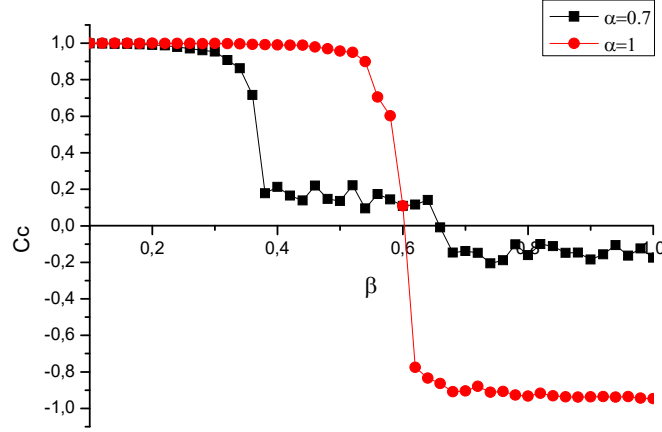


Figure 22: the cross-correlation between the different parameters of the traffic flow in both lanes versus the extraction rate β for $P_i=0.1$ and $\alpha=0.7/1$.

5.1.5.1. The order parameter

When the system is in a symmetric phase, the cross correlation of the flows Q1 and Q2 is maximum. When the system is in asymmetric phase, this cross correlation is very low. More importantly, the latter undergoes a first order transition when the whole system is in the asymmetric phase of transition (LD-HD). Then, could we consider this cross-correlation as an order parameter?

An order parameter is a physical quantity that differs from a phase to another[98]. It *“is related to the symmetry breaking at the phase transition and distinguishes the symmetry-broken states in the ordered phases”*[30]. Moreover, it disappears discontinuously at the transition point for first order transition[98], [30], [99].

For the case of one-dimensional traffic systems with open boundaries, which exhibit first order transitions that are induced by the boundaries and depend on the control parameters (α, β) , to our knowledge, no exact order parameter that characterized these transition has been developed.

Nevertheless, according to the definition, we can speculate that the cross-correlation of the flows Q1 and Q2 is an order parameter that describes the symmetric, the asymmetric and the transition phases of the considered quasi-one dimensional traffic system with a junction.

5.1.5.2. The effect of the injection strategy

The correlation of the two roads does not depend on the injection strategy. Indeed, by considering the mini-system strategy as the injection strategy, we have replotted the cross correlation of the flows (Q1,Q2) (figure 23-black squares).

According to the figure 23, we can absolutely state that the computed cross-correlation is strategy-independent.

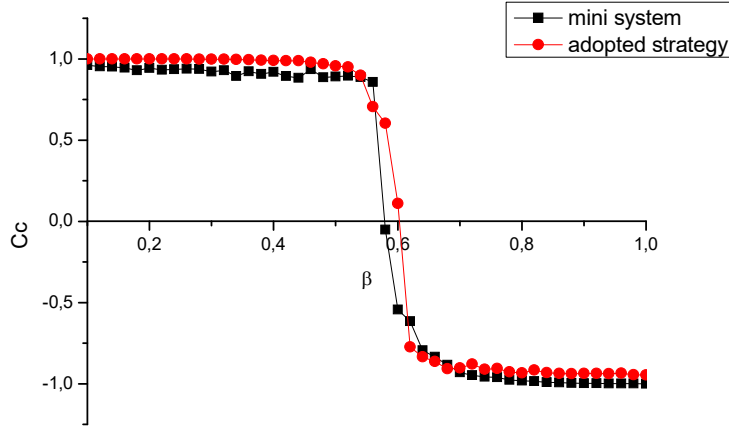


Figure 23: the correlation between the flows in both lanes versus the extraction rate β for $P_i=0.1$ and $\alpha=1$: mini-system (black squares), adopted strategy (red circles)

5.1.6. Summary

When an extrinsic anisotropy parameter is induced into the node, the responses of both lanes to the boundaries are affected, and a SSB is observed. By investigating the injection scenarios, we have found that the entries of the two lanes are strongly correlated due to a self-organization processing at the node. This correlation induces changes on the behaviors of both the privileged and the non-privileged lanes. Indeed, through a cross correlation test, we have proved that the flows of both lanes are interdependent especially in symmetric phases. Finally, according to the differences of its behavior with respect to the symmetry of the system phases, we have proposed that this cross correlation can be considered as an order parameter that characterizes the transition of a quasi-one dimensional traffic system with a junction.

5.2. Merging node

5.2.1. Introduction

As stated previously, studies usually differentiate between merge and diverge nodes. [35].

Indeed, while a diverge node models an incoming road splitting into two outgoing segments, a merge node connects two upcoming flows to one outgoing link[34].

Hence, due to the major dynamics differences, each type of nodes necessitates a standout logic[35].

Furthermore, the studies mentioned above highlighted the existence of an interdependence between the upstream roads and the downstream roads[34]. However, to our knowledge, few if not none, deeply investigated the existence of a relationship between the downstream (upstream) links connected by the diverging (merging) node.

Our highest aim is to answer the following questions: Will the broken symmetry persist? Will the exits of the two roads, located at the merging node, be correlated? Will the two roads be correlated? How will the differences between merge and diverge affect the global phase diagram? And more importantly, will we be able to confirm that the cross-correlation is an order parameter despite the type of the node?

Simulation Conditions:

To run the simulation, we consider a cellular automaton double lattice. Each lattice represent an independent road of $L=1000$ cells.

To reach the steady state, we execute 50000 Monte Carlo iterations and average 40 initial configurations to eliminate statistical fluctuations.

We consider that the two roads are identical and have the same geometric and traffic characteristics: both roads have the same length, the same maximum velocity $V_{\max}=5$. Only the deterministic case $Pr=0$ (Pr being the ratio of randomization[27, p. 2]) is investigated, to only focus on the effect of the anisotropic node.

In real traffic, each road can be subject to a different demand. Those demands are usually translated into an injection probability α_1 into the first road and α_2 into the second lane.

However, unequal demand ($\alpha_1 \neq \alpha_2$) engenders an extrinsic asymmetry. This may bias our investigation, knowing that our aim is to verify the occurrence of a spontaneous symmetry breaking as a response to the anisotropic merge.

Therefore, we consider a single injection rate $\alpha_1=\alpha_2=\alpha$.

In this study, as in the case of the diverge, we define the anisotropy parameter Pe as the probability of choosing one road over the other to be freed.

Finally, unless stated differently later in the section, we adopt an anisotropy parameter $Pe=0.1$. This value favors a road over the other. Indeed, when two vehicles aim to leave the system through the node at the same time, the vehicle in the second road is more likely to exit with a probability $1-Pe=0.9$.

5.2.2. Flow and density

To tackle the investigation, we study the flow and the density of the two roads, each one aside.

5.2.2.1. 1st road

The figure 24 displays the behaviors of the flow and the density of the first road: they have three distinct behaviors with respect to β .

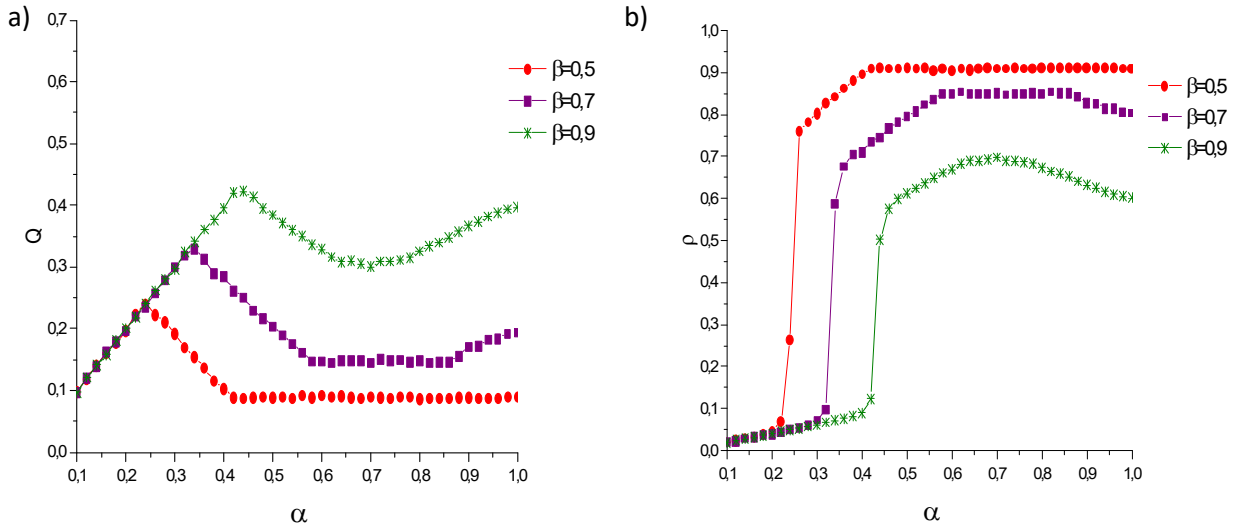


Figure 24: a) flow and b) density of the first road versus the injection rate α for different values of the extraction rate β .

We recall that a one-dimensional system undergoes only one discontinuous transition from the low-density phase to the high-density at $\alpha_c \approx \beta$ (figure 26) [32].

i. When $\beta < 0.7$

When $\beta=0.5$, both the flow and the density undergo **two transitions**: a discontinued

transition at $\alpha = \alpha_{c1} = 0.25$ and a continued one at $\alpha = \alpha'_{c1} = 0.42$ (figure 26). Those transitions are unusual in the measure where they do not appear in the case of a one-dimensional system [32].

At $\alpha = \alpha_{c1} = \beta/2$, the first road undergoes a first order transition, i.e. the space-time diagram displays the co-existence of two distinct phases (figure 25-a). At $\alpha = \alpha'_{c1}$, it transits continuously to the High-density phase (the space-time diagram (figure 25-b) does not show any domain wall).

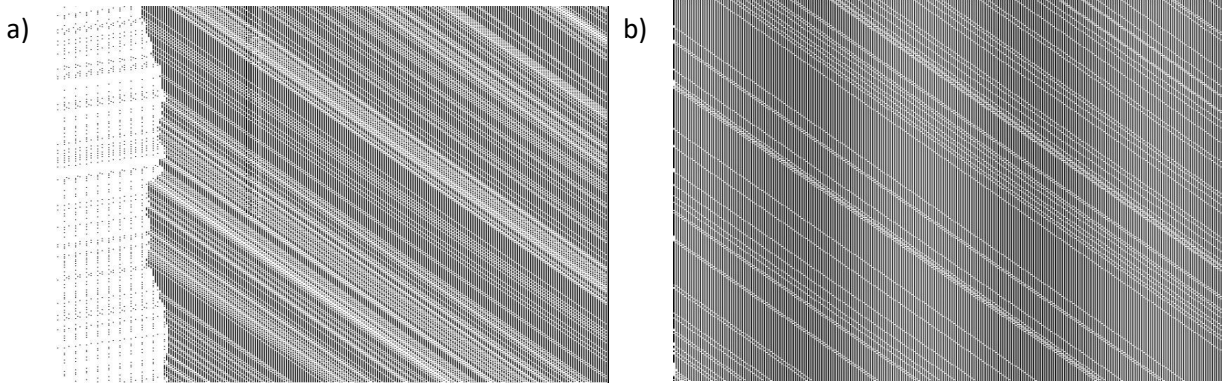


Figure 25: space-time diagram for $\beta=0.5$ and a) $\alpha=\alpha'_{c1}=0.25$, b) $\alpha=0.42$: the black cells are occupied (vehicle) and the whites are empty

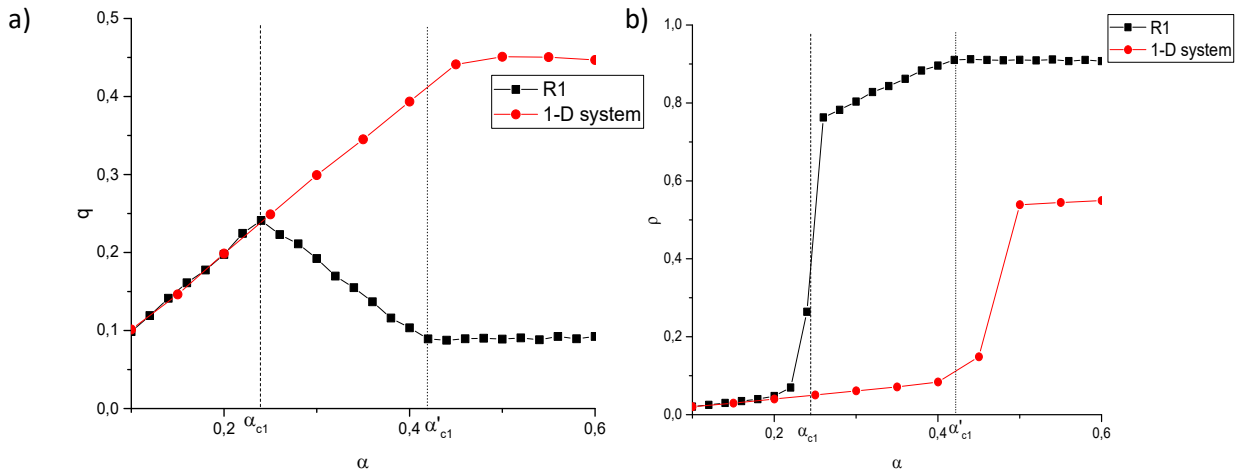


Figure 26: comparison between the observables of the first road and of the one-dimensional system for $\beta=0.5$: a) the flow b) the density

According to the figures 25-26-27, the flow and the density exhibit three phases:

- When $\alpha < \alpha_{c1}$: the first road is in the low-density phase:
 - The mean velocity and the gap are very important.

- The density is very low while the flow is increasing.
- When $\alpha > \alpha'_{c1}$: the first road is in the high-density phase:
 - The density and the flow become constant.
 - The mean velocity and the gap are very low and almost zero.
- When $\alpha_{c1} < \alpha < \alpha'_{c1}$: the first road is in an unusual phase. Against the typical behavior of the density of a one-dimensional system[32], the density continues increasing while the flow starts decreasing.

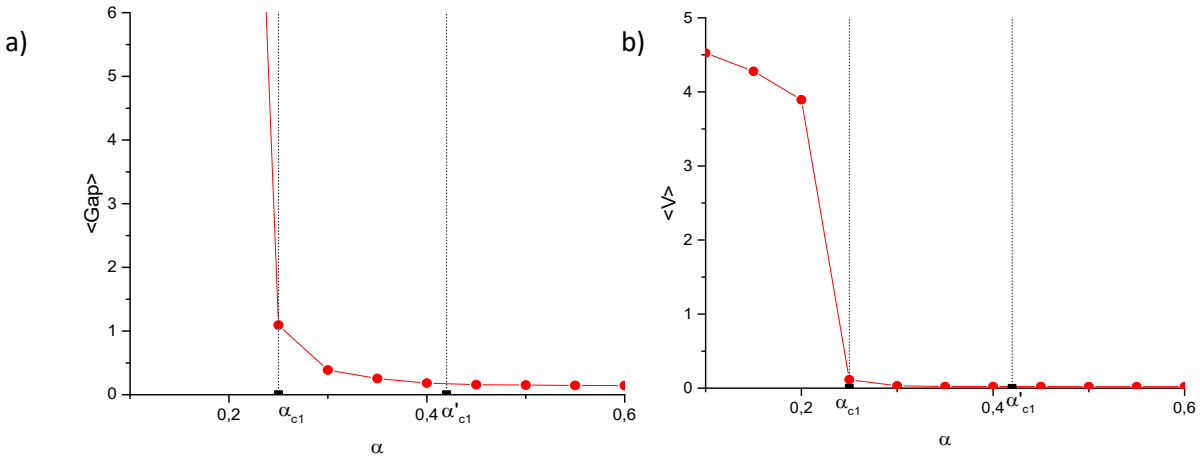


Figure 27: a) mean gap and b) mean velocity of the first road versus the injection rate α for the extraction rate $\beta=0.5$.

Such uncommon behavior leads us to wonder about the identity of this phase. Is it a low-density phase or a high-density phase?

We recall that:

- $\rho(\alpha < \alpha_{c1}) < \rho(\alpha_{c1} < \alpha < \alpha'_{c1})$ and $\rho(\alpha < \alpha'_{c1}) > \rho(\alpha_{c1} < \alpha < \alpha'_{c1})$.
- The gap in this phase is lower than the gap of the low-density phase but higher in comparison to the high-density phase.
- The mean velocity in this phase is lower than the velocity of the low-density phase but higher in comparison to the high-density phase.

Subsequently, we suspect that this phase corresponds to another form of high-density phase.

In order to confirm our hypothesis, we plot the space-time diagrams of the two phases when $\alpha > \alpha_{c1}$ (figure28).

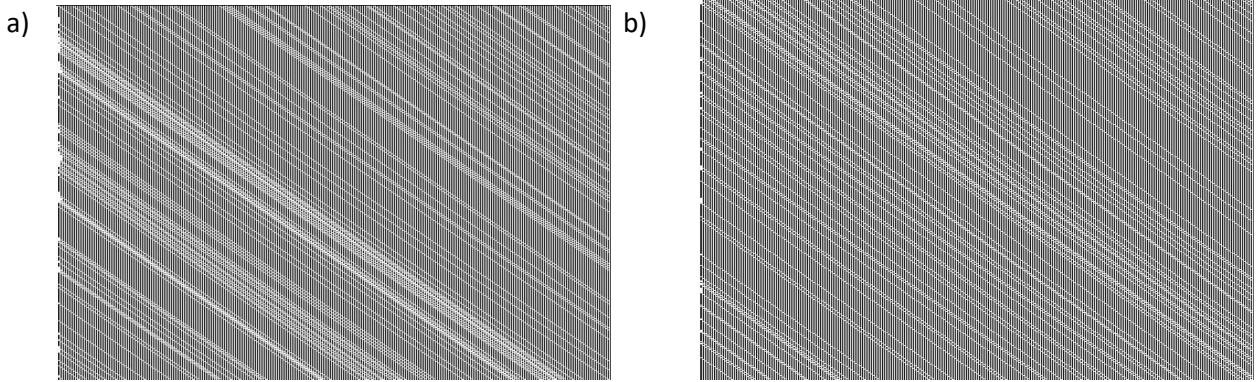


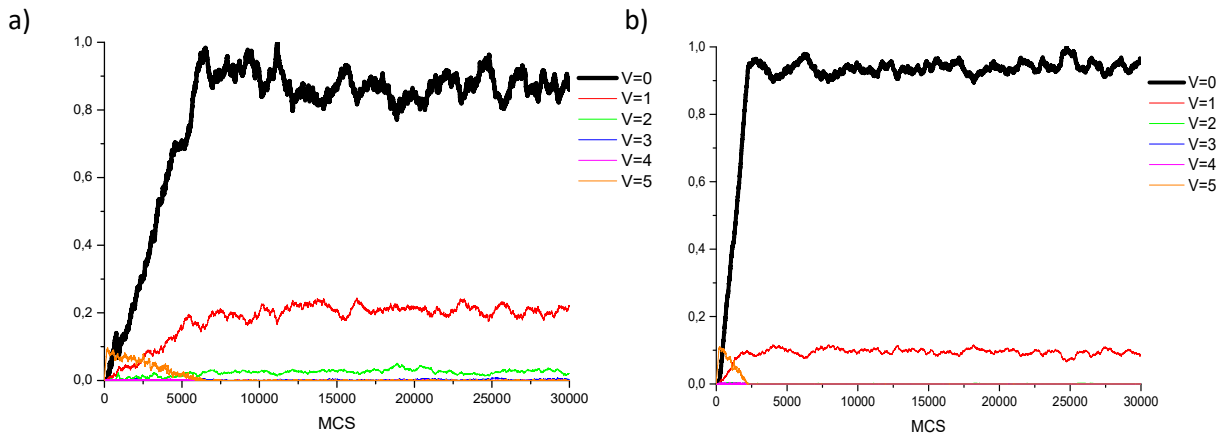
Figure 28: space-time diagram for $\beta=0.5$ and a) $\alpha=0.35$, b) $\alpha=0.6$: the black cells are occupied (vehicle) and the whites are empty

Accordingly, we observe that this new phase belongs to the high-density phase (figure28-a).

Therefore, in this range of $\beta < 0.7$, knowing the differences in gap and velocity, we can state that the first road undergoes firstly a discontinuous transition at $\alpha = \alpha_{c1}$ from the low-density phase to a high-density that we will refer to by HD1. Then, at $\alpha = \alpha'_{c1}$, it transits again, yet continuously, from the HD1 to the usual High-density phase that we will denote HD2.

However, *are those two phases any different?*

With the aim of responding to this question, we investigated the distribution of the dominant velocities in time in both regions of the high-density (figure29).



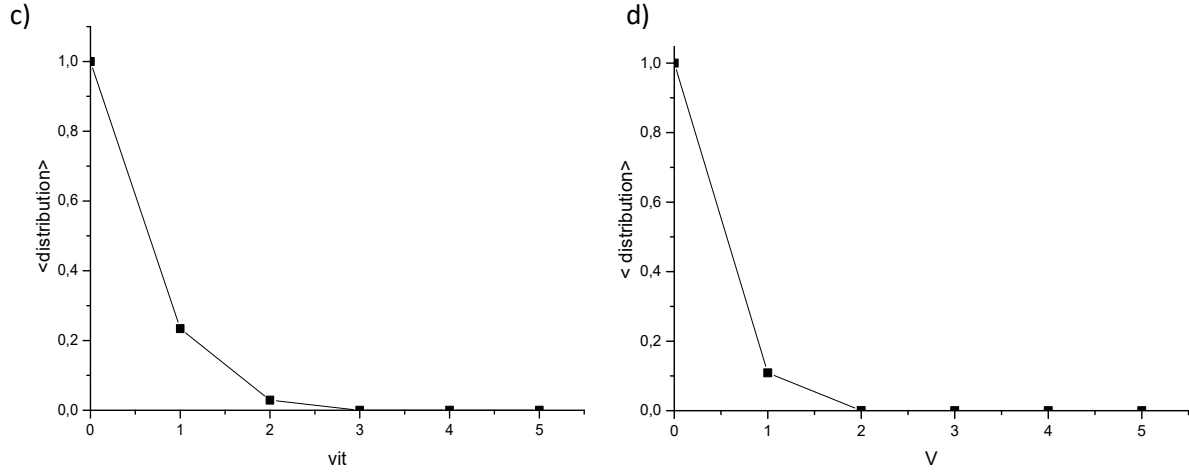


Figure 29: distribution of the velocities (V) in time (MCS being the time step) for $\beta=0.5$ in the HD1 a) $\alpha=0.3$, and in the HD2 b) $\alpha=0.5$. Mean distribution $\langle \text{distribution} \rangle$ of the velocities for $\beta=0.5$ in the HD1 c) $\alpha=0.3$, and in the HD2 d) $\alpha=0.5$

According to the figures 29, we observe that in the HD1, a wider range of velocities are present on the road $\{0,1,2\}$; while in the HD2, there are only two velocities $\{0,1\}$ with a greater predominance of the stopping vehicles ($V=0$).

To push the investigation further, we plotted the velocity profile at a random instant in both phases HD1 and HD2 (figure30).

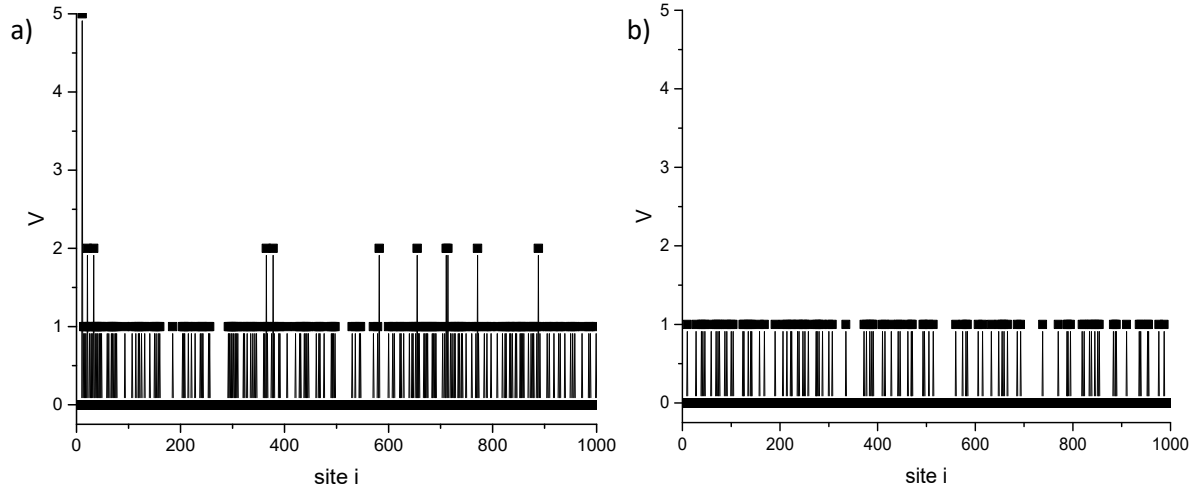


Figure 30: velocity profile at a random instant for $\beta=0.5$ and a) $\alpha=0.3$ (HD1) b) $\alpha=0.5$ (HD2), V being the velocity at the random instant for each vehicle present on the road

The velocity profiles highlight a difference between the two phases. Indeed, they exhibit wider velocity fluctuations when in the HD1 (figure30-a) in comparison to the HD2 (figure30-b).

Nevertheless, in some literature, the high-density phase is usually referred to as

congestion. This same congestion contains a region called jamming phase in which the velocity is close to none and the density is maximum[100], [30]. Other works preferred to divide the high-density phase into a congestion phase where the traffic is variable and a jamming phase where the density is stable and maximal[101].

Subsequently, keeping in mind the differences of the mean gap and velocity in figure 4, and according to the last definition, we can suggest that the high-density phase HD1 corresponds to *the congestion phase* while the HD2 can be represented as *the jamming phase*.

ii. When $\beta=0.7$

When $\beta=0.7$, the first road transits three times (figure31).

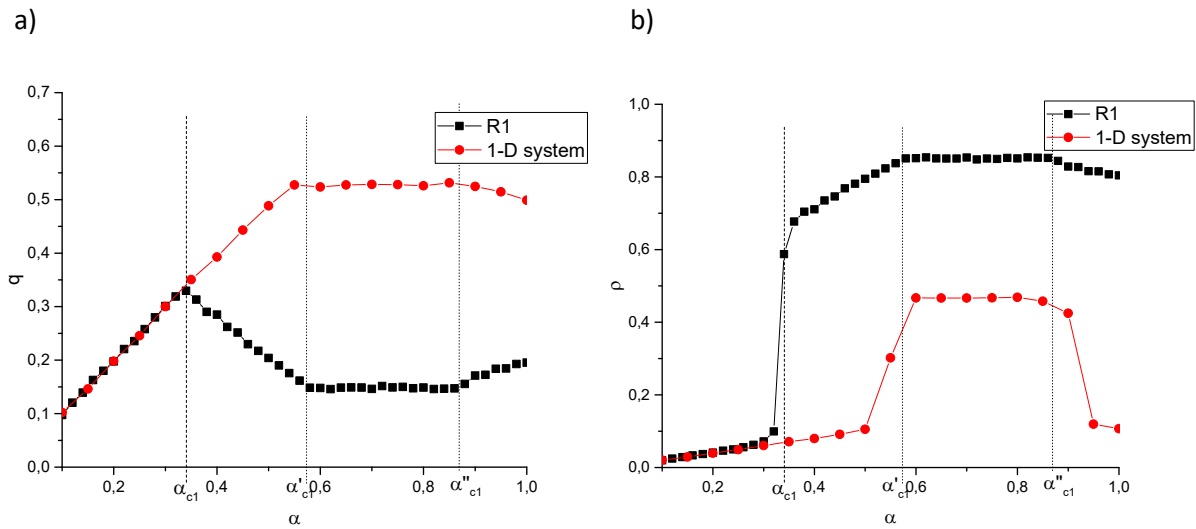


Figure 31: comparison between the observables of the first road and of the one-dimensional system for $\beta=0.7$: a) the flow b) the density

Indeed, it undergoes the same two transitions as when $\beta < 0.7$, firstly discontinuously from the low-density phase to the congestion phase at $\alpha = \alpha_{c1}$ and then continuously to the jamming phase at $\alpha = \alpha'_{c1}$.

However, we perceive that at $\alpha = \alpha''_{c1}$, the flow starts increasing again while the density is decreasing (figure 24-purple squares). According to the gap and the mean velocity (figure32), we can affirm that this phase is the congestion phase.

Consequently, in comparison with the behavior of a one-dimensional system that exhibits a re-entrance phenomenon from the High-density phase to the low-density phase (figure31) [32], we believe that this behavior matches the re-entrance phenomenon from the jamming phase to the congested phase.

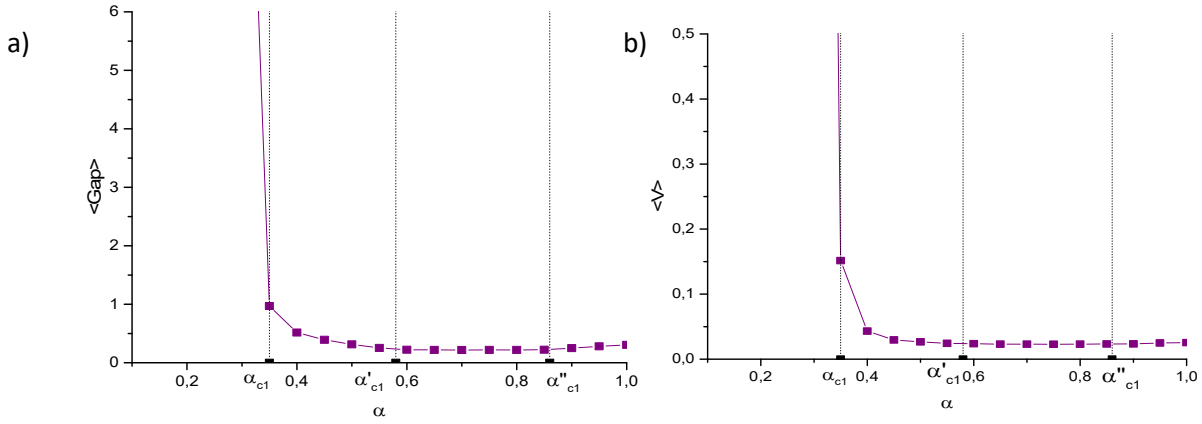


Figure 32: a) mean gap and b) mean velocity of the first road versus the injection rate α for the extraction rate $\beta=0.7$.

iii. When $\beta > 0.7$

When $\beta=0.9$, the first road only transits once from the low-density phase to the high-density phase at $\alpha=\alpha_{c1}$ (figure24-green asterisk).

If $\alpha < \alpha_{c1}$, the first road is governed by the low-density phase. At $\alpha=\alpha_{c1}$, the density transits discontinuously to the high-density phase.

If $\alpha > \alpha_{c1}$, the density slightly increases until $\alpha=\alpha'_{c1}$ when it start decreasing within the phase high-density phase. Since the flow and density are not constant in this range of α , this phase corresponds to the congestion phase.

Thus, for the high values of β , the jamming phase is reduced to a single point (figure24-green asterisk) and the first road only transits from the low density phase to the congested phase at $\alpha=\alpha_c$.

5.2.2.2. 2nd road

The figures 33 exhibit the flow and the density of the second road.

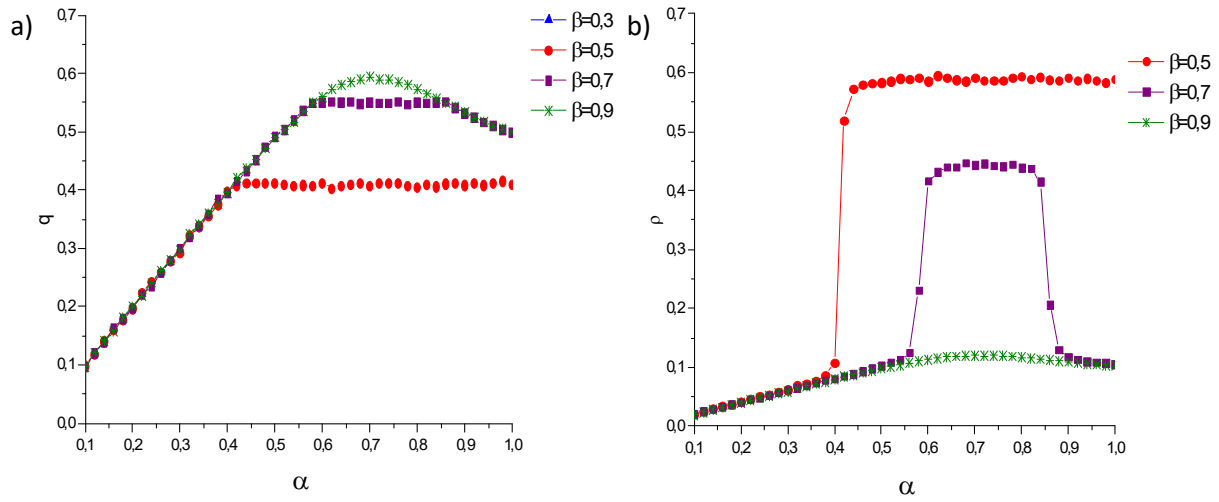


Figure 33: a) flow and b) density of the second road versus the injection rate α for different values of the extraction rate β .

Same as those of the first road, their behaviors vary with respect to $\beta=0.7$. However, this road have a similar behavior to a one-dimensional system.

When $\beta < 0.7$, i.e. $\beta = 0.5$, the density undergoes a first-order transition from the low-density to the high-density phase at $\alpha = \alpha_{c2} = 0.42$. According to the figure 34, the gap and the velocity vary from a maximum value directly to zero. No congested phase is observed. Subsequently, the second road transits discontinuously from the low-density phase to the jamming phase.

When $\beta = 0.7$, the density undergoes two first-order transitions from the low-density to the jamming phase at $\alpha = \alpha_{c2} = 0.57$ and the cross way at $\alpha = \alpha'_{c2} = 0.87$. This is re-entrance phenomenon.

When $\beta > 0.7$, i.e. $\beta = 0.9$, the density remains in the low-density.

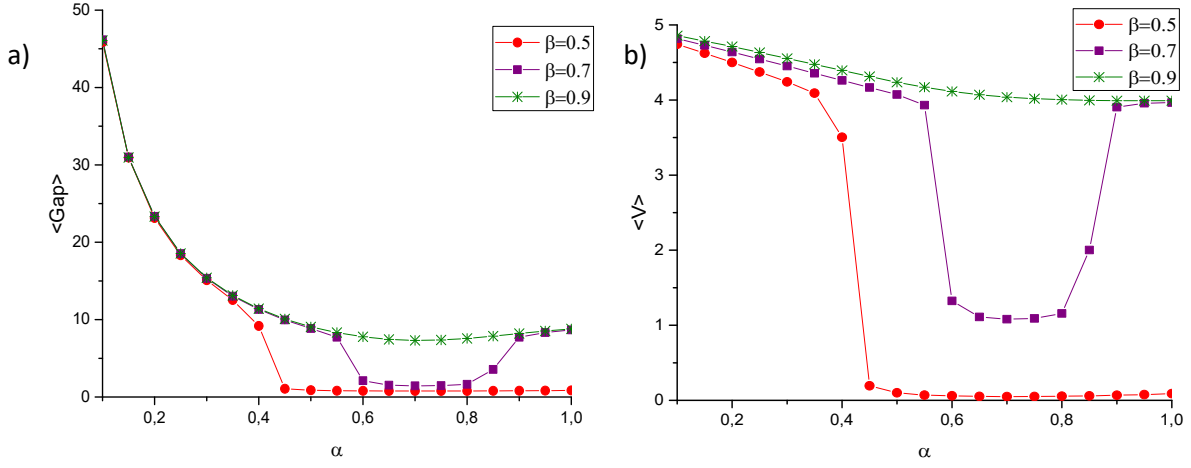


Figure 34: a) gap and b) mean velocity of the second road versus the injection rate α for different values of the extraction rate β .

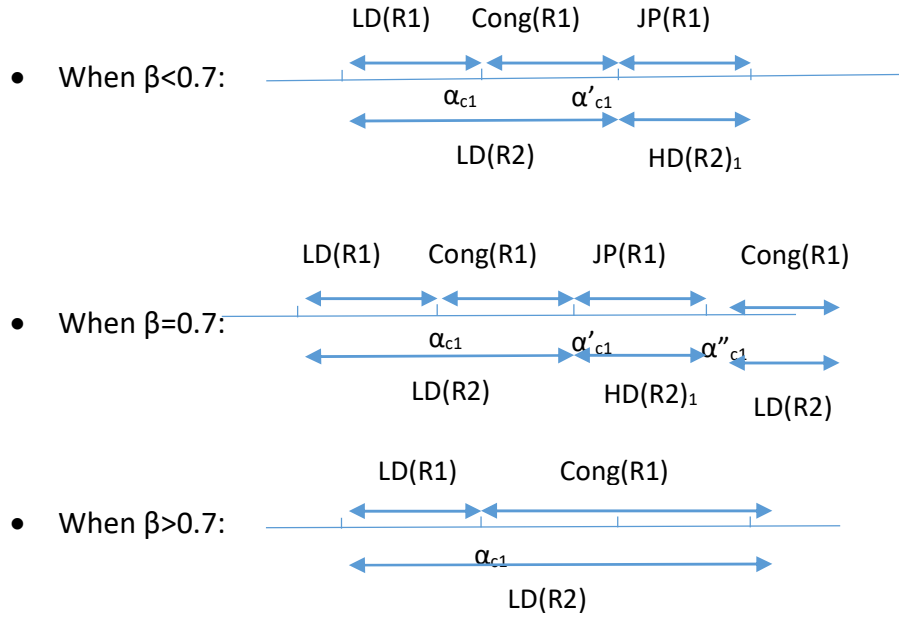
5.2.2.3. Conclusion

In accordance with the subsection 5.2.2, non-usual behaviors emerged.

We observed that the high-density phase of the first road contains two regions: Congestion and Jamming phase. In addition, we highlighted a new type of re-entrance from the jamming phase to the congested phase.

Meanwhile, the second road has conserved the well-known behavior of a one-dimensional system.

Finally, we found that the boundaries between those phases governing the first road correspond to the transition of the second road:



Consequently, many questions rise:

- Why does the first transition of the first road occurs at $\alpha = \alpha_{c1} = \beta/2$?
- Why the flow and the density of the first road are not constant in the congested phase unlike their usual behavior in a high-density phase?
- How does the re-entrance phenomenon occur in both roads?
- Why do the two roads transit at the same $\alpha = \alpha'_{c1} = \alpha_{c2}$?
- Are the two roads interdependent?

Previously, we found that the diverging node also generates a cross-correlation between the two connected roads. This correlation guarantees the establishment of the different phases in each road and represents the response of the global system to a self-organization process located at the anisotropic node.

This confirms that understanding the behavior of the whole system could only be achieved by the investigation of the anisotropic merging node in the light of the evolution of the second road.

5.2.3. Investigation of the effect of a merge

In the case of a diverging node, the anisotropy is responsible of the spontaneous symmetry breaking[102]. The effect of this anisotropy was most showcased through the probability of occurrence of the different injection scenarios.

In this respect, we believe that the key to interpreting the new results is the investigation of the extraction scenarios.

5.2.3.1. The self-organization at the node

Let us consider $\beta=0.7$ to guarantee the establishment of all the phases previously described (sub-section 5.2.2).

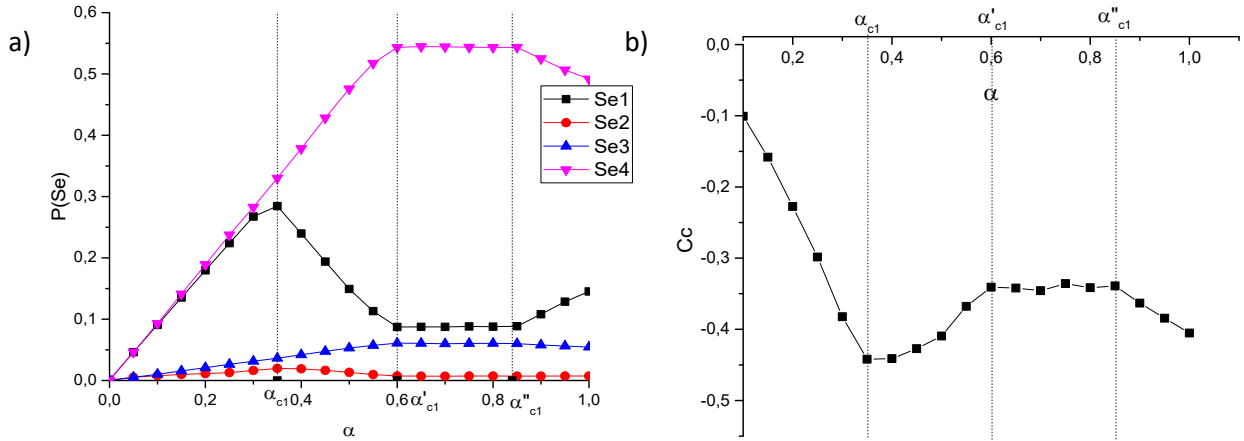


Figure 35: a) the ratio of the occurrence of the scenarios Se_1 , Se_2 , Se_3 and Se_4 versus the injection rate α the extraction rate $\beta=0.7$, b) the cross correlation between the ratio of occurrence of the scenarios Se_1 and Se_4 versus the injection rate α of the extraction rate $\beta=0.7$

In the figure 35-a, the predominant scenarios are Se_1 and Se_4 :

- When $\alpha < \alpha_{c1}$: the two scenarios are equal and are increasing with α .
- When $\alpha_{c1} < \alpha < \alpha'_{c1}$: the scenario Se_4 continues increasing while the scenario Se_1 is decreasing.
- When $\alpha'_{c1} < \alpha < \alpha''_{c1}$: the behaviors of the two scenarios are constant: Se_4 is the predominant scenario.
- When $\alpha''_{c1} < \alpha$: the behaviors of the two scenarios switch: Se_4 is decreasing while Se_1 is increasing.

In the respect of the latter, we compute the cross-correlation of the ratio of occurrence of the preponderant scenarios Se_1 and Se_4 . According to the figure35-b, the scenarios Se_1 and Se_4 are anti-correlated (negative cross-correlation):

- When $\alpha < \alpha_{c1}$: the cross-correlation is weak at first and increases with α until it reaches -0.45.
- When $\alpha_{c1} < \alpha < \alpha'_{c1}$: the cross-correlation is important but it slightly decreases.

- When $\alpha'_{c1} < \alpha < \alpha''_{c1}$: the cross-correlation is constant.
- When $\alpha''_{c1} < \alpha$: the cross-correlation starts increasing again.

Knowing that only one vehicle can be extracted at a time, i.e. only one scenario occurs at each iteration, we can suspect that a scenario induces the other one[103], [104].

In order to understand the mechanism of the establishment of this predominance, we follow the time occurrence of all the scenarios.

The figures 36 show that there is a pseudo-alternation of the two predominant scenarios Se₁ and Se₄. Moreover, we observe that the smaller the demand α , the keener is this alternation.

This alternation highlights a self-organization process at the node.

However, *why are those two scenarios preponderant? How does this self-organization process at the node? And what are the consequences of this self-organization?*

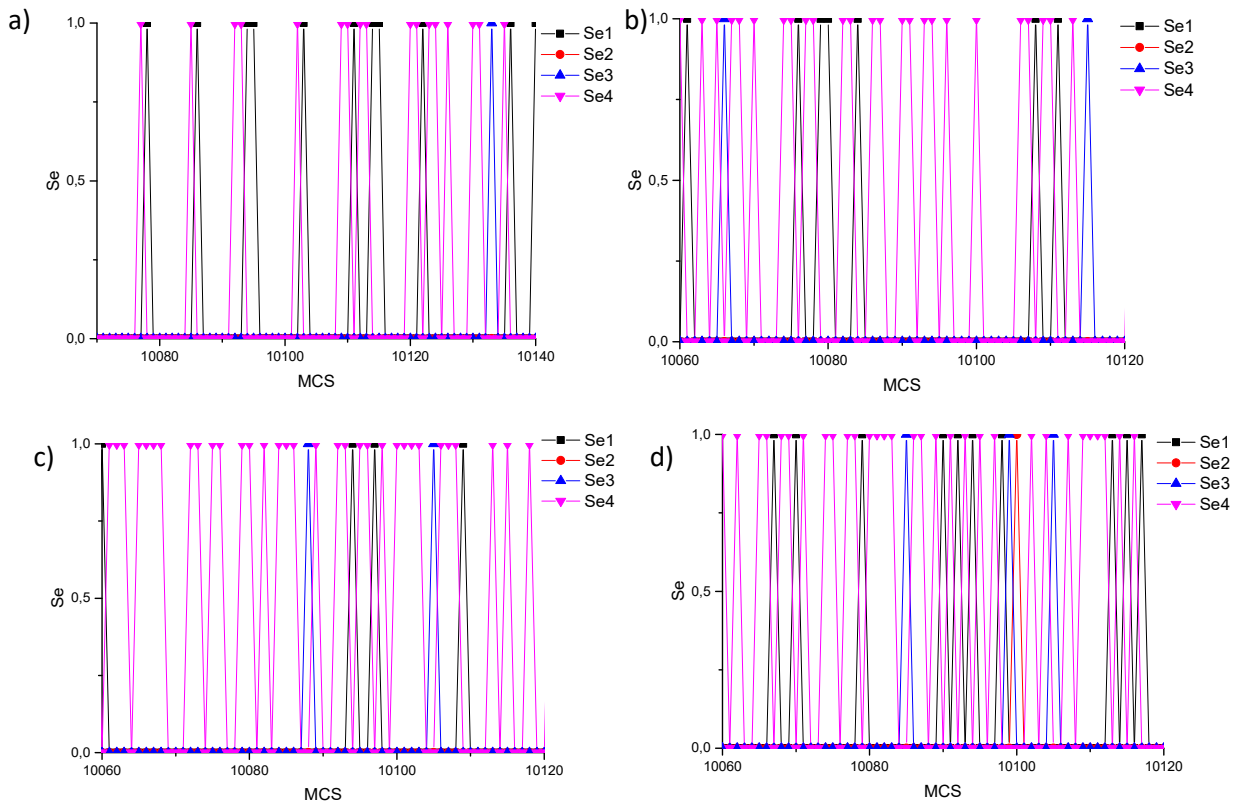


Figure 36: the occurrence in time of the different scenarios for $\beta=0.7$ and $Pe=0.1$ and a) $\alpha=0.2$ b) $\alpha=0.5$ c) $\alpha=0.7$ d) $\alpha=0.95$: this occurrence is quantified by 0 if the scenario does not occur and 1 if it does

5.2.3.2. Phase diagram

In order to answer the last question, we plot the global phase diagram of the whole system: we combine the transitions of the two roads (figure37).

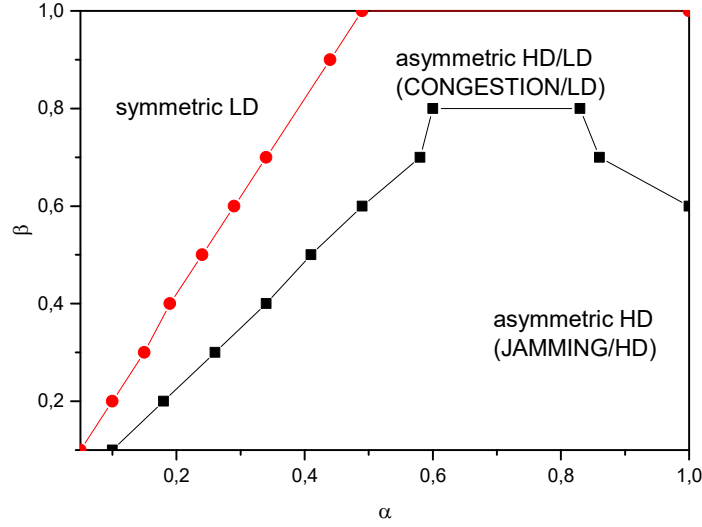


Figure 37: phase diagram of the global system (1st road/2nd road)

According to figure 37, there are three distinct phases:

- Symmetric LD: (LD/LD)
- Asymmetric phase of transition HD/LD: (CONGESTION/LD)
- Asymmetric HD: (JAMMING/HD)

The phase diagram brought to the evidence that, for all the values of β , the transition of the privileged road corresponds to the transition of the non-privileged one (1st road) at $\alpha = \alpha_{c2} = \alpha'_{c1}$.

Moreover, the existence of those phases highlights a spontaneous symmetry breaking as for the bridge model [91]–[94], [87], [88].

5.2.3.2.1. Symmetric LD: (LD/LD)

When $\alpha < \alpha_{c1}$, both roads are in the low-density phase. In this range, the two scenarios controlling the exits are equally probable (figure35-a).

To explain these results, we follow the temporal evolution of the flow in the roads from the injection of the first vehicles.

At $t=t_0$ (first instant at which the injection condition is verified and a vehicle can be injected), since the two roads are identical, empty and symmetric, two vehicle are injected simultaneously, each one in a lane (figure38-a). They travel with a velocity V_{max} . Then, at $t=t_1$, they arrive at the two exits at the same time.

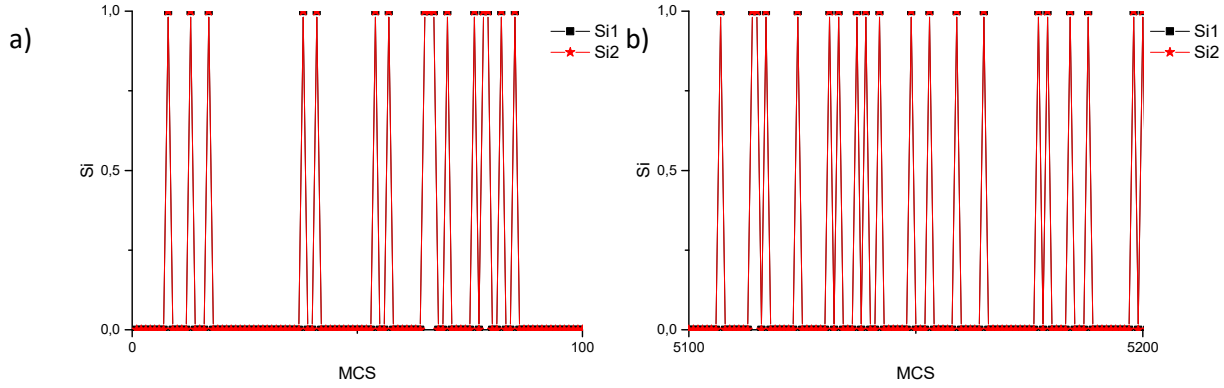


Figure 38: the occurrence in time of the different injection scenarios for $\beta=0.7$ and $Pe=0.1$ and $\alpha=0.2$
a) at the beginning of the simulation b) throughout the simulation: this occurrence is quantified by 0 if the scenario does not occur and 1 if it does

By the effect of the anisotropic parameter Pe , a vehicle is more likely to be extracted from the second road by Se_4 while the other vehicle is obliged to wait for a later instant. The symmetry of the two roads is broken.

However, the very low injection rate makes it harder for another vehicle to arrive at the following instant to the exit of the second lane. Subsequently, in a later iteration (the effect of $\beta \neq 1$), the remaining vehicle will leave the first road according to Se_1 . **The symmetry is restored.**

This process is then repeated throughout the simulation (vehicles are injected simultaneously (figure38-b)). Each time the symmetry is broken, it would be restored by the effect of the low demand and the very large gap (figure39-a).

This symmetry is confirmed by the difference between the mean gaps. Indeed, we computed the $\Delta(GAP) = GAP_2 - GAP_1$ (figure39-b). We observed that, in this range of α , the difference is almost none. Recalling that vehicles are injected at the same time, they leave by the same process.

An alternation of the two scenarios Se_1 and Se_4 takes place guaranteeing a self-organization (figure36-a).

To conclude, this self-organization at the node guarantees the formation of equal flows in the two roads.

Hence, the behavior of the system is symmetric (figure37).

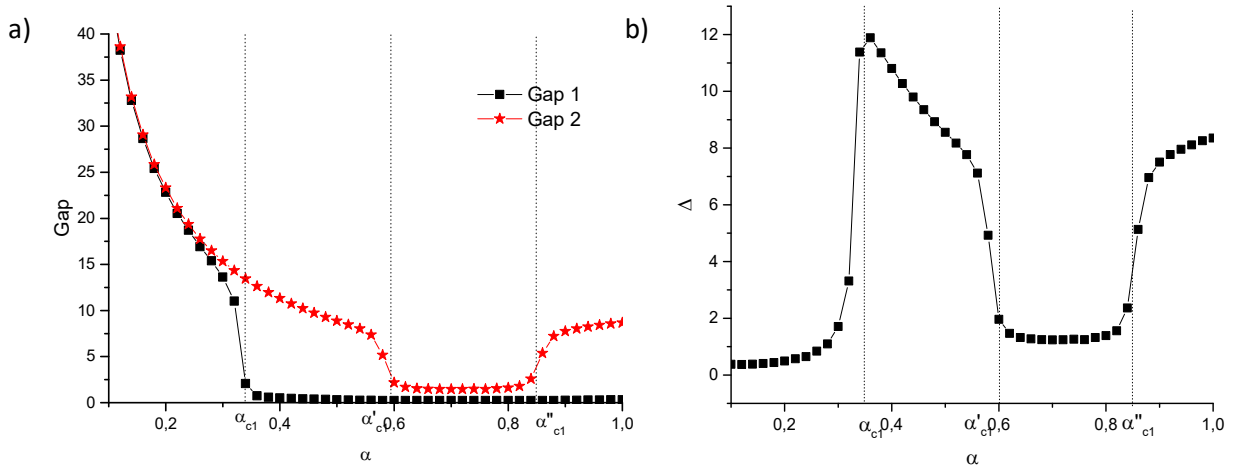


Figure 39: a) the average gap of the first road Gap1 and of the second road Gap2 versus the injection rate α for the extraction rate $\beta=0.7$ b) the difference between the average gap of the first road Gap1 and of the second road Gap2: $\Delta(\text{GAP}) = \text{GAP2} - \text{GAP1}$

5.2.3.2.2. Asymmetric phase of transition HD/LD: (CONGESTION/LD)

• Transition of the 1st road:

At $\alpha = \alpha_{c1}$, the 1st road transits to the congested phase while the second one still is in the low-density phase.

By the mechanism of the merge, i.e. the extraction of one vehicle at a time, the extraction probability is divided by two $\beta_{\text{eff}} = \beta/2$.

As for $\alpha < \alpha_{c1}$, the process of injection and extraction from $t=t_0$ to $t=t_1$ is the same. Since the two roads are empty, the symmetry is restored quickly.

However, by the effect of the growing demand α , more vehicles are present in the roads and arrive at the ends simultaneously and rapidly. Indeed, the gap between the vehicles in both roads is smaller (figure39-a).

Consequently, due to the parameter anisotropy Pe , when a vehicle is extracted from the privileged road according to Se_4 , the probability that the vehicle remaining in the first lane is extracted in the next iteration decreases ($P(Se_1)$ is decreasing (figure35-a)). The difference between the gaps in both lanes is more important (figure39-b). The reestablishment of the symmetry becomes harder.

Thus, the reduced extraction rate strikes the non-favorited lane first. The latter transits then to the high-density phase, generating the transition to the phase (CONGESTION/LD) (figure37).

- Continuous evolution of the first road in the High-density phase:

As for the low-density phase, because of the self-organization process that favors the second road (figure36-b), a hindrance is growing at the end of the first road. The flow of the first road decreases.

This phase is considered as a phase of transition of the global quasi-one-dimensional system to the High-density phase.

5.2.3.2.3. Asymmetric HD: (JAMMING/HD)

When $\alpha'_{c1} < \alpha < \alpha''_{c1}$, the hindrance generated by β also affects the second road. The shockwave reaches the entry of the second lane, and vehicles cannot be injected. The second road is also in the high-density phase. At this stage, both lanes are in the high-density phase and only β controls the system. The flows are constant.

However, by the pattern of the self-organization (figure36-c), i.e. the pseudo-alternation of the two scenarios Se_1 and Se_4 , vehicles are more likely to leave the second road due to the anisotropy. The ratio $P(Se_4)$ is greater than $P(Se_1)$.

Subsequently, the symmetry is broken, which generates the asymmetric HD.

5.2.3.2.4. Re-entrance: (CONGESTION/LD)

When $\alpha''_{c1} < \alpha$, due to the injection strategy, the second road transits to the low-density phase through the re-entrance phenomenon [32]. In fact, by the effect of the frustration at the entry, less vehicles enter this road. Then, vehicles arrive sparsely to the end of the second road and do not pile up at its exit [32] (wider gap figure39-a).

Here again, a pseudo-alternation of the two scenarios occurs (figure36-d), but with a wider presence of the Se_1 (the ratio $P(Se_4)$ decreases while the $P(Se_1)$ is increasing).

As a response to the self-organization, more vehicles leave the first road (figure 35-a, 36-d). The first road also transits to the congested phase.

The asymmetric phase of transition (CONGESTION/LD) reappears.

5.2.3.2.5. Summary

The analysis of the temporal occurrence of the different extraction scenarios have confirmed the establishment of a self-organization process.

Indeed, at the node, only two scenarios are preponderant and anti-correlated. Their alternation generates a self-organization at the node. This process generates a spontaneous symmetry breaking and controls the transitions of the two roads.

5.2.3.3. The correlation of the roads

In the case of the diverging node, this punctual cross-correlation guarantees the cross-correlation of the two roads. Would this cross-correlation persist considering a merging node?

We plot the cross-correlation of the flows of the two roads, as a function of the injection rate α .

For each value of (α, β) , this cross-correlation is a mean value that was calculated, over the whole time simulation and averaged, according to the following formula:

$$C_c = \frac{\sum_t [(q_1(t) - \langle q_1 \rangle) * (q_2(t) - \langle q_2 \rangle)]}{\sqrt{\sum_t [(q_1(t) - \langle q_1 \rangle)]^2} \sqrt{\sum_t [(q_2(t) - \langle q_2 \rangle)]^2}} \quad (2.8)$$

The random variables are q_1 and q_2 , the flows in the first road and in the second road successively.

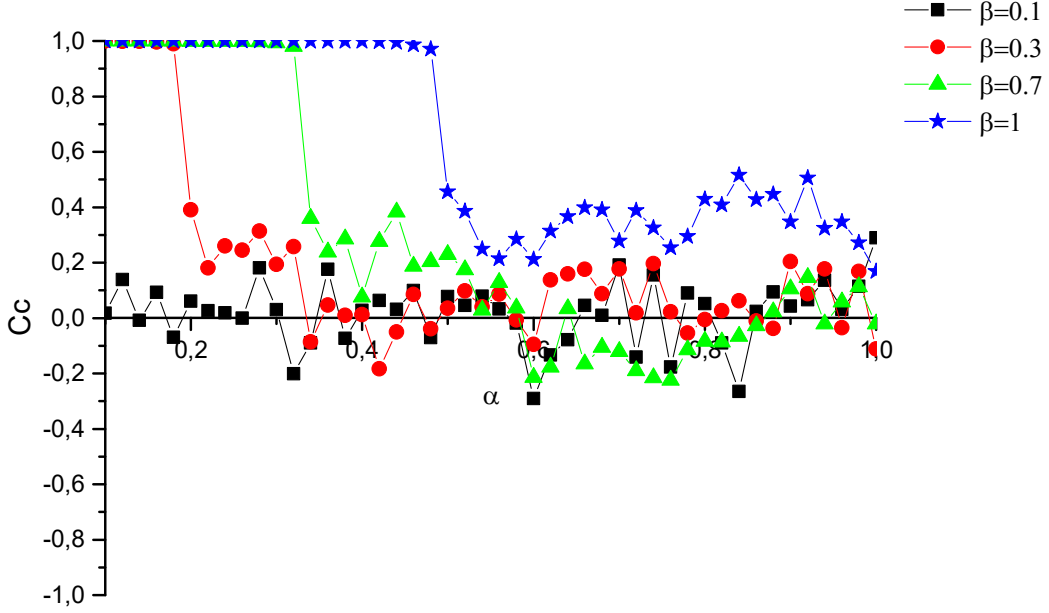


Figure 40: the cross correlation between the flow of the first road and the second road versus the injection rate α for different values of the extraction rate β

With regards to the figure 40, the flows of the two roads are highly correlated ($C_c \approx 1$) when they both are in the low density phase. When the first road undergoes a discontinuous transition to the high-density phase, the cross-correlation follows the same path. Afterword, the cross-correlation continues decreasing until the two roads transit to the asymmetric high-density.

Hence, the cross-correlation persists for the merging node.

Moreover, order parameter is a physical quantity that varies according to phases. It distinguishes the symmetry-broken states in the ordered phases.

Accordingly, this same cross-correlation can be considered as an order parameter[105], [30], [99] that defines the transitions of a quasi-one-dimensional system composed of two lanes connected by a node despite its type.

5.2.4. Summary

Knowing that there are many differences between the dynamics of a merge and those of a diverge, our main aim was to confirm that an anisotropic node creates a correlation between connected links despite its type. In this respect, simulations have shown non-usual behaviors. Indeed, while the privileged road preserved the familiar behavior of a one-dimensional system, the non-privileged one undergoes a discontinuous transition from the low-density phase to the congestion phase then a continuous one to the jamming phase. In addition, we highlighted a

new type of re-entrance from the jamming phase to the congested phase. By following the patterns of the extraction of vehicles, we found that the exits of the two lanes are correlated and a self-organization process takes place at the node. This self-organization induces differences on the behaviors of both lanes generating a spontaneous symmetry breaking through the establishment of three phases: a symmetric low-density, an asymmetric high-density and an asymmetric phase of transition high-density/low-density. Finally, a cross correlation test proved that the flows of both lanes are interdependent in the symmetric phase. Accordingly, we suggested that this cross correlation can be considered as an order parameter that characterizes the transition of a quasi-one dimensional traffic system with a node regardless of its type.

5.3. Merge-diverge system

Let us consider the case where a lane is privileged both at the entry and at the exit, for instance $P_i=0.1$ and $P_e=0.1$.

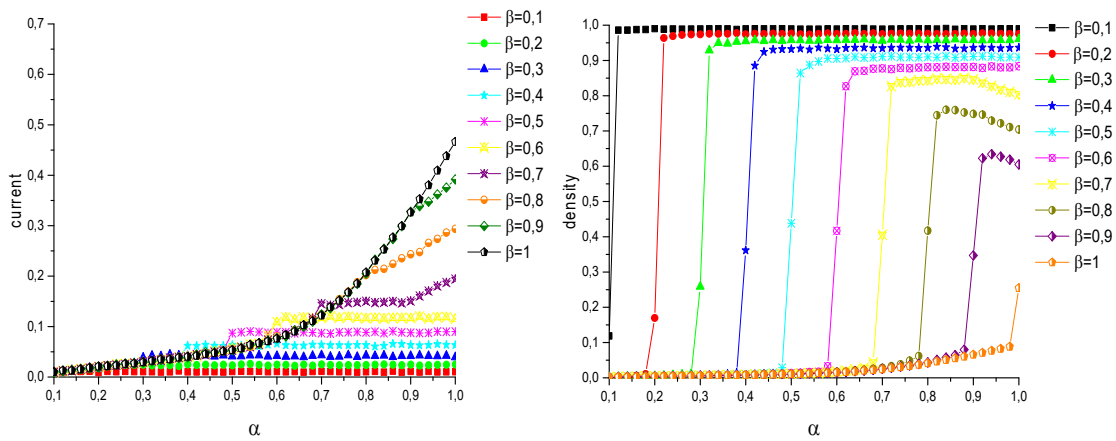


Figure 41: a) flow and b) density of the first road versus the injection rate α for different values of the extraction rate β , $P_i=0.1$ and $P_e=0.1$

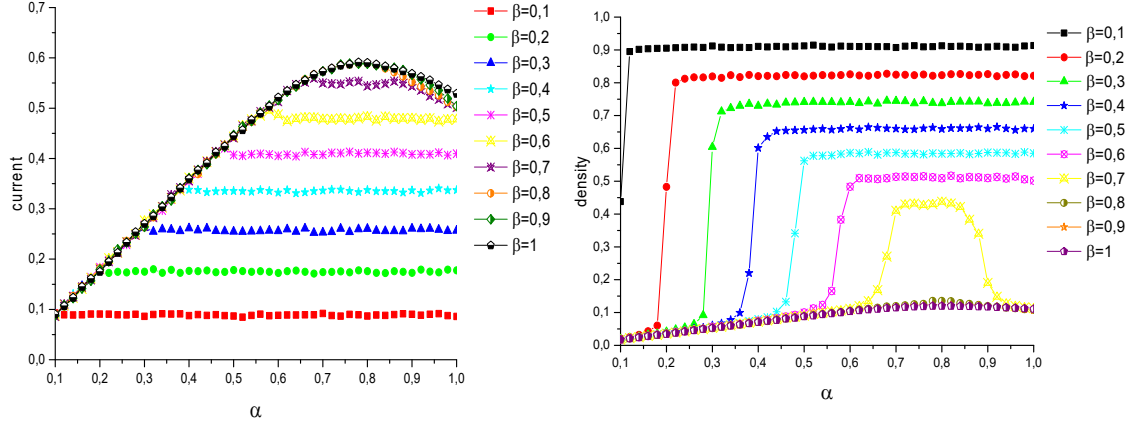


Figure 42: a) flow and b) density of the second road versus the injection rate α for different values of the extraction rate β , $P_i=0.1$ and $P_e=0.1$

According to the figures 41-42, the first lane –none-privileged one- has a similar behaviour to when the two roads are only connected by a diverge node, however, with a more pronounced obstruction (very low current for higher values of β)

The privileged lane preserves a behaviour of a one-dimensional system.

The other case is where a road is privileged at the entry and obstructed at the exit, i.e. $P_i=0.9$ and $P_e=0.1$.

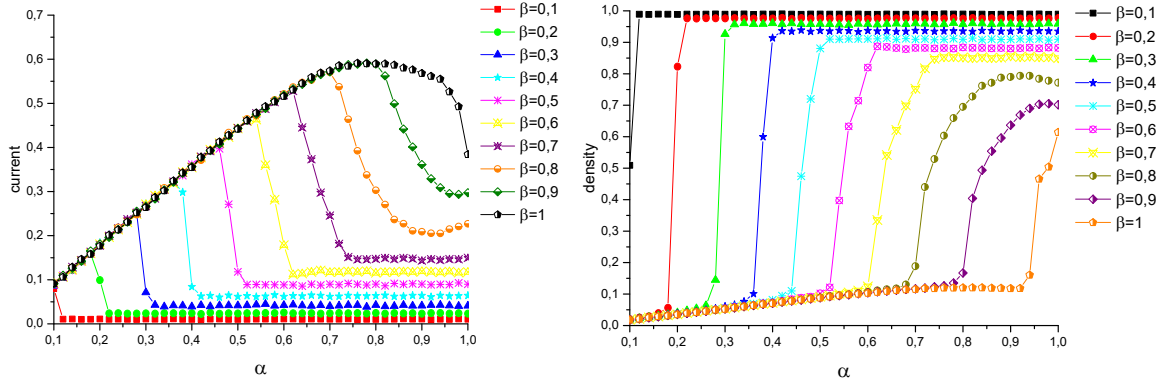


Figure 43: a) flow and b) density of the second road versus the injection rate α for different values of the extraction rate β , $P_i=0.9$ and $P_e=0.1$

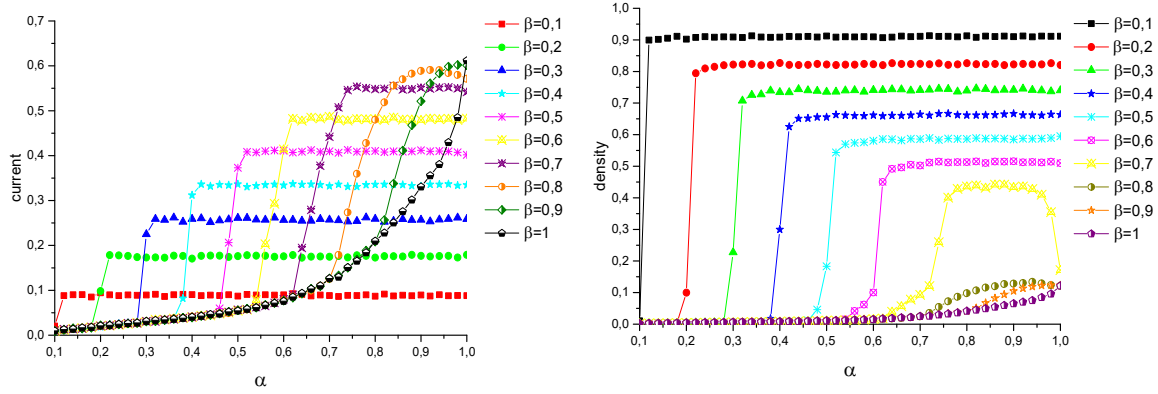


Figure 44: a) flow and b) density of the second road versus the injection rate α for different values of the extraction rate β , $P_i=0.9$ and $P_e=0.1$

According to the figures 43- 44, the non-privileged lane at the exit is controlled by the merging node (similar behaviour as in the figure 24), while the other road is controlled by the diverge node and exhibits as similar response as displayed in figure 12.

A primary cross correlation exam have shown a strong cross correlation when both lanes are in a symmetric low density phase.

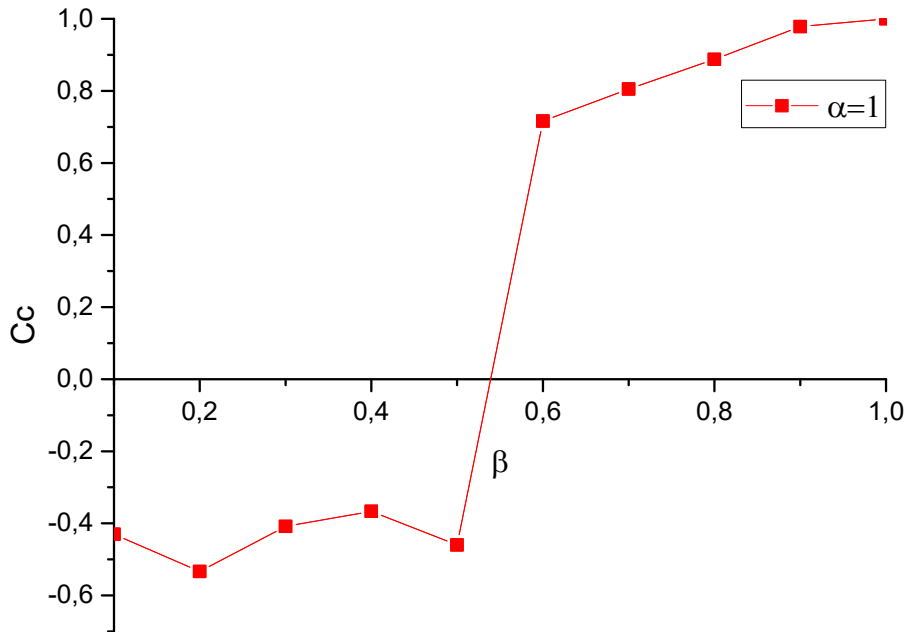


Figure 45: the cross correlation between the flow of the first road and the second road versus the extraction rate β for an injection rate $\alpha=1$

A further investigation is crucial to confirm all the previous results.

6. Conclusion

In this section, we have studied a quasi-one-dimensional system, composed of two roads connected via a single node and where no lane changing is allowed. We were able to point out a self-organization behavior and to exhibit the correlation of the two roads. In order to achieve those results, we have operated in four steps.

i.Highlighting a self-organization process:

In our investigation, we started by considering a two-lanes road of which both lanes are identical and of which the entry is neutral (when both first sites are empty, the upcoming vehicle is injected randomly). Then, we altered the characteristics of one lane and observed the response of the second lane. Among those alterations, we created a perturbation in one of the lanes that may push more vehicles to enter the other lane. We implemented a compact default into the first lane with a deceleration probability. Subsequently, those changes generated new current and density behaviors on both lanes and brought out new system-organization's features. Indeed, a spontaneous symmetry breaking is observed. Those observations made us conclude that privileging one lane over the other creates a self-anisotropy within the system that would overcome it through a self-organization mechanism operating in the node. Finally, we were capable of presenting a diagram that displays this self-organization with respect to the different density phases.

Moreover, we have computed the cross-correlation of the flows of the two lanes. We found that they are strongly correlated when in symmetric phases. This finding brought us to our second step of investigation.

ii.Diverge node:

In order to bring more details about what truly happens in the system when one of the lanes is privileged, we adopted a quasi-one-dimensional system of two identical lanes and we have implemented an extrinsic anisotropy parameter P_i into the entry. This parameter proceeds only when the two first cells are available and pushes the vehicle to choose a lane over the other. In this respect, firstly, we plotted the phase diagram of the system which highlighted the existence of an asymmetric phase of transition. Then, we studied the occurrence of the different injection scenarios and the cross-correlation rates between them in order to interpreter, microscopically, the different phases. We found that the two main scenarios, that overtake the system and that pseudo-alternate, are strongly correlated. This correlation highlighted a self-

organization within the system, which guarantees the establishment of the different phases. To conclude this investigation, we needed to confirm the correlation of the two roads. Consequently, we plotted the cross correlation between the main traffic observables (flows) of the two lanes. We found that the two lanes are correlated in the symmetric phase while they are not when in the asymmetric phase. Moreover, this correlation does not depend on the injection strategy. This brought us to the assumption that the cross-correlation may be considered as an order parameter that characterizes the transition of a quasi-one dimensional traffic system with a junction.

iii. Merge node:

The different types of nodes have a major impact on the performance, the levels of service and the safety of connected facilities.

We attempted to understand microscopically, the impact of the differences between a merging node and a diverging one on the results mentioned above.

In this respect, we considered a quasi-one-dimensional system composed of a single merging node connecting two separated roads at the left boundaries. Then, we implemented an anisotropy parameter Pe that favors one lane over the other when both exits are occupied. We were able to point out the relationship between the connected roads, in the response of the existence of the anisotropic merge.

Firstly, we described the new response of the flow and the density of each road. While the privileged (second) road behaves as one-dimensional system, the first road undergoes two transition from the low-density phase to the high-density phase. Indeed, the latter road transits discontinuously from the low-density phase to the high-density phase and continues evolving continuously within the same phase until both the density and the flow become constant. According to a deep investigation of the velocity, we suggested that this road transits from the low-density phase to a congested phase then to a jamming phase.

Then, to understand the mechanism behind these behaviors, we investigated the merge, i.e. the ratio of occurrence of the different extraction scenarios. We found that only two scenarios control the node. Those scenarios were found to be alternating in such a way that they generate a self-organization process. The latter is confirmed by a cross-correlation of the exits guaranteeing the establishment of the different phases.

Furthermore, we found a spontaneous symmetry breaking by plotting the global phase diagram. Indeed, this diagram exhibited the existence of a symmetric low-density phase, an asymmetric high-density phase and an asymmetric phase of transition. This broken symmetry is proposed to be the organization of the system as a response to the anisotropy at the node. Finally, the flows of the two roads are strongly correlated in the symmetric low-density phase.

By comparing those results to the findings of the case of the diverge, we can state that despite the differences in the behaviors of the two roads, both the merging and the diverging nodes with an anisotropic parameter, create a cross-correlation between the two in the symmetric phases, through a self-organization process.

iv. Merge-diverge system

The superposition of the two types of nodes has intrigued us.

A primary investigation highlighted a superposition of the impacts of both roads, where merge always controls the exit and the diverge oppresses the entry of roads.

The cross-correlation exam showed that the two road are correlated when both

Nevertheless, those only remain as primary results.

A deep investigation of the propagation of the waves impact of each node and the mechanisms of their interactions is crucial.

v. Sum Up

To sum up, in this section, we were able to demonstrate that creating anisotropy at a boundary of a non-connected quasi one-dimensional system generates a strong correlation between the two lanes through a self-organization process. We were able to confirm that the bare existence of an anisotropic node creates an important connection between the two connected segments regardless of it being a merge or a diverge. This connection is a cross-correlation that we suggest as an order parameter quantifying the transition of quasi-one-dimensional systems with nodes.

It is worth to mention that our work may represent a descent example of a complex system, where collective behavior cannot be generated by the superposition of individual behaviors. Moreover, this section is a humble effort aiming to shell the mechanism and the outcome of a different type of nodes and an attempt to make the first step in the path of multi-lanes systems with open boundaries. The bigger challenge would then be investigating the assembling of numerous types of nodes while keeping in mind that previously observed phenomena would not necessarily be present due to the complexity and the nonlinearity of the traffic.

Another aspect that would be challenging is confronting all the previously mentioned results to real traffic data. This would be interesting as far as it is important to verify the validity of the phase diagram and to complete the fundamental diagram. An empirical investigation would also enlarge the spectra of the types of the facilities studied. Indeed, in addition to nodes connecting symmetric roads, we would be capable of treating the effect of merging or diverging behavior on on-ramps or off-ramps, arterial and principal roads, joined roads with lane changing... We would reproduce fundamental diagram by the mean of different CA models, reinvestigate the establishment of different traffic phases... Finally, we would be able to follow the evolution of the shock waves generated by the effect of the merging behavior, calculate their velocity and define their effects and boundaries.

Chapter 3:
Cognitive anticipation Cellular
Automata model: an attempt to
understand the relation between
the traffic states and
rear-end collisions

1. Introduction

1.1. Congestion

1.1.1. Definition

Traffic congestion has now become the most visible, most pervasive and most immediate transport problem plaguing the major cities of the developing countries on a daily basis.

Traffic congestion is a disorder in transport system that is characterised by slower speeds, longer trip times, and increased vehicular queueing. Traffic congestion on urban road networks has increased substantially, since the 1950s.

1.1.1.1. Congestion according to HCM

i. Capacity

The capacity of a road is the maximum hourly rate at which vehicles are expected to pass a point or a uniform road section during a given time period under normal roadway, traffic, and control conditions.

In other words, Vehicle capacity is the maximum number of vehicles that traverse a given point during a specified period under prevailing conditions.

ii. Demand

Demand refers to vehicles arriving; volume to vehicles discharging.

If there is no queue, demand is equivalent to the traffic volume at a given point on the roadway.

iii. Level of service

Level of service (LOS) is a quality measure that describes functioning conditions within a traffic stream.

A level of service is generally measured in terms of speed, travel time, freedom to maneuver, traffic interruptions, and comfort and convenience.

There are six types of LOS, from A to F, with LOS A representing the best operating conditions and LOS F the worst. Each level of service represents a range of operating conditions and the driver's perception of those conditions.

iv. Congestion

Subsequently, Congestion can be defined as the state of traffic where the demand exceeds the Road capacity.

This traffic state usually corresponds to the Level of service E or F, at the worst case.

1.1.1.2. Congestion According to the Physics of Traffic

i. Definition

There is no general nor precise definition of congestion in the traffic theory.

A congested road can refer to a segment where the mean velocity is much lower than the desired speed.

One can also think of congestion when vehicles are not moving for most of the time, or moving only for a short distance.

Typically, congestion is associated to large densities that are close to the segment capacity.

In large Congested segment, Blanks (regions with no vehicles) are usually observed.

ii. Types of congestion

There are different causes behind the emergence of congestion:

- ✓ Bottlenecks induced congestion:

Bottlenecks are points where the capacity is reduced due to lane reduction, merges, or accidents.

The inflow being larger than the capacity, a jam emerge downstream the bottleneck.

- ✓ Spontaneous traffic jams:

Some jams seem to appear from nowhere.

They are usually observed and detected through aerial photography.

This is what makes the study of congestion very intriguing and interesting.

1.1.2. Impacts of congestion

Traffic congestion affects the quality of life and economic productivity. Indeed, it increases fuel consumption, the cost of moving people and goods, the number of accidents and exhaust pollutants harmful to human health.

1.1.2.1. Impact on the drivers

Traffic congestion is found to increase mental stress and to disrupt peoples' daily schedules.

Actually, drivers in congested roads are more likely to experience more stress and aggression.

The daily disappointment with the commute has been found to produce undesirable psychological and physiological responses, including high blood pressure, increased negative mood states, lowered tolerance for frustration, increased irritability.

Congestion disrupts the daily schedules of work and family activities. The impact of personal time lost in congestion not only includes stress and disruption to family life, but perhaps more importantly, it includes the opportunity cost of that lost time.

For employers, this could be the loss of productivity of employees who show up late for work[3].

1.1.2.2. Environmental impact

Due to the extensive growth of the number of personal owned vehicles over the past decade, the circulation conditions, especially in large cities, have severely deteriorated.

Alongside excessive travel time and energy consumption, Traffic congestion also, decreases productivity, imposes costs on the society and causes pollution[106], [107].

Indeed, during congestion, vehicles spend more time on the road, undergoing numerous acceleration and deceleration events.

This usually leads to a surge in emissions of the pollutants like:

- Carbon monoxide (CO),
- Carbon dioxide (CO₂),
- Volatile organic compounds (VOCs)
- Hydrocarbons (HCs),
- Nitrogen oxides (NO_x),
- Particulate matter (PM)...

Those vehicle emissions have found to expose the health of travelers and non-travelers living near roadways by elevating the risks of:

- Non-allergic respiratory morbidity,
- Cardiovascular morbidity,
- Cancer, allergic illnesses,
- Adverse pregnancy and birth outcomes, and
- Diminished male fertility

1.1.2.3. Economic impact

Congestion has a huge impact on the economics of every country[2]–[4], [108].

For instance, in the UK, the congestion costed the country around 30 billion £ by the end of 2010. Those numbers can only get worse by the evolution of the traffic.

The costs of congestion can take different forms. According to NCHRP reports, there are three main types of congestion costs:

- Direct travel costs of all business-related travel, including vehicle operating expenses and the value of time for drivers (and passengers);
- Logistics and scheduling costs, including effects on inventory costs such as stocking, perishable items, and just-in-time (JIT) processing;
- Reduction in market areas for workers, customers and incoming/outgoing.

Traffic analysts have proposed multiple methods of estimating congestion cost, but most communally, it is calculated according to the following[2], [5]–[8]:

- Firstly, calculating the average traffic speed
- Secondly, comparing it to the desired speed
- Finally, multiplying the difference by the value of time to define the global cost.

1.2. Safety

1.2.1. Definition

Traffic accidents are defined as collisions that involve one or multiple vehicles.

Also identified as car accident, motor vehicle collision, or car crash, a traffic accident occurs when a vehicle collides with a moving obstruction as: another vehicle, pedestrian, animal, road debris, or with a stationary obstruction, such as a tree, pole or building.

Traffic collisions often result in injury, disability, death, and property damage as well as financial costs to both society and the individuals involved.

In brief, Road transport are the most dangerous situation people deal with on a daily basis.

1.2.2. Causes

Traffic accidents can be caused by a various number of factors that can be grouped under two major categories:

- Human factors
- Road environment factors

1.2.2.1. Human factors

Actually, according to different crash reports[109], Up to 93% of road accidents are due to human factors (57% of crashes due to driver factors only, 27% to road and driver factors combined, 6% to vehicle and driver factors combined, 3% road factors only, 3% to combined road, driver and vehicle factors).

Many human factors can contribute in the risk of collisions, including:

1.2.2.2. Driving Skills

A driver can be referred to as good driver, if he has the ability of:

- ✓ controlling a car including a good awareness of the car's size and capabilities
- ✓ reading and reacting to road conditions, weather, road signs, and the environment
- ✓ alertness, reading and anticipating the behavior of other drivers.

However, It has been found that over-confident drivers do only reassess their driving ability when in a near-miss or an accident[21].

1.2.2.3. Impairment

Driver impairment refers to factors that prevent the drivers from driving at their normal level of skill, for instance[21]:

- ✓ Alcohol
- ✓ Physical impairment (Poor eyesight and/or physical impairment, Sleep deprivation...),
- ✓ Age: Youth or old age

1.2.2.4. Driving behaviors, i.e., aggressive driving, distracted driving

- ✓ Aggressive or speeding drivers contribute in up to 30% of fatal or serious injuries accidents[22].
- ✓ Distracted drivers, usually by mobile devices run a risk by up 12 times of getting into a car accidents.[110]

1.2.2.5. Road environment

Conferring to a US study, road environment can hold up to a 34% share in serious car accidents (alone or combined to other factors)[109].

Indeed, the road or environmental factor can either contribute directly to the circumstances of the crash, or do not allow any room for the driver to recover.

However, when reporting the causes of an accident, it is frequently the driver who is blamed rather than the road. The tendency is to overlook the human factors that are correlated to the roads, such as the subtleties of design and maintenance that a driver could fail to observe or inadequately compensate for.[111]

Subsequently, design and maintenance, with well-designed intersections, road surfaces, visibility and traffic control devices, can result in significant improvements in collision rates.

1.2.3. Types of accidents

While any collision between a motor vehicle and a person or object can constitute a traffic accident, they often fall into a few common categories based on their characteristics. Field observations differentiated three main types of accidents:

- Accidents between vehicles and pedestrians or Bicyclists
- Single vehicle accidents:

- ✓ Collision Involving a Fixed Object
- ✓ A Collision Involving a Parked Vehicle
- Accidents between vehicles while travelling.

1.2.4. Some Statistics

The latest type of accidents is the most concerned by the traffic theory since it is induced by the interaction between moving vehicles. The investigation of those accidents is then to be the most appropriate for us. Nevertheless, are those collisions more dangerous than the other types of accidents that they require a standout deep investigation?

To answer this question, we will conduct, in the following, a statistical analysis that defines the ratio of accidents between vehicles among all the types of accidents and quantifies the fatalities that caused by them.

N.B: Unless stated otherwise, we mean by traffic accidents collisions between vehicles while traveling.

1.2.4.1. Accidents due to the traffic

According to statistical data of traffic accidents in Europe and North America [112], the numbers differ from a country to another being a function of demographical, political and socio-economic circumstances. (figure 46)[113]–[117]

Actually, if we define the ratio of accidents due to the traffic (RAT) as follows:

$$RAT = \frac{\text{number of accidents due to the traffic}}{\text{total number of accidents}} \quad (3.1)$$

We can observe that it represents a strong heterogeneity: it can reach very high values 80%, for some countries when it cannot exceed 30% for others (figure 46).

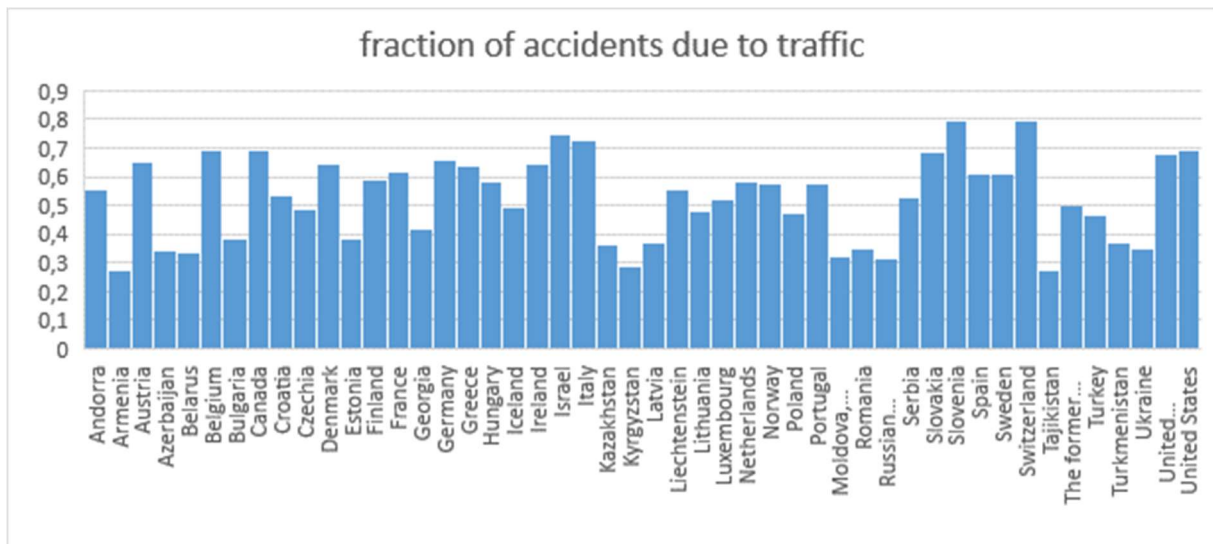


Figure 46: the ratio of accidents due to traffic RAT for different countries

This observation leads us to compute the yearly mean *RAT* of this sample and follow its evolution from 1993 to 2015.

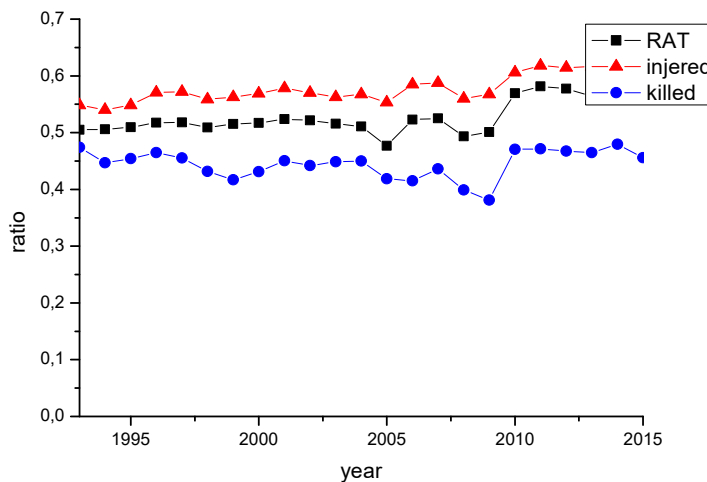


Figure 47: the yearly mean ratio of accidents due to traffic RAT (black squares), the yearly mean ratio of fatalities caused by accidents due to traffic: injured (red triangles) and the killed (blue circles) versus the years from 1993 to 2015

The figure 47 represents the yearly evolution of the mean values of *RAT* (black squares). We observe that despite the heterogeneity of the present sample the mean *RAT* does not show differences in behaviour from a year to another. Indeed, if we consider the first period (1993 to 2009) we observe that the mean *RAT* fluctuates slightly around 50%. The same remark holds for second period i.e., from 2011 to 2015 where the mean *RAT* takes the value of 58%.

Furthermore, traffic accidents are responsible for the biggest share of crushes, killed and injured people in comparison to the other types of accidents.

The urban investigation has shown the same patterns: the mean yearly ratio in the urban area maintains a value around 60% over the years.

1.2.4.2. Rear end collisions

Moreover, the rear end collisions hold, recently, a non-negligible share of fatalities compared to the other types of accidents due to traffic (figure 48). For this purpose, we narrow our investigation to only focus on that type of collisions. We denote their contribution by RAC .

$$RAC = \frac{\text{number of rear-end collisions}}{\text{total number of accidents due to the traffic}} \quad (3.2)$$

Indeed, after knowing an increase during the first years, we state that the RAC remains around 20% since 1999 (figure 48- black squares).

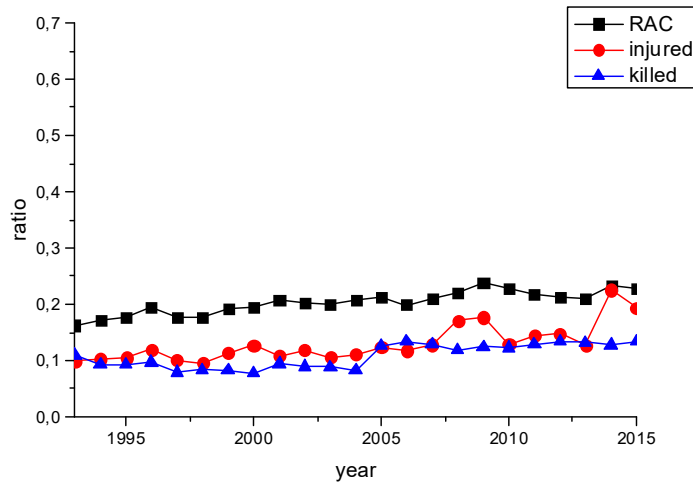


Figure 48: the yearly mean ratio of rear-end collisions RAC (black squares), the yearly mean ratio of fatalities caused by rear-end collisions: injured (red triangles) and the killed (blue circles) versus the years from 1993 to 2015

1.2.4.3. Conclusion

Through the statistical analysis, we conclude that:

- The collisions between vehicles hold the biggest share between all the types of accidents (can reach 80%) which makes them a crucial phenomenon that needs deep investigation.

- Despite the heterogeneity of the sample, and even though all the countries have necessarily known an evolution from 1993 to 2015, the mean *RAT* and *RAC* kept an almost constant value over this period of time. This made us believe in the existence of a universal causality behind the accidents that, apparently, does not depend on the nature of the facilities nor on the fleet ...

N.B: By analogy to the statistical physics that explain the macroscopic phenomena through microscopic details, we think that this causality is the result of mechanisms of interaction between the driver and the traffic.

The frame of this work cannot confirm, entirely this hypothesis. It will remain an open question for the scientists to approve or deny. In our opinion, the most relevant result is that we were able to highlight the important share of accidents due to the traffic. Thus, this finding confirms the importance of investigating the road security within the frame of the traffic theory.

Moreover, we will not discuss all the types of those accidents, we will only focus on the rear-end collisions.

It is worth to mention that this statistical analysis is not complete and would require an independent investigation that would justify the remarks stated previously.

1.3. Causality relationship

A strong transportation system is known for being one of the pillars of the economic growth of a country and of the prosperity of its citizens. The nature of the fleet, its cost and its speed affect significantly the capacity of a region to fully exploit its resources, thus directly influence its economic vitality. However, developing such efficient transportation system cannot be without any flaws. Indeed, encouraging more road using may put the drivers at the risk of having an accident, either consciously or unconsciously. Subsequently, every manager of a traffic network would face the dilemma of ameliorating the movement of people and goods while reducing, to the minimum, the risks of accidents that follow this amelioration.

1.3.1. The traffic safety in the physics literature

Actually, the urge to improve the fluidity of the travelling facilities has represented a major concern of the USA since the 30's. Since those early years, many researches have been produced in the aim to make the driving experience more comfortable (see[39], [118], [119], [9], and the references within).

Alongside that, the heavy consequences of traffic accidents have not gone unnoticed and

have brought the need of investing in the interdisciplinary sciences. Then, the scientific world has known new dynamics: after the 60's, many paper and journals, focusing on this flea, have seen the day [120]–[124]. Kazimierz Jamroz has described the evolution of the theories and the models on the road safety [10].

Unfortunately, despite all the efforts, the same dilemma persisted or kept reappearing in another form [125, p. 17] while no clear answer has been brought to the following question: *how can we ameliorate the mobility on roads while assuring the highest level of security?*

1.3.2. Disconnection when studying the safety and the fluidity

Analysing the scientific literature has shown that there may be a disconnection when treating the relationship between the road safety and the traffic [10].

On the one hand, we can state that the security aspect of the road traffic has usually been studied all by itself, without, considering the fluidity. This may be due to two main reasons:

- The first reason is that the scientific demarche levies on only considering the relevant parameters of the problem: by nature, the major cause of the scientists is to save the human lives; the safety is then more relevant than the fluidity.
- The second reason is the fact that the amelioration of the fluidity and the reduction of the congestion are fully the responsibility of the traffic theory and engineering, those that we implicitly trust. This emerge from the belief that sciences and technologies are capable of resolving all of the humanity problems[125, p. 17].

On the other hand, the evaluation and the studying of the traffic performances as far as the fluidity is concerned, were established on safe basis, no accidents were predicted. Indeed, the researchers that have addressed the traffic theories aimed, primarily, to understand the mechanisms behind the formation and the propagation of jams, to define traffic states, to sort out the causes behind traffic congestion and finally to propose models of traffic that are inspired from the statistical physics and the fluid mechanics [30], [39], [118]. In the same frame, guides, technical reports and traffic manuals were developed so as to provide analysis methods (roads capacities, levels of service, delays caused by congestion...) and technical solutions (design, lanes number, optimum width...). The road safety was not considered in this type of work. For instance, the HCM does not include the safety when establishing service level [79, p. 26].

1.3.3. The relationship between the traffic phases (LOS) and the safety in the literature

In the attempt to remedy this situation, researchers have tapped into the traffic theory. In this respect, Oh et al have studied the risks of accidents as a function of real-time traffic parameters. They have shown that the risk accidents occurrence depends on the standard deviation of velocity[11]. Golob et al have also proven that the road safety is mainly affected by the mean volume and the median speed as well as by the temporal variation of volume and velocity[12]. Xu et al have evaluated the security performances in relation with the traffic states; they have found that each traffic phase corresponds to a certain degree of unsafety[13]. In this same context, Yeo et al have shown that the accidents rate in the congestion state is five time higher than when in the free flow[126]. Many other papers have been produced in the field of real time crash risk models, for instance [127]–[134].

1.4. Safety problems as human result

The majority of the studies mentioned above were based on real data that are provided by the countries authorities. However, these data can present some shortcomings[14]–[18].

Firstly, the row data is usually collected by human effort which can come with some observation errors [19], [17]. Moreover, the probability of accident is luckily very low (in space and in time), otherwise the consequences would be drastic, which makes the gathered data insignificant or insufficient in small period of time[17], [19], [135]. Finally, the unexpected evolution of the dynamics of the traffic [17], [19] makes it harder to fully relay on those data: accidents are usually the result of the complex evolution of the traffic through several phases that is not exhibited through statistical data[136], [17].

Thus, relying solely on statistics may bring major difficulties when in the need of resolving current problems[19]. For instance, the limits and the issues brought by this type of data brings a certain amount of uncertainty when defining the hot spots. Subsequently, the validity of the proposed resolutions to dissolve them becomes questionable and creates a dilemma between long term and short term solutions, knowing the costs that comes along[137]–[139].

1.4.1. The surrogate safety measures

To avoid these issues, researchers have exploited the potential of surrogate safety measures within the simulation models to treat the collisions between vehicles [140]–[143], [20], [144], [145], [19], [17]. They have developed simulation models that would help study predefined collisions situations, in order to evaluate the safeness of the adopted measures before their application by traffic managers. The strength of those models is their capability of

estimating the probability of accidents occurrence based on microscopic traffic parameters such as vehicle speed, acceleration, time headway, and space headway [20].

1.4.2. The human impact is considered as an automatic step

It is worth to mention that all the previously cited works investigated the accidents occurrence as an automatic and intrinsic result of the traffic itself.

Nonetheless, there has been another tendency that claims that all the safety measures have already been considered in the engineering methods and that the road accidents are predominantly a consequence of the driver behaviour (errors, distraction, age, gender, disease...)[140], [146]–[150]. Thus, the traffic safety should, more likely, be considered in the light of the social sciences.

In this respect, a fundamental question arises: what does the human behaviour refer to?

To answer this question, it is primordial to know that a driver interacts with his/her environment. This interaction is the key to guaranteeing a movement without incidents. The environment can be for example:

- The road: width, number of lanes ...
- The climate
- The pedestrians
- The traffic: type of drivers (aggressive, careful), composition of the fleet (heavy trucks, buses ...)

The multiple components of a driver environment highlighted the fact that there are different behaviours that need to be elucidated. Studying those behaviours and responses should help in shelling the mechanisms of the interaction between the traffic and the driver, thus drawing near the causes of accidents.

2. Problematics

We can conclude that treating the issues related to the road safety requires the intervention of both the traffic theory and the social sciences, such as psychology or psychosociology.

In this Section, we will present a modest attempt of combining the two fields by proposing a CA model that will consider the interaction between the driver and his/her environment. By analogy to the statistical mechanics, we will investigate the response of the driver to the traffic

situations when going from the microscopic to the macroscopic scale, and we will examine the effects of one driver behaviour on the whole traffic, when taking the cross path.

For simplification aims, we will study the behaviour of a driver in a well-defined situation: the vehicles will be driven in one direction, under the different traffic states and parameters. Our object will be to define one mechanism responsible of the rear-end collisions between vehicles.

This following sections will be organised as follows: firstly, we will define the model on which we will base our discussion later. Finally, we will gather all the results into a conclusion.

3. Cognitive anticipation CA model

3.1. The urge to implement the human impact in CA

In order to quantify and reproduce accidents likelihood, scientists have opted for surrogates safety measures, for instance: time to collision, stopping distance index, vehicles speeds and headways... (see: [151]and the references within). Those measures were implemented into several simulation models, among them, cellular automata that we will adopt to carry on our study.

The traffic cellular automata "TCA" represent one of the most exploited methods of modelling the traffic due to their computational efficiency (for review see(Schadschneider et al., 2011, pp. 213, 243–307), and the references within). Indeed, the TCA models are based on discretization of the time and space thus of: position, speed and acceleration of the vehicle.

Several TCA models have seen the lights during the last 3 decades. The NaSch model is one of the most popular[27]. Also known as the stochastic traffic cellular automaton, the NaSch model incorporate four basic steps necessary to reproduce most observed phenomena in the real traffic, namely the spontaneous Jam.

Nevertheless, this TCA model, among others, shows many limitations especially as far as the safety aspect of the traffic is concerned. In fact, this model can be described as intrinsically accident-free since it was based on secure bases and all collisions were prevented. Other models, on the other hand, are not intrinsically safe, but do not represent real cases of accidents when the simulations are run. Those TCA only displays dangerous situations instead of accidents[30, p. 332].

In general, as their name suggests, TCA models quantify the human reactions in an automatic way, whereas, each driver is an independent intelligent agent who thinks, learns and decides differently [36, p. 5]. Therefore, the human behaviour should be taken into account when trying to reproduce real events such as *collisions*.

3.2. Anticipation process in the frame work of cellular automata models

In the attempt to simulate the human behaviour, researchers have defined different parameters or moving steps such as randomization or more importantly anticipation.

The anticipation can theoretically be defined by the susceptibility of drivers to predict the behaviour of their predecessors (velocity, deceleration, headway...).

This behaviour has largely been studied in the scope of the car following models (to name a few: [152]–[155]. In the frame TCA, many models have incorporated the anticipation during deceleration as a tool to avoid collisions, [119], [156]–[159] .

On the other hand, fewer introduced the anticipation as a cause of accidents during acceleration. Hamdar et al stated that drivers, while observing the behaviour of their predecessors, may take the risk of making an accident in order to increase their velocity [160].

Nevertheless, the previous models incorporated the anticipation as an automatic step, i.e, all the drivers anticipate in the same way, whereas, in fact, no one can assure that two drivers would have the same respond to the same situation. Additionally, this anticipation was performed as a step among others, and did not result from a certain process.

Our field experiments have highlighted that the anticipation during acceleration is an

intricate reaction of drivers to the strong interaction between them.

Actually, due to the anisotropy of the traffic, drivers mainly manoeuvre with respect to their predecessors[23], [96]. A ***transfer of information*** between successive vehicles is then present. Indeed, this communication is guaranteed by the strong correlation of their velocities as proven empirically by Appert-Ronald[161] and through simulations by Lakouari et al [162].

Thus, shelling the drivers' response to those interactions, we were able to state that anticipation is a complex human driving progression that may lead to speed improvement but could also be responsible of generating rear-end collisions.

In this thesis, ***we define anticipation as a driver's tendency to accelerate on the basis of their expectation of the next move of the leading driver. This expectation is preceded by a learning process on the previous actions of their leader.***

We will show in the next subsection that the learning process results from cognitive considerations and differs from one driver to another.

3.3. Cognitive process

In order to deeply understand the cognitive process followed by a driver, we have opted for the moving observer method (experimental approach). Indeed, by the mean of an embedded camera, we recorded the behaviour of a driver while travelling. We were mainly focused on:

- Detecting the situations that may lead to a rear-end collision.
- Measuring the frequency of the occurrence of those situations.
- Defining the causes behind the existence of those situations.

N.B: the results of this field experiment are beyond the scope of this article and will be discussed in a future paper.

By synthesizing all of that information, we were able to state that the anticipation process, that we believe to be strongly responsible of the potential rear end collision, is performed in four steps:

- Step 1: Attention: during this first step, the follower driver monitors the leading driver and records its accelerations and decelerations history.
- Step 2: Perception: at this stage, the follower driver analyses the behaviour of the leading driver based on:

- ✓ The historic of his/her leader's acceleration (deceleration): is he/she a careful driver? How does he/she perform in front of obstacles or sudden incidents?
- ✓ The evolution of the empty space between the two vehicles
- Step 3: Learning: The recurrence of this analysis allows the follower driver to understand and learn about the behaviour of his/her leading driver.
- Step 4: Decision-making: based on the results of his/her analysis and learning about his/her predecessor, the driver may anticipate, if he/she is urged to synchronize his/her speed with his/her leading vehicle.

To incorporate the anticipation process, we were brought to translate the learning process (step1-3) into measurable quantities and Boolean conditions. To do so, we will define new pillar parameters:

- Historic parameter H: this variable registers the accelerations and the decelerations of each single vehicle: if a driver accelerates, its H is incremented by 1, if not, it is decremented by 1.
- Threshold learning parameter Hs: this variable determines the minimum number of accelerations that should be realized by a driver so as his/ her follower can predict his/ her next move. It is an attempt to quantify the level of the caution of a driver. It varies from 1 to Hsmax to represent different levels of caution. If a driver succeeds an anticipation attempt, he/ she becomes more confident in his /her judgment and Hs is decremented by 1. If he/she fails, Hs is brought to Hsmax. Each driver would be attributed initially, with an Hs chosen randomly from 1 to Hsmax, to reproduce the differences between drivers.

It is worth to mention that modelling the human behaviour is not a trivial exercise[163] and far beyond the scope of this article. To our knowledge, no one has measured or found the unity of learning. Nevertheless, the values added, subtracted, compared and taken by H and Hs are only a mean to quantify those two parameters.

Furthermore, step 4 cannot be executed automatically by all the drivers. Each driver reacts differently, i.e. might or not anticipate, even if the learning process is performed.

As a consequence, it is crucial to consider the differences of the psychology of the drivers. In other words, we should know and try to capture the behaviour of each driver while driving so as to understand the way he/she anticipates. In the next subsection, we will present some finding regarding this point of view.

3.4. Conservative and aggressive drivers

As stated previously, we should increment the Human behaviour at certain level of our model. Before doing this we should be able to understand why two drivers in the same situation may (or not) react in the same way while driving.

In this respect, a driver behaviour questionnaire “DBQ” was proposed by Reason et al. [164].

The DBQ aims to define the types of actions lead by a driver when in a certain situation. Indeed, those actions, that may or not cause an accident, are correlated to demographical specificities (age, sexes...) [148], [149] and more strongly to the state of mind of the driver[165]

.

Accordingly, different categorizations of drivers have been proposed:

- Drivers who commits errors/violations[164].
- Mindful/angry drivers[165].

In the same perspective, and so as to consider all those types of drivers in the anticipation process, we propose the following classes:

- Conservative drivers: who are mindful but can make unintentional errors. Such driver may anticipate after a careful reading on his/her predecessor. Indeed, even if the learning process is performed, this kind of driver is indecisive. Thus its anticipation takes time and not always smooth.
- Aggressive drivers: who are angry and deliberately commits violations. This Kind of drivers will not take seriously the learning step and may anticipated after a short amount of time.

3.5. Our cognitive cellular automata model

In order to perform simulations, we will write the psychological cognitive process presented above in CA language. In this respect, we will consider the NaSch Cellular Automaton Model with periodic boundaries in which we will implement the cognitive anticipation process.

3.5.1. Recall on the Standard NaSch Model

The strength of the NaSch model is its ability to be extended to study more complicated situations. It is based on specific but simple steps that govern the movement of vehicles [27]. In the following, we will recall and comment on these steps. Let us focus on one vehicle which we denote by I and its leader by $I+I$.

X_i^t : is the position of the vehicle " I " at a given instant of time t .

X_{i+1}^t : is the position of the vehicle " $I+I$ " at the time t .

V_i^t : is the velocity of the vehicle I at the time t .

V_{i+1}^t : is the velocity of the vehicle $I+I$ at the time t .

According to the parallel dynamics approach, the position and the velocity of the vehicle I are updated (from the time t to $t+1$) as follow:

- Step 1 is about acceleration: $V_i^{t+1} = \text{Min}[(V_i^t + 1), V_{max}]$, where V_{max} is the maximal velocity of vehicles. This rule reflects the human innate to move ahead.
- Step2, deceleration: $V_i^{t+1} = \text{Min}(V_i^{t+1}, D_i^t)$ where $D_i^t = [(X_{i+1}^t - 1) - X_i^t]$ is the gap between the leading vehicle ($I+I$) and the following one I . This step limits the previous one for safety purpose.
- Step 3, randomization: $V_i^{t+1} = \text{Max}[(V_i^{t+1} - 1), 0]$ with a probability $\mathbf{Pr}$. It is well known that this probability is what makes NaSch model able to reproduce the formation of the phantom Jam. Indeed, $\mathbf{Pr}$ quantifies the driver's response to the variation of the external conditions. In the following, this deceleration parameter would only reflect the probability that a driver may face a perturbation namely a sudden event in the road that would force him/her to decelerate, for instance, drivers that join the flow from ramps and may cause unexpected braking.
- Vehicle's motion: $X_i^{t+1} = X_i^t + V_i^{t+1}$

3.5.2. Anticipation process in CA language

At low density, the gap D_i^t is large enough that vehicles do not interact. As long as the density of cars increases, vehicles are more constrained to "cooperate" in order to avoid rear-end collisions. The definition of $D_i^t = [(X_{i+1}^t - 1) - X_i^t]$ ensures that no rear-end collision will occur between vehicles I and ($I+I$). Indeed, the dynamics of NaSch model are a compromise between speed improvement and collision avoidance (steps 1 & 2).

However, rear-end collisions take place in real traffic. According to our previous discussion (section 3.2 and 3.3), the anticipation process allows speed improvement to the detriment of the safety. In the CA language, anticipation means that:

$$X_i^{t+1} = X_{i+1}^t \quad (3.3)$$

It is based mainly on two conditions:

$$\mathbf{C1:} \quad D_{c_i}^t \leq R_i^{t+1} \quad (3.4)$$

where,

$D_{c_i}^t = [X_{i+1}^t - X_i^t]$: the critical gap between vehicle I and his leading $I+1$.

and

$R_i^{t+1} = \text{Min}[(V_i^t + 1), V_{max}]$: the risk velocity. If the driver maintains this velocity he/she will surely have a collision with the leading car.

As a consequence, $\mathbf{C1}$ is a spatial condition. It translates the situation when the vehicles' gap makes it impossible for the drivers to travel at their desired speed R_i^{t+1} that they feel the urge to predict and anticipate the next move (next time steps $t+1$) of their predecessors.

If $\mathbf{C1}$ is not verified, it means that the vehicles I and $I+1$ are far enough that there is no need for anticipation.

$$\mathbf{C2:} \quad H_{i+1}^t \geq H_{s_i}^t \quad (3.5)$$

This condition translates the learning process: the fact that the driver of vehicle I has, in his/her personal opinion, enough information about his/her predecessor that will able him/her to anticipate. It is a conciliation between the level of caution $H_{s_i}^t$ of the following driver (I), and the recorded behaviour (acceleration/deceleration) H_{i+1}^t of the leading ($I+1$).

It is worth to mention that the respect of condition $\mathbf{C2}$ will depend on the psychology of the driver I . In the previous section (3.4), we distinguished two types of behaviour.

For an aggressive driver, if both condition $\mathbf{C1}$ and $\mathbf{C2}$ are fulfilled, then he/she surely anticipates i.e. try to $X_i^{t+1} = X_{i+1}^t$ (3.3)

However, if $\mathbf{C1}$ is verified whereas $\mathbf{C2}$ is not, the driver may anticipate with a probability $\mathbf{Pe}$. For such drivers, the learning process limits the anticipation so they "Gamble: deliberately commits violations " in order to improve their speed and reduce their journey time.

For a conservative driver, both conditions $\mathbf{C1}$ and $\mathbf{C2}$ must be verified. After that, he /she

may anticipate with a probability Pe .

3.5.3. Rear-end collision

According to the anticipation definition (section 3.2), the driver of vehicle I expects that $I+I$ will move in the next time steps ($t+1$). The success or the failure of the anticipation surely depend on the state of X_{i+1}^{t+1} .

If $X_{i+1}^{t+1} = 0$.i.e. the leading vehicle has moved forward, it follows that the anticipation was a successful maneuver from the following driver I . Fortunately, the rear-end collision was avoided. In this case:

$$X_i^{t+1} = X_{i+1}^t \quad (3.3)$$

and

$$H_{s_i}^{t+1} = \text{Max}[(H_{s_i}^t - 1), 1] \quad (3.6), \text{ the driver } I \text{ becomes more self-confident.}$$

If $X_{i+1}^{t+1} \neq 0$.i.e. the leading vehicle has not moved forward, then the anticipation was not a successful maneuver from the following driver I . In this case, the driver I decelerates and his/her velocity is reduced to none so as to try to avoid a collision.

$$V_i^{t+1} = 0 \quad (3.7)$$

This brutal brake may or not generate rear-end collision. In this model, we are not concerned by the occurrence of a real rear-end collisions. In other words, this situation only represents a potential collision that will not solicit the elimination of the concerned vehicles.

After that the driver I becomes aware $H_{s_i}^{t+1} = H_{smax}$ (3.8) and stays in the safe position $X_i^{t+1} = X_{i+1}^t - 1$ (7) (3.9) obtained by the execution of NaSch rules.

N.B: In the following, rear-end collisions, collisions or accidents refer to potential rear-end collisions.

3.5.4. Algorithm of the cognitive anticipation model

This algorithm sums up the main stages of our cognitive anticipation CA model. For simplicity, let us consider the case of a conservative driver. The movement of this driver will be performed according to the following steps:

Step 1:**Acceleration and deceleration**

$$V_i^{t+1} = \text{Min}[(V_i^t + 1), D_i^t, V_{\max}]$$

Step 2:**randomization**Yes, with a probability Pr No, with $1-Pr$ **Step 3: Following the standard NaSch rules****Step 4: Anticipation*****Update the velocity***

$$V_i^{t+1} = \text{Max}[(V_i^{t+1} - 1), 0]$$

Update position

$$X_i^{t+1} = X_i^t + V_i^{t+1}$$

Record acceleration/deceleration***If $V_i^{t+1} \geq V_i^t$ (Acceleration)******Then $H_i^{t+1} = H_i^t + 1$*** ***Else (deceleration) $H_i^{t+1} = H_i^t - 1$*** ***1) Spatial condition C1:***

$$D_{c_i}^t \leq R_i^{t+1}$$

2) Learning condition C2:

$$H_{i+1}^t \geq H_{s_i}^t$$

3) Attempt to anticipate with a probability Pe :

$$X_i^{t+1} = X_{i+1}^t$$

Step 5:**Anticipation and accidents detection**If the vehicle I has fulfilled all the conditions in step 4, then two cases are possible: $X_{i+1}^{t+1} \neq 0$ Rear-end collision

$$V_i^{t+1} = 0$$

$$H_{s_i}^{t+1} = H_{s_{\max}}$$

 $X_{i+1}^{t+1} = 0$ Successful anticipation

$$X_i^{t+1} = X_{i+1}^t$$

$$V_i^{t+1} = D_{c_i}^t$$

$$H_{s_i}^{t+1} = \text{Max}[(H_{s_i}^t - 1), 1]$$

3.5.5. Monte Carlo simulations

In order to run the simulations and reproduce rear-end collisions, we translate the algorithm above into a program that would be compiled by programming machine.

To guarantee the realization of the stochastic process of the model, we resort to the Monte Carlo simulation. Indeed, each MC simulation generates one specific realization of the stochastic process: by generating a random number r from $[0,1]$ and comparing it to a fixed probability (in our case: probability of randomization Pr , of anticipation Pe). For instance, if $r \leq Pe$, the process of anticipation will happen, if $r > Pe$, it will not [30, p. 58,59].

In this respect, we execute 50000 Monte Carlo iteration while we average 40 initial configurations to eliminate statistical fluctuations.

4. The investigation of the effect of the anticipation on rear-end collisions

As defined in the previous section, the anticipation process, which is believed to be among the generators of rear end collisions, strongly depends on the gap between vehicles. Therefore, in this section, we will follow the behaviour of this phenomenon (anticipation) in relation with the traffic states and track how it leads to rear end collisions.

It is worth to mention that we will quantify the traffic states by considering the variation of the density for simplification purposes. This can also be performed using the traffic volume or the vehicles' mean velocity.

4.1. Conservative drivers

We start our investigation by taking into account one type of drivers, for instance, conservative drivers. If not stated otherwise, $V_{max}=5$, $Pe=0.8$, $Pr=0.005$ and $H_{smax}=5$.

4.1.1. Anticipation, rear end collision and traffic states

We define the rate of anticipation “ Ra ” by the mean value of the ratio of the number of drivers that attempted anticipating to the total number of drivers.

We plot this rate as a function of the density ρ of vehicles for different values of Pe (figure 49) so as to show how the anticipation evolves according to the state of the traffic flow.

The figure 49 represents the variation of R_a for two values of Pe . It highlights that the R_a , like other natural phenomena, follows a Gaussian law. Indeed, drivers mainly anticipate for a specific range of densities $[\rho_{s1}, \rho_{s2}]$, where ρ_{s1} corresponds to the density at which the anticipation starts to occur ($R_a \geq 0$) while ρ_{s2} represents the density at which the driver's manoeuvre fades away ($R_a \approx 0$).

To understand the R_a 's Gaussian behaviour, we investigate (according to traffic density) the accomplishment of the two main conditions: the spatial condition (1) " $R_i^{t+1} \geq Dc_i^t$ " and the learning condition (2) " $H_{i+1}^t \geq Hs_i^t$ ". We recall that these conditions must be fulfilled simultaneously to perform anticipation (see the model section (3.5) for more details).

On the one hand, figure 50 displays that when $\rho < \rho_{s1}$, the spatial condition is mostly not verified since $Dc_i^t > R_i^{t+1}$. Thus, the anticipation does usually not occur.

On the other hand, for higher densities $\rho > \rho_{s2}$, figure 51 shows that the mean Historical parameter $\langle H \rangle \approx 0$. Thus, the learning conditions is not satisfied and the anticipation rate nearly approaches none for this range of density.

When $\rho_{s1} \leq \rho \leq \rho_{s3}$, the number of vehicles for which both conditions are verified increases as well as R_a according to the density ρ . For $\rho = \rho_{s3}$, the spatial and learning conditions are fulfilled for all drivers and the anticipation is very permeant, it takes its maximal value (figure 49).

When $\rho_{s3} < \rho \leq \rho_{s2}$ (figure 49), the learning conditions is, in the average, not always verified (figure 51), which brings the decrease of the anticipation rate R_a .

N.B: According to the figure 49 (and other figures omitted here for space management), the density thresholds ρ_{s1} , ρ_{s2} and ρ_{s3} do not depend of Pe nor Pr . However, those thresholds depend on V_{max} which since they also correspond to the traffic phase transitions (as will be presented in the following).

The question that arises then is: *how do the traffic states contribute in the appearance and the disappearance of the anticipation?*

We observe that the drivers mainly anticipate for medium densities $[\rho_{s1}, \rho_{s2}]$ (figure 49). According to the fundamental diagram, those densities correspond to the congested traffic state (figure 52).

The free flow state ($\rho < \rho_{s1}$): Drivers run at their desired speed. There is no interaction between the drivers and the gap between the vehicles is very large (low densities): the spatial condition is mostly not verified (figure 50) and very few successful anticipations occur.

The jamming state ($\rho > \rho_{s2}$): Drivers are obliged to decelerate which significantly affects their historical parameter H and prohibits the verification of the learning condition (figure 51): there is no anticipation.

The congested traffic state ($\rho_{s1} \leq \rho \leq \rho_{s2}$), drivers start approaching from each other. The gap between the leader and the follower forced the latter to drive at a velocity lower than what he/ she wants. Such situation may urge some drivers to anticipate.

Indeed, the spatial condition is verified by the effect of the density (figure 50) while the learning condition is still checked (figure 51). Major anticipations are then present as an attempt to maintain the velocity of the free flow state. At $\rho = \rho_{s3}$, the anticipation becomes a collective behaviour of drivers.

It is worth to mention that the obtained fundamental diagram corresponding to this case of anticipation where only conservative drivers are considered does not differ from the one obtained by the standard NaSch model (figure 52). However, this model is able to shed light on the congested traffic state and marks off its limit $[\rho_{s1}, \rho_{s2}]$.

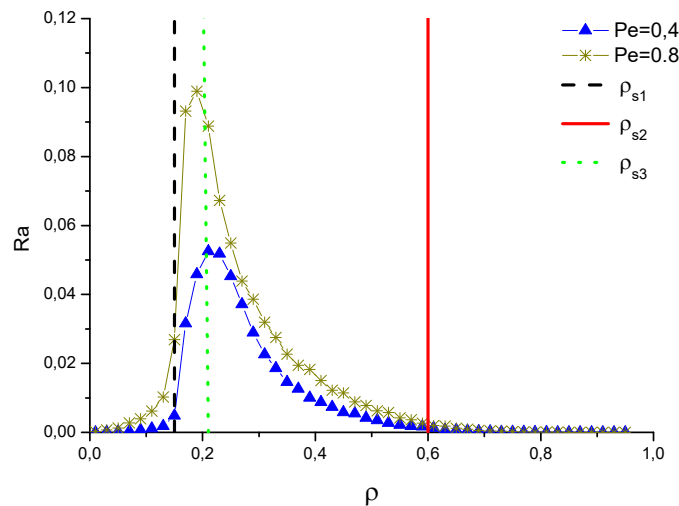


Figure 49: the variation of the rate of anticipation R_a versus the density ρ for different values of Pe .

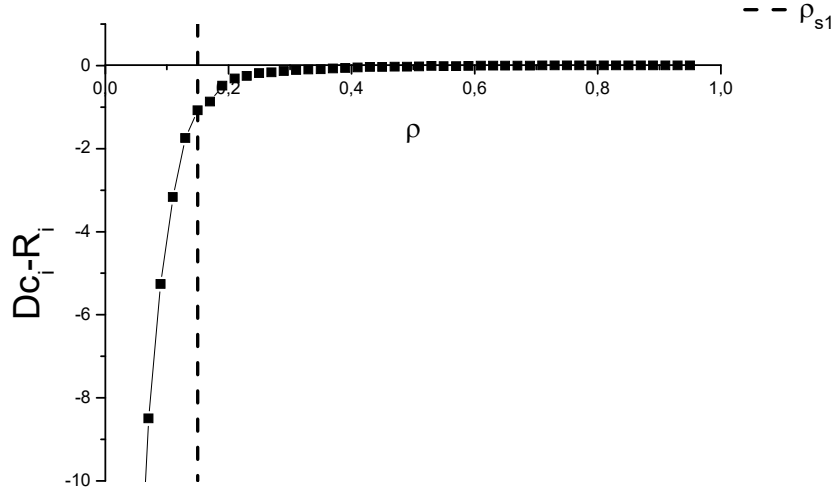


Figure 50: accomplishment or not of the spatial condition for $Pe=0.8$. We plot here the mean difference between the speed of anticipation R_i and the critical gap Dc_i versus traffic density ρ .

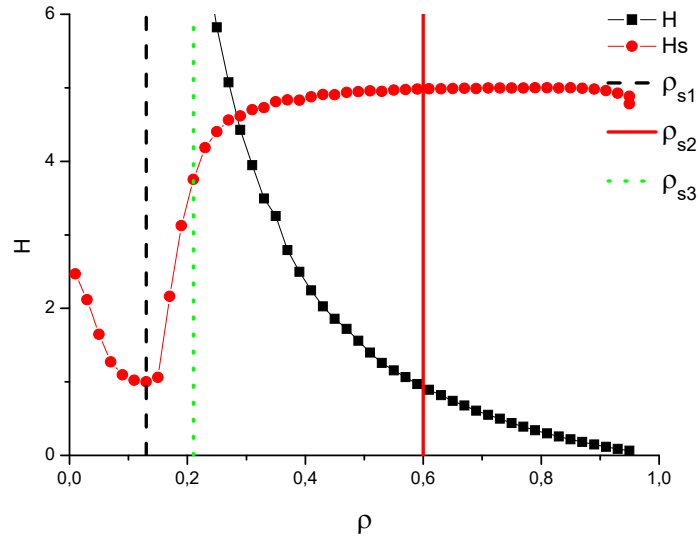


Figure 51: the learning condition versus the density ρ for $Pe=0.8$: the historic H (black scare) and the mean learning H_s thresholds (red circles).

Nevertheless, the anticipation is not a safe manoeuvre: the appearance of this process brings accidents along. Indeed, at $\rho=\rho_{s1}$, potential rear end collisions appear (figure 53). Moreover, the ratio of those probable accidents Pcr follows the tendency of the variations of Ra (Gaussian law): it increases with the increase of Ra and decreases with its decrease. At the density ρ_{s2} , potential accidents also disappear. Therefore, potential rear-end collisions strongly result from the anticipation, they are then more likely to occur in the congested traffic state.

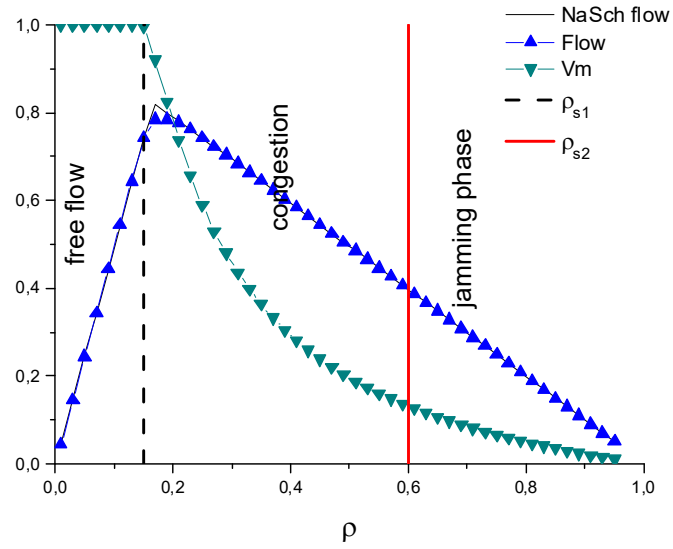


Figure 52: fundamental diagram (flux versus density) and normalized velocity ($V/V_{\max}$) versus the density ρ for $Pe=0.8$.

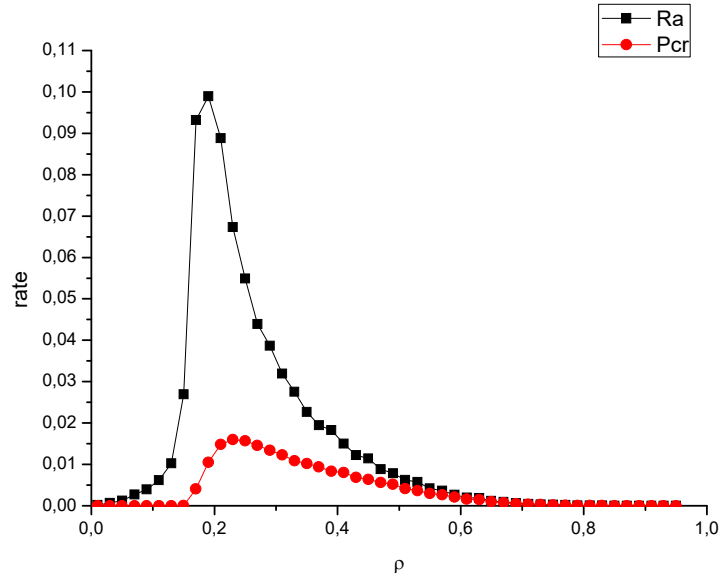


Figure 53: rate of potential collisions P_{cr} compared to the rate of anticipation P_a versus the density ρ , for $Pe=0.8$

4.1.2. Drivers' behaviour and the traffic states

In the previous subsection, we have explained that the anticipation is a collective response of the drivers to the congested traffic state. It is important now to understand how this collective behaviour emerges according to traffic states.

The figure 51 shows the variation of the mean learning threshold parameter H_s that represents the degree of caution of drivers, versus traffic density.

For ($\rho < \rho_{s1}$), the traffic is in the free flow state (no anticipation). The mean H_s is around 2.5, which shows the heterogeneity between the drivers as far as their caution is concerned.

When the density increases, by the effect of the traffic, few successful anticipations take place, those drivers reduce their degree of awareness, which brings a decrease of the mean H_s observed in figure 51. At the density $\rho = \rho_{s1}$, all the drivers have an H_s that is equal to 1.

Note that $\rho = \rho_{s1}$ is the density at which the traffic undergoes a phase transition: It switches from free flow to the state of congestion. Thus, this traffic flow transition has forced the drivers' community to self-organized in homogeneous but hazardous situation ($H_s=1$). Following that, the lack of caution combined with the effect of the shortage of space due to the density generate the first potential accidents. This results in the augmentation of H_s for the concerned drivers, from 1 to 5 ($H_s=H_{smax}$ and $V=0$), while the remaining drivers are not affected (figure 51) since the mean value of H_s is lower than 5.

This event starts a chain reaction of rear end collisions. Certainly, for $\rho_{s1} < \rho < \rho_{s3}$, the mixture of drivers' H_s combined with the congested state of traffic produce more potential accidents that affect again the H_s and go on. When the mean learning threshold reaches H_{smax} at $\rho = \rho_{s3}$, the human behaviour is homogenous; the level of awareness is maximum for all the drivers and the number of potential accidents starts decreasing.

In the range of density $\rho_{s3} < \rho < \rho_{s2}$, the interaction between vehicles is still strong (congested state) but the drivers are more aware.

The safe state is restored at $\rho \geq \rho_{s2}$ (the traffic is in the Jamming state, so no anticipation is needed).

4.1.3. Summary

To sum up, the analysis of the traffic states, the anticipation and the accidents probabilities shades lights on the existence of a complex causality relation between the traffic flow states, the drivers' behaviours states and consequently accidents' occurrence.

Indeed, the traffic states (free flow, congestion and jamming) are correlated to the driver's behaviour states (anticipation/no anticipation). The phase transitions occur for the same transitions' densities ρ_{s1} and ρ_{s2} .

At ($\rho=\rho_{s1}$), the traffic flow undergoes a phase transition from free flow to the congested state. In the same way, the drivers' behaviour switches from the state of no anticipation to the anticipation state.

At ($\rho=\rho_{s2}$), the traffic flow changes from the congested state to the jamming state. Also, at the same density, the drivers' behaviour undergoes a phase transition from the state of anticipation to the no anticipation state.

Moreover, when the first transition ($\rho=\rho_{s1}$) takes place, the successful anticipations lead the drivers to self-organize but into a hazardous situation ($\langle H_s \rangle = 1$). This situation generates a potential rear-end collision. This first rear end collision is what brings back the heterogeneity in the human awareness ($1 < H_s < 5$) which leads to more and more accidents. Surprisingly, this situation provokes another self-organization i.e. the drivers become more aware ($\langle H_s \rangle = H_{smax}$) and the number of accidents decreases progressively.

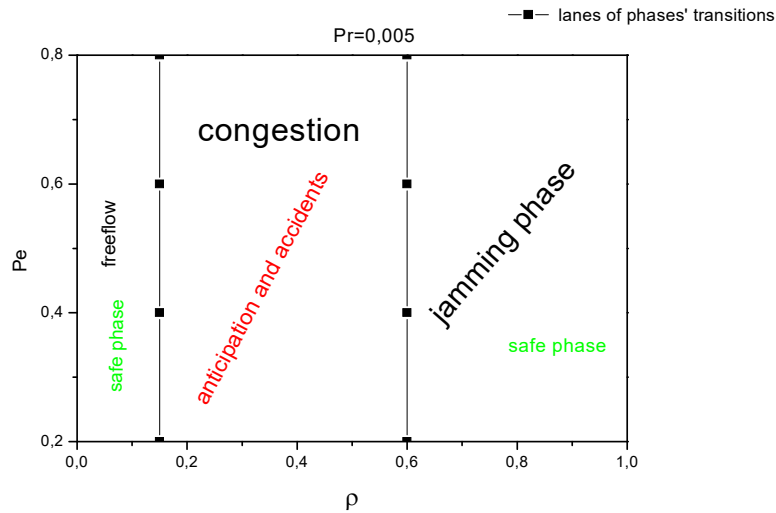


Figure 54: traffic and security phase diagram: define the three traffic phases (free flow, congestion and jamming phase) along with the corresponding security phases for different densities and anticipation probabilities, when $Pr=0.005$.

The figure 54 sums up the different traffic and security phases when only conservative drivers are considered.

4.2. Aggressive drivers

In the following, we consider $Pr=0.005$ and $H_{smax}=5$.

After initiating the anticipation process in the previous section, we will now investigate the impact of only considering the second type of drivers “the aggressive drivers” on the results stated above (4.1).

On the one hand, the figure 55-a represents a comparison of the ratio of anticipation R_a between the conservative and the aggressive drivers. We observe that R_a corresponding to the aggressive drivers is very important compared to the other type of drivers. Firstly, the ratio of anticipation starts increasing much earlier in the low densities at a density ($\rho'_{s1} < \rho_{s1}$). Indeed, in this range of densities, the spatial condition controls the anticipation process, as the learning condition is usually verified (figure 51). In such situation, conservative drivers anticipate with a probability P_e while aggressive drivers surely anticipate despite the value of P_e (see section 6.5). After that, R_a keeps growing even in the higher densities ($\rho > \rho_{s3}$), so as it reaches very high values whereas conservative drivers start ceasing anticipation. This is due to the fact that those aggressive drivers do not always respect (effect of P_e) the learning condition of anticipation (condition 2) that is responsible of the decrease of the R_a as in the section (4.1.1).

On the other hand, the figure 55-b compares the probabilities of the potential rear-end collisions for both conservative and aggressive drivers. Those probabilities start increasing at the same density $\rho = \rho_{s1}$ for both types of drivers. This shows the existence of a secure and more fluid interval of densities $[\rho'_{s1}, \rho_{s1}]$ (*This finding will be discussed later*). However, no safe state is restored in the higher densities ($\rho > \rho_{s3}$).

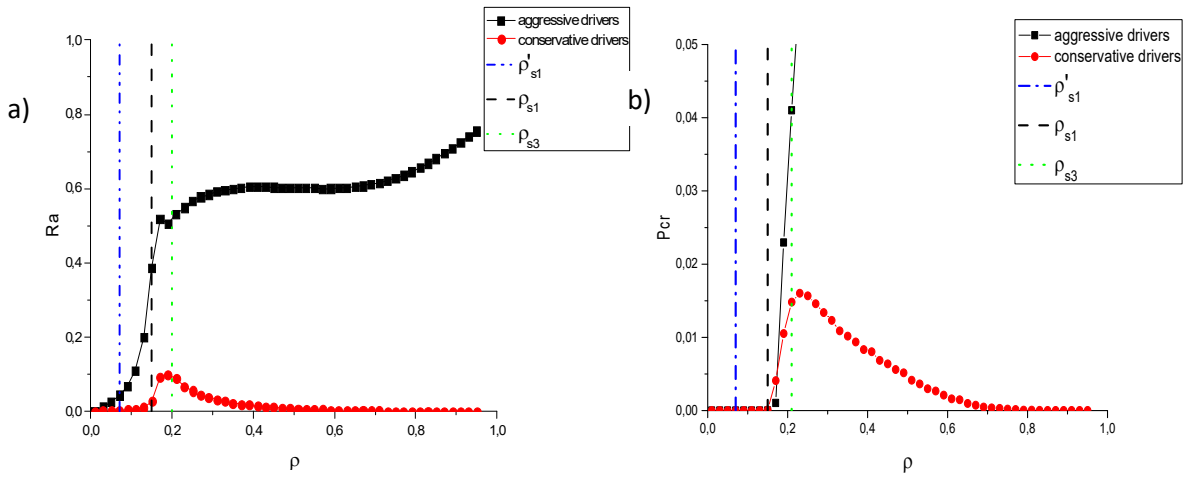


Figure 55: a) ratio of anticipation R_a versus the density ρ of both aggressive and conservative drivers when $P_e=0.8$, b) probability of rear-end collisions versus the density ρ of both aggressive and conservative drivers when $P_e=0.8$

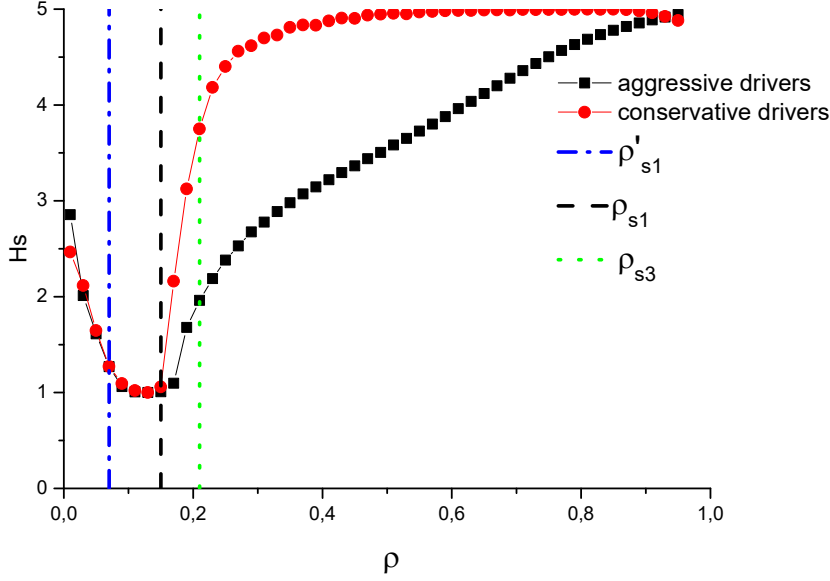


Figure 56: mean learning threshold $\langle H_s \rangle$ of both aggressive and conservative drivers for $Pe=0.8$ versus the density ρ

Moreover, the figure 56 shows the behaviour of the mean learning threshold $\langle H_s \rangle$ versus traffic density for both types of drivers. In the low densities $\rho < \rho_{s1}$, the mean H_s decreases until it reaches 1 despite the type of the drivers. When $\rho > \rho_{s1}$, the mean learning threshold starts increasing as a result of the potential accidents that bring some drivers to the highest level of caution, i.e., $H_s = H_{smax}$. However, unlike the previous case, this mean H_s does not go back to H_{smax} unless the density is very important, $\rho \approx 1$. Therefore, the system needs more traffic density to restore a homogenous state ($H_s = H_{smax}$ for all drivers).

This highlights the resistance of aggressive drivers to the traffic conditions. Consequently, this resistance translates into a higher risk of potential collisions. Actually, their rate increases exponentially when increasing the density (figure 55-b).

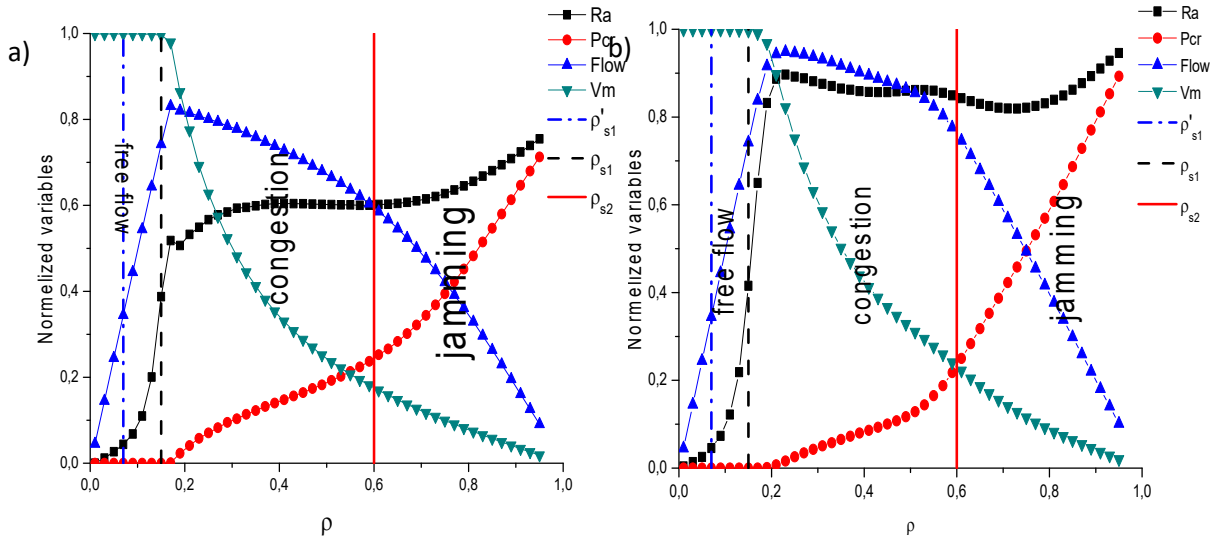


Figure 57: different observables for a) $Pe=0.8$ and b) $Pe=1$: rate of anticipation Ra , probability of collisions Pcr , flow and normalized velocity (V/V_{max}) versus the density ρ

Furthermore, unlike the case of conservative drivers where the first transitions (no anticipation/anticipation; free flow/congestion) happen at the same density, the figures 57 shows that the aggressive drivers generate two different transitions: a first transition at $\rho=\rho'_{s1}$ where anticipations appear and a second transition at $\rho=\rho_{s1}$ where the system switches from a free flow safe state to a congested unsafe one.

These findings rise the question about whether this type of drivers would have any impact on the fluidity of the traffic.

In this respect, we plot the flux corresponding to $Pe=0.8$ and $Pe=1$.

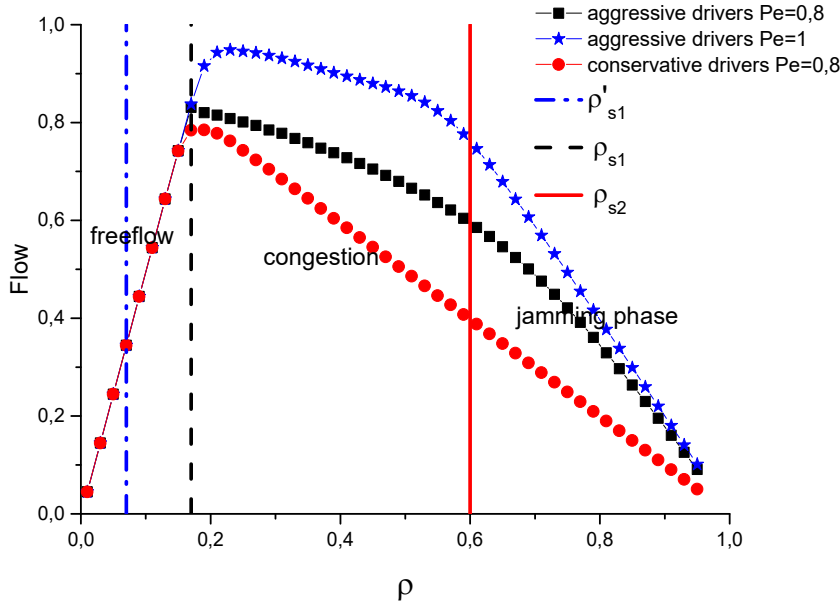


Figure 58: the fundamental diagram of both types of drivers for $Pe=0.8$ and $Pe=1$ (flux versus density)

According to the figure 58, we can identify three different flow behaviours:

- When $\rho \leq \rho_{s1}$: the system is in the free flow state.
- When $\rho_{s1} \leq \rho \leq \rho_{s2}$: the system is in the congested state (figure 59)
- When $\rho = \rho_{s1}$: the system undergoes a transition from the free flow state to the congestion state (figure 60)
- When $\rho > \rho_{s2}$: the system is in the jamming state.
- When $\rho = \rho_{s2}$: the system undergoes a transition from the congestion to the jamming state (figure 61)

4.2.1. In the vicinity of the traffic flow transition (free flow/congestion)

Based on the figure 58, the system is characterized by the free flow when $\rho \leq \rho_{s1}$.

Indeed, when $\rho \leq \rho'_{s1}$, the gap is sufficiently big that all drivers drive at their desired speed (figure 57). No anticipation is needed.

When $\rho > \rho'_{s1}$, few anticipations take place. However, due to their low number, the flow is not affected.

Nevertheless, when ρ approaches ρ_{s1} , the effects of the congestion appear and the gap between the vehicles decreases in comparison to the free flow state. At this point, the anticipation intervenes so as the drivers maintain their wanted velocity (figure 57). This anticipation leads to an increase of the mean velocity which results into an amelioration of the flow (figure 58). This amelioration is more important when $Pe=1$. Indeed, by using an intelligent transportation system (for instance vehicle to vehicle communication “V2V”[166]) that allows the drivers to anticipate, we can improve, in a very secure way, the flow by 11% up to a density of 0,21. The challenge that rises at this step is how to implement this finding in the V2V concepts.

4.2.2. The effects of the aggressive behaviour on the congestion

When $\rho > \rho_{s1}$, the flow q starts decreasing with the density ρ but its slope $\frac{dq}{d\rho}$ remains very low. Its values are higher than the case of conservative drivers and of the standard NaSch model too (figure 58). The anticipation is however more important while more potential accidents appear: it is the congestion.

In fact, even though the anticipation is higher, the drivers can no longer operate at their desired speed (figure 57). The impact of the density is more present: the average gap is smaller in comparison to the free flow state. A competition between the anticipation that symbolizes the drivers’ will to maintain their wanted speed and the density that represents the space appears.

To understand this competition, we will perform a microscopic spatio-temporal investigation.

In the following, we will consider $Pe=1$ in order to make the anticipation a sure event that only depends on the spatial condition (the density) (see section (3.5) for more details), in the aim to showcase their competition.

We consider $\rho=0.3$ and we draw the corresponding space-time diagram (figure 59).

The figure displays two types of lines:

- Vertical lines representing anticipating drivers: by the effect of the anticipation, when a driver empties a cell, the follower occupies it instantly.
- Inclined lines representing platoons.

As stated in the previous sections (3.5 and 4.1), an anticipating driver may face a potential accident which will force him/her to brutally brake. This incident, as shown in figure 59 creates a small jam or platoon that propagates in time and space in the opposite direction of the traffic and of which the slope varies in time (nonlinear behaviour). At an undefined instant, this mini jam, that is usually observed in empirical time space diagrams[167], dissociates and numerous and successive anticipations occur (vertical lines in figure 59). Those same anticipations may lead to more potential accidents and so on. This is a retroactive chain of reaction (anticipation -> accident -> platoon -> anticipation).

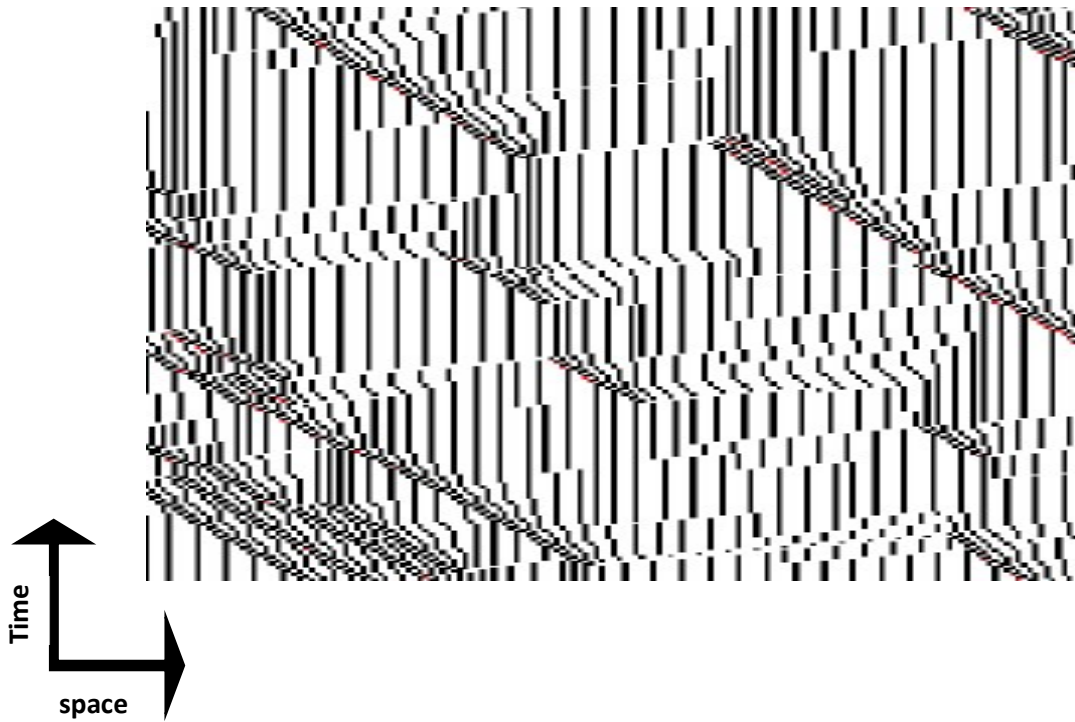


Figure 59: space-time diagram for $\rho = 0.3$: red cells represent potential rear-end collisions, vertical lanes represent anticipations, the black for full cell (vehicle) and the white for an empty cell

This phenomenon is characterized by the competition between the anticipation and the platoons' creation persists until $\rho = \rho_{s2} \approx 0.6$.

4.2.3. The jamming phase

When $\rho > \rho_{s2}$, the average gap tends to none and the anticipation does not improve significantly the velocity of the drivers (figure 57-b). The density wins the competition over the anticipation, and the flow starts decreasing rapidly.

However, this situation brings major probable accidents since the anticipation is still existent because the learning condition is not respected, while no space is available.

4.2.4. The transition points

The Points $\rho=\rho_{s1}\approx 0.15$ and $\rho=\rho_{s2}\approx 0.6$ correspond to the transition points between the three state: free flow, congestion, and Jamming.

The space-time diagrams at those critical densities show the coexistence of two phases at a time:

$\rho\approx \rho_{s1}$: the coexistence of the free flow and the congestion: the appearance of two slopes, negative and positive (figure 60).

$\rho\approx \rho_{s2}$: the coexistence of the congestion that has nonlinear slope and the Jamming state that is defined by jams of which the slope is linear (figure 61).

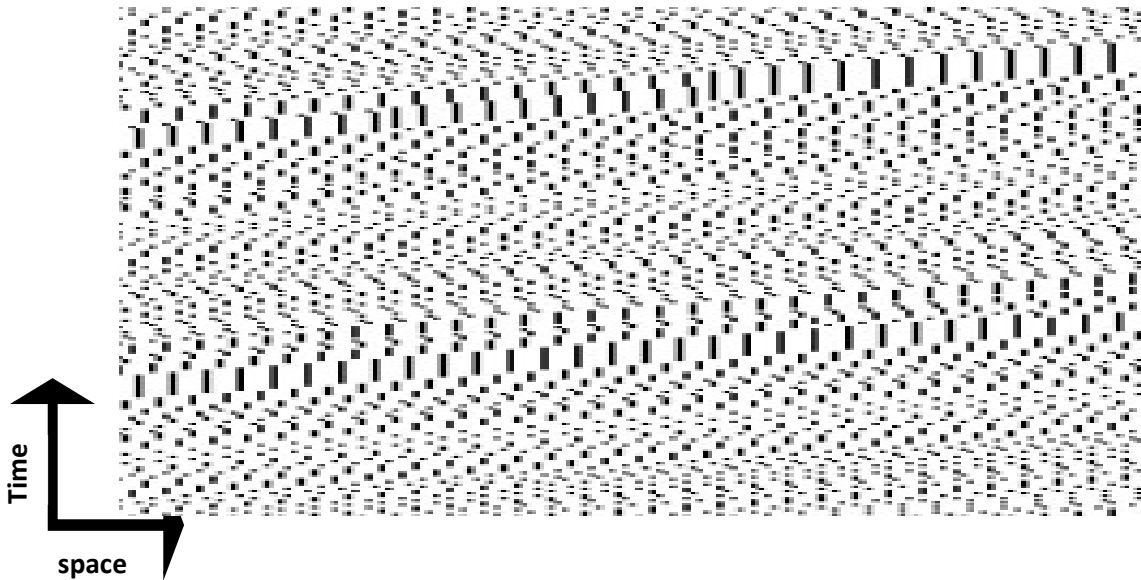


Figure 60: space-time diagram for $\rho=0.15$: vertical lanes represent anticipations, the black for full cell (vehicle) and the white for an empty cell

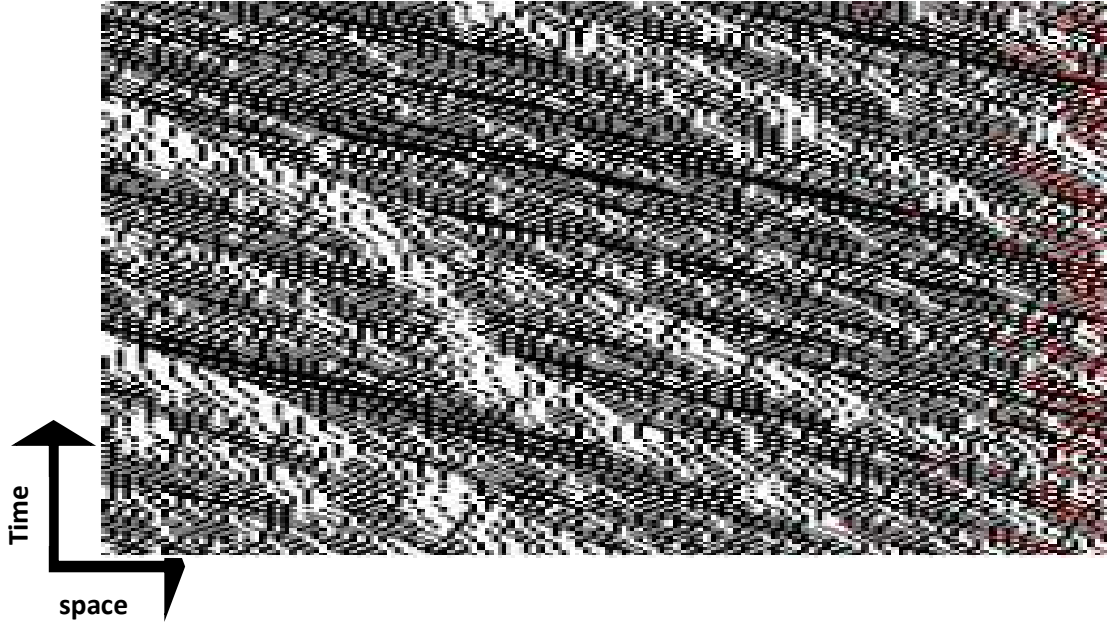


Figure 61: space-time diagram for $\rho=0.6$: red cells represent potential rear-end collisions, vertical lanes represent anticipations, the black for full cell (vehicle) and the white for an empty cell

4.3. Heterogeneous traffic

The differences between the flow of the standard NaSch model and the flow of this cognitive anticipation model, in the congestion phase, shown in the figures (52,57), approach the scattering observed in the empirical fundamental diagram. This brings as to speculate that the heterogeneity of the traffic as far as the drivers' behaviours are concerned may be partly responsible, as advanced in [28], [29].

In this respect, we propose this third variant of the algorithm in which the two types of drivers are present in the road that will offer a more realistic representation of the traffic. We define a new probability P_a that designates the expected behaviour of a driver: if the random number is less than P_a , the driver will anticipate as an aggressive driver. If not, he/she will be a conservative driver.

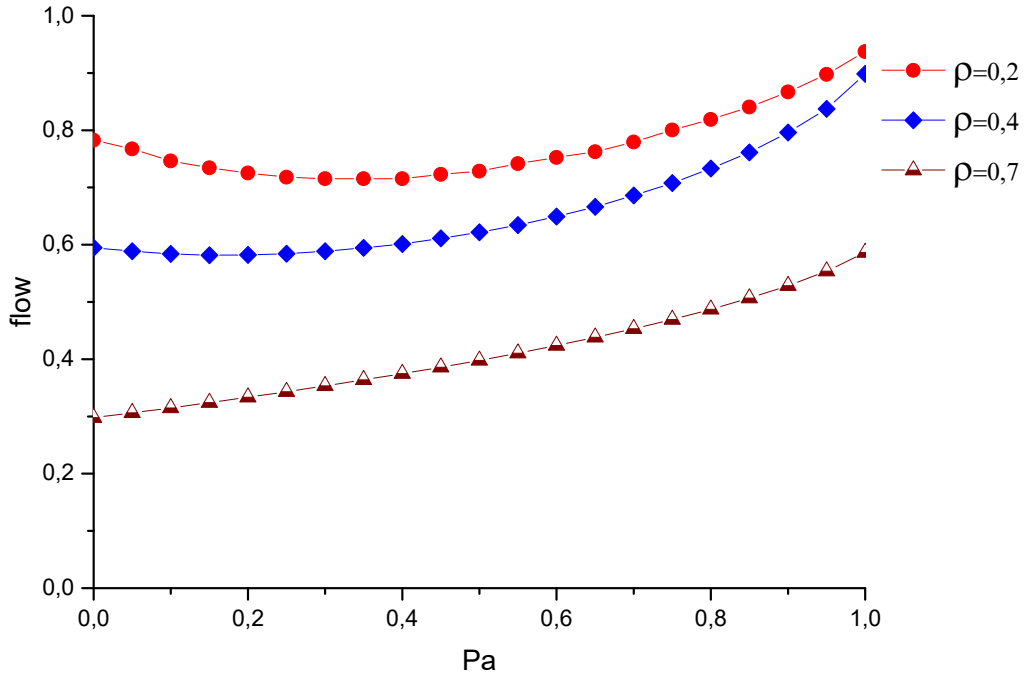


Figure 62: variation of the flow as a function of P_a that represents the fraction of aggressive drivers for different densities ρ

According to the figure 62, we observe that the evolution of the flow varies with respect to P_a . Indeed, for low densities, the flow plot evolves from a parabolic shape to a linear shape.

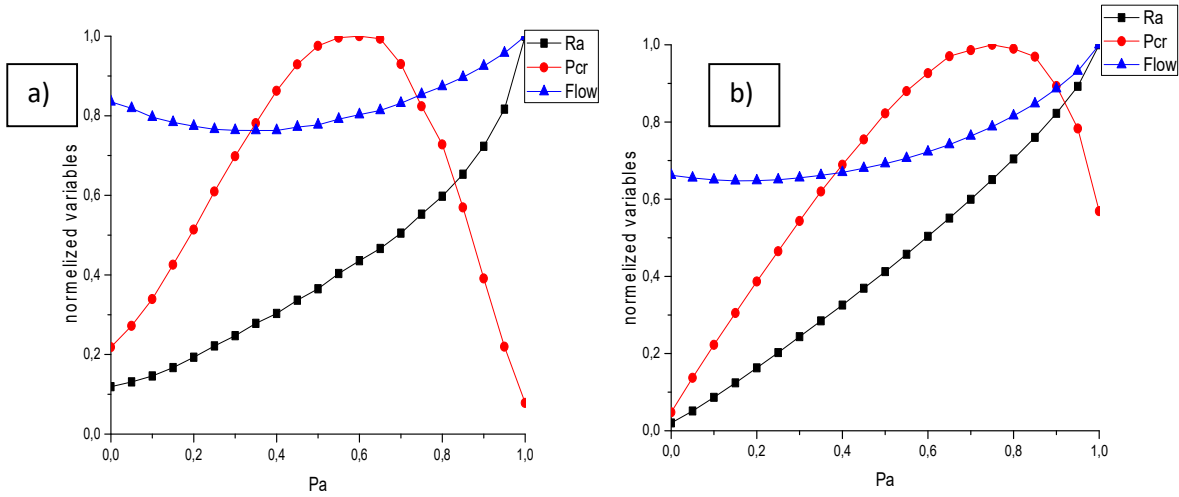


Figure 63: variation of the flow, probability of rear-end collisions P_{cr}/P_{crmax} and rate of anticipation R_a/R_{amax} as a function of P_a for a) $\rho=0.2$, b) $\rho=0.4$

To understand this behaviour, we plot the flow, the accident's and the anticipation's rates for $\rho=0.2$ (figure 63-a).

In fact, when P_a is very low, the appearance of potential accidents combined with very little anticipation leads to a decrease of the flow. When P_a reaches a threshold $P_{a_{th}}$, the probability of accidents decreases while the anticipation keeps increasing. This brings an amelioration of the flow. These same observations hold for $\rho=0.4$ with a difference in $P_{a_{th}}$ (figure 63-b).

The figure 64-a displays the variation of $P_{a_{th}}$ in function of the density. This variation of $P_{a_{th}}$ shows that there is no standard dangerous mixture of drivers that can be held responsible of the most potential accidents. The density of vehicles is the one that determines degree of risks that can face a mixed fleet.

Therefore, to guarantee a safe and fluid circulation, a combination of strong anticipation (aggressive drivers that do not respect the learning condition) and a relatively low density should be respected (figure 63-a). However, this cannot be achieved without the contribution of the V2V technologies.

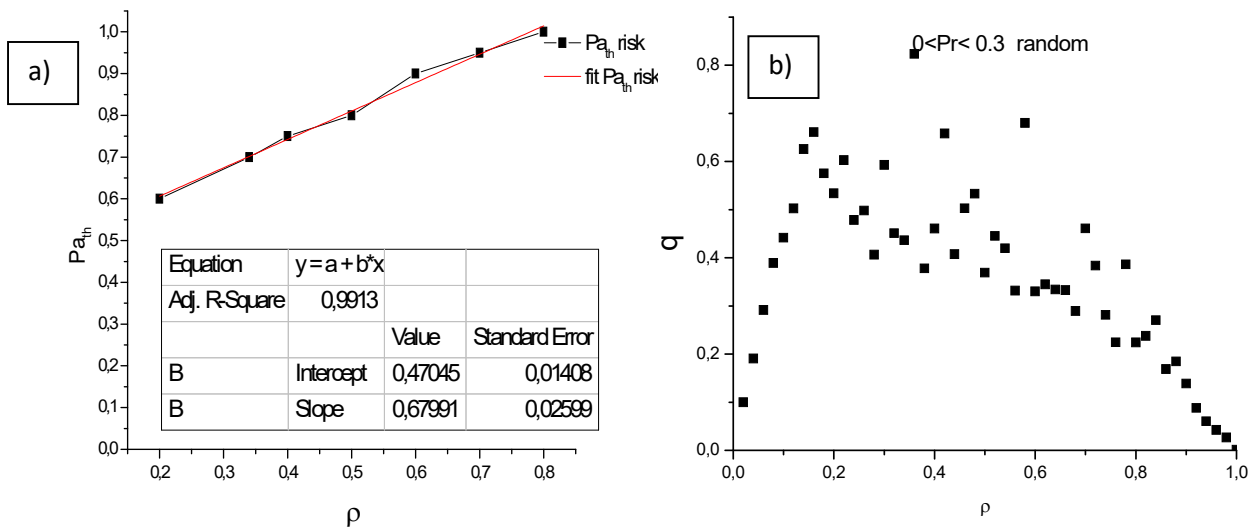


Figure 64: a) variation of $P_{a_{th}}$ in function of the density ρ ; b) fundamental diagram for random P_a : ratio of aggressive drivers, and random Pr : probability of random braking ($0 < Pr < 0.3$)

To generalize those observations on the behaviour of the flow, we plot the flow for a random Pa and a random Pr.

The figure 64-b confirms that the heterogeneity of the drivers contributes in the wide scattering of the fundamental diagram in the congestion phase.

A similar finding was developed by Sakai et al when they have found that varying deceleration and acceleration probabilities generates a variation in the magnitude of the scattered area in a fundamental phase diagram [168].

4.4. Hot spots

Behind knowing the causes of accidents, defining the region where potential accidents may take place is also crucial.

In this respect, we adopt a road of 500 cells and we insert a perturbation zone at 400 to 405 with a deceleration rate Pr=0.5. We run the simulation and we observe the spatial distribution of accidents for different densities.

We only consider conservative drivers with Pe=1.

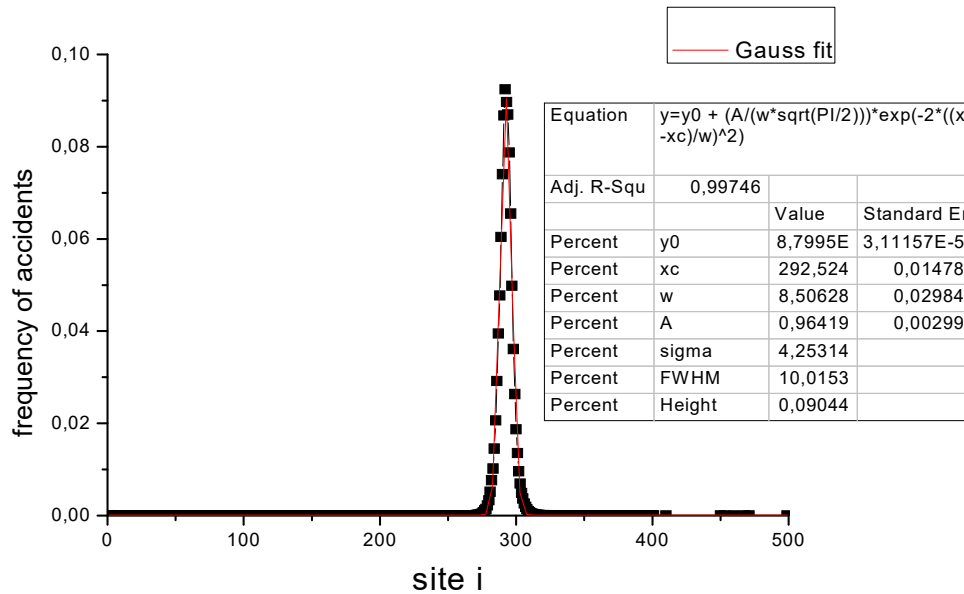


Figure 65: spatial distribution of accidents for $\rho=0.2$

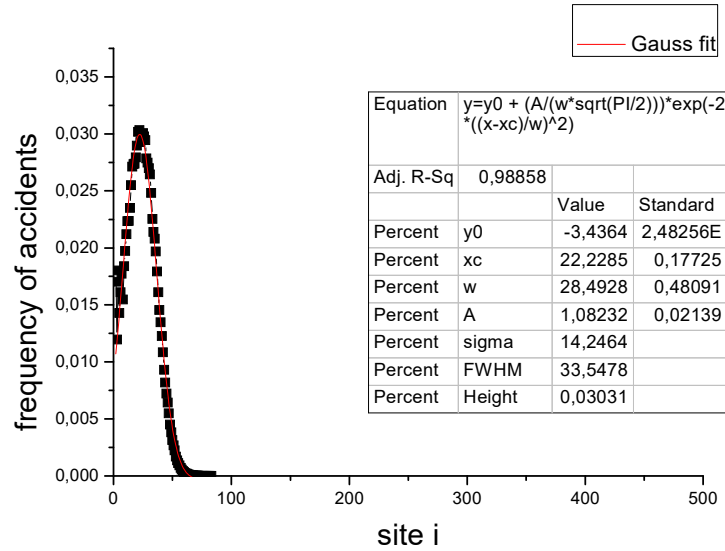


Figure 66: spatial distribution of accidents for $\rho=0.5$

We can observe that the spatial distribution of accidents follows the Gaussian law. The centre of the plot moves when we increase the density (figures 65, 66).

The perturbation zone creates a deceleration wave that generates a high density (figure 67). The dissipation of this wave generates an interface between the low and high density. This causes numerous potential accidents.

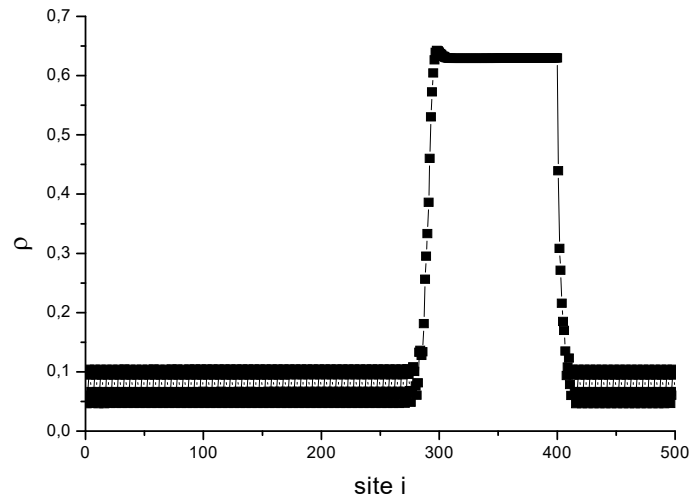


Figure 67: density profile for $\rho=0.2$

It would then more beneficial to the zone of the perturbation than the zone of the accidents.

5. Conclusion

In this section, we have tried to combine the tools of the physics of traffic (statistical mechanics) with cognitive psychology to understand how a driver's behaviour influences the traffic and vice versa.

Indeed, to analyse the safety of traffic facilities, scientists have opted for the surrogate safety measures founded models as an alternative approach to the statistical based methods. Through numerical simulations, they were able to reproduce different types of accidents by defining new parameters or incorporating additional movement steps that may be behind those incidents. However, few of these models, if not none, have considered the human behaviour when modelling collisions.

For this purpose, through the means proposed by the statistical mechanics, we developed a new cellular automata model, inspired by field experiments, in which we implemented, in addition to the regular rules of movement, the anticipation. Indeed, based on a cognitive psychological model that we named “cognitive anticipation model”, we defined the anticipation by the tendency of drivers, based on historical data of the leading vehicles, to or not to accelerate. This dilemma sectioned our article so as two study two types of drivers:

- Conservative drivers: those drivers take their decision on anticipation by judging the behaviour of their predecessor. Considering only this type of chauffeurs represents a realistic schema as far as the security aspect is concerned, since the probability of accidents is very weak and follows the Gaussian law. Moreover, those potential rear-end collisions are strongly correlated to the anticipation. Indeed, they only occur in a limited interval of densities in which the anticipation is present. This range of densities happens to correspond to the congestion state. Thus, this model's case is able to delimit the scope of the congestion state that stimulates the anticipation and may cause collisions. But more importantly, this configuration highlights the complexity of the relationship between the state of traffic and the driver response as shown by the variation of the mean learning threshold plot. Indeed, the transitions of the traffic states generate a self-organization of the drivers; either into a hazardous state ($\langle H_s \rangle = 1$) that may generate accidents or into a safe state ($\langle H_s \rangle = 5$).

Then, the anticipation represents the response of the driver, as an individual to a general situation that forced him/her to go against his/her will. This response can

have major consequences: in this case, the congestion obliged him/her to decelerate and to not adopt his / her desired speed, which urged him/her to anticipate and probably cause a collision.

- Aggressive drivers: who choose to overlook the historic of the leading vehicle and accelerate despite their analysis. Even though representing a greater risk in the higher densities, the investigation of this range of drivers has shown that allowing the existence of a small risk of anticipation would allow a significant amelioration of the flow in the congested state (up to 11% compared to the standard case of NaSch). The problem that prevails at this stage is the fact that those drivers may compromise the security of the traffic.

The dilemma of the fluidity/ security appears again but can be settled through the vehicle-to-vehicle communication technologies (V2V).

In addition, in the attempt to reproduce a real traffic situation, we studied next, a traffic flow with a mixture of both conservative and aggressive drivers. This investigation displays a scattering in the fundamental diagram. This statement joins previous statements that proposed that the heterogeneity of the traffic flow might be among of the causes behind the scattering observed in the experimental fundamental diagram.

Furthermore, we inspected the features of hot spots. We found that to resolve this problem, measures should be taken at the perturbation zones instead of the accidents areas, since the latter strongly depend of the density. Moreover, this finding has highlighted the complexity of the information transmission and reception while driving.

Actually, the anticipation can be reduced to the simple fact that a driver would expect the leading driver to free his/her position at the following instant. This prediction is generally the result of a long process of learning and is expected to always be successful. However, sometimes, anticipation leads to collisions. In fact, each vehicle I only reacts with respect to the vehicle $I+1$ in front of him/her, the vehicle $I+1$ with $I+2$ and ongoing to $I+n$ with $I+n+1$. Thus, if a perturbation occurs at the position of $I+n+1$ at an instant t , a shock wave of which the speed is unknown for the drivers, would form at this same position $I+n+1$ and the same instant t . It is then impossible to predict when and where this information (deceleration) wave would reach the vehicle I . Subsequently, this uncertainty makes the learning process limited in space and time, which generates rear-end collisions.

It is worth to mention that we have based our investigation on only one type of anticipation, which is the anticipation by acceleration that we have considered as a major cause of rear-end collisions. However, even if this investigation has brought into the evidence interesting information about the mechanism behind the accidents occurrence, conducting extensive empirical studies to confirm our assumption seem to be an interesting field of research as far as the security and the fluidity aspects of the traffic are concerned.

General conclusion

Transportation is important in every human's life. Each day, people risk their lives by taking the roads, in order to attend their schools, go to their jobs, to entertain themselves, or for many other reasons... everyday, they are also faced by long waiting queues and acute congestion.

Being a necessity more than luxury, how can we improve people's road experience and improve their safety on a daily basis?

In this thesis, we presented our humble intake and approach to assert this dilemma.

Our work was divided into two main sections:

- The effect of anisotropy on the traffic flow behavior: investigation of a single node: in which we highlighted the correlation between two roads connected via a node and where no lane changing is allowed; in other words, we underlined one of the phenomena that are responsible of congestion propagation in connected roads (traffic networks)
- Cognitive anticipation cellular automata model: an attempt to understand the relation between the traffic states and rear-end collisions: in which we have investigated the impact of human behavior "anticipation" on road safety and its relation with the traffic fluidity.

1. The effect of anisotropy on the traffic flow behavior: investigation of a single node:

In this section, we have studied a quasi-one-dimensional system, composed of two roads connected via a single node and where no lane changing is allowed. We were able to point out a self-organization behaviour and to exhibit the correlation of the two roads.

In our investigation, we started by considering a two-lanes road of which both lanes are identical and of which the entry is neutral (when both first sites are empty, the upcoming vehicle is injected randomly). Then, we altered the characteristics of one lane and observed the response of the second lane. Among those alterations, we created a perturbation in one of the lanes that may push more vehicles to enter the other lane. We implemented a compact default into the first lane with a deceleration probability. Subsequently, those changes generated new current and density behaviours on both lanes and brought out new system-organization's features. Indeed, a spontaneous symmetry breaking is observed. Those observations made us conclude

that privileging one lane over the other creates a self-anisotropy within the system that would overcome it through a self-organization mechanism operating in the node. Finally, we were capable of presenting a diagram that displays this self-organization with respect to the different density phases.

Moreover, we have computed the cross-correlation of the flows of the two lanes. We found that they are strongly correlated when in symmetric phases. This finding brought us to our second step of investigation.

In order to bring more details about what truly happens in the system when one of the lanes is privileged, we adopted a quasi-one-dimensional system of two identical lanes and we have implemented an extrinsic anisotropy parameter P_i into the entry. This parameter proceeds only when the two first cells are available and pushes the vehicle to choose a lane over the other. In this respect, firstly, we plotted the phase diagram of the system which highlighted the existence of an asymmetric phase of transition. Then, we studied the occurrence of the different injection scenarios and the cross-correlation rates between them in order to interpret, microscopically, the different phases. We found that the two main scenarios, that overtake the system and that pseudo-alternate, are strongly correlated. This correlation highlighted a self-organization within the system, which guarantees the establishment of the different phases. To conclude this investigation, we needed to confirm the correlation of the two roads. Consequently, we plotted the cross correlation between the main traffic observables (flows) of the two lanes. We found that the two lanes are correlated in the symmetric phase while they are not when in the asymmetric phase. Moreover, this correlation does not depend on the injection strategy. This brought us to the assumption that the cross-correlation may be considered as an order parameter that characterizes the transition of a quasi-one dimensional traffic system with a junction.

The different types of nodes have a major impact on the performance, the levels of service and the safety of connected facilities.

We attempted to understand microscopically, the impact of the differences between a merging node and a diverging one on the results mentioned above.

In this respect, we considered a quasi-one-dimensional system composed of a single merging node connecting two separated roads at the left boundaries. Then, we implemented an anisotropy parameter P_e that favors one lane over the other when both exits are occupied. We were able to point out the relationship between the connected roads, in the response of the

existence of the anisotropic merge.

Firstly, we described the new response of the flow and the density of each road. While the privileged (second) road behaves as one-dimensional system, the first road undergoes two transition from the low-density phase to the high-density phase. Indeed, the latter road transits discontinuously from the low-density phase to the high-density phase and continues evolving continuously within the same phase until both the density and the flow become constant. According to a deep investigation of the velocity, we suggested that this road transits from the low-density phase to a congested phase then to a jamming phase.

Then, to understand the mechanism behind these behaviors, we investigated the merge, i.e. the ratio of occurrence of the different extraction scenarios. We found that only two scenarios control the node. Those scenarios were found to be alternating in such a way that they generate a self-organization process. The latter is confirmed by a cross-correlation of the exits guaranteeing the establishment of the different phases.

Furthermore, we found a spontaneous symmetry breaking by plotting the global phase diagram. Indeed, this diagram exhibited the existence of a symmetric low-density phase, an asymmetric high-density phase and an asymmetric phase of transition. This broken symmetry is proposed to be the organization of the system as a response to the anisotropy at the node. Finally, the flows of the two roads are strongly correlated in the symmetric low-density phase.

By comparing those results to the findings of the case of the diverge, we can state that despite the differences in the behaviors of the two roads, both the merging and the diverging nodes with an anisotropic parameter, create a cross-correlation between the two in the symmetric phases, through a self-organization process.

To sum up, in this section, we were able to demonstrate that creating anisotropy at a boundary of a non-connected quasi one-dimensional system generates a strong correlation between the two lanes through a self-organization process. We were able to confirm that the bare existence of an anisotropic node creates an important connection between the two connected segments regardless of it being a merge or a diverge. This connection is a cross-correlation that we suggest as an order parameter quantifying the transition of quasi-one-dimensional systems with nodes.

2. Cognitive anticipation cellular automata model: an attempt to understand the relation between the traffic states and rear-end collisions:

In this section, we have tried to combine the tools of the physics of traffic (statistical mechanics) with cognitive psychology to understand how a driver's behaviour influences the traffic and vice versa.

Indeed, to analyse the safety of traffic facilities, scientists have opted for the surrogate safety measures founded models as an alternative approach to the statistical based methods. Through numerical simulations, they were able to reproduce different types of accidents by defining new parameters or incorporating additional movement steps that may be behind those incidents. However, few of these models, if not none, have considered the human behaviour when modelling collisions.

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Then, the anticipation represents the response of the driver, as an individual to a general situation that forced him/her to go against his/her will. This response can have major consequences: in this case, the congestion obliged him/her to decelerate and to not adopt his / her desired speed, which urged him/her to anticipate and probably cause a collision.

- Aggressive drivers: who choose to overlook the historic of the leading vehicle and accelerate despite their analysis. Even though representing a greater risk in the higher densities, the investigation of this range of drivers has shown that allowing the existence of a small risk of anticipation would allow a significant amelioration of the flow in the congested state (up to 11% compared to the standard case of NaSch). The problem that prevails at this stage is the fact that those drivers may compromise the security of the traffic.

The dilemma of the fluidity/ security appears again but can be settled through the vehicle-to-vehicle communication technologies (V2V).

In addition, in the attempt to reproduce a real traffic situation, we studied next, a traffic flow with a mixture of both conservative and aggressive drivers. This investigation displays a scattering in the fundamental diagram. This statement joins previous statements that proposed that the heterogeneity of the traffic flow might be among of the causes behind the scattering observed in the experimental fundamental diagram.

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3. New openings:

It is worth to mention that our work may represent a descent example of a complex system, where collective behaviour cannot be generated by the superposition of individual behaviours.

On the one hand, this thesis is a humble effort aiming to shell the mechanism and the outcome of a different type of nodes and an attempt to make the first step in the path of multi-lanes systems with open boundaries. The bigger challenge would then be investigating the assembling of numerous types of nodes while keeping in mind that previously observed phenomena would not necessarily be present due to the complexity and the nonlinearity of the traffic.

Another aspect that would be challenging is confronting all the previously mentioned results to real traffic data. This would be interesting as far as it is important to verify the validity of the phase diagram and to complete the fundamental diagram. An empirical investigation would also enlarge the spectra of the types of the facilities studied. Indeed, in addition to nodes connecting symmetric roads, we would be capable of treating the effect of merging or diverging behavior on on-ramps or off-ramps, arterial and principal roads, joined roads with lane changing... We would reproduce fundamental diagram by the mean of different CA models, reinvestigate the establishment of different traffic phases... Finally, we would be able to follow the evolution of the shock waves generated by the effect of the merging behavior, calculate their velocity and define their effects and boundaries.

On the other hand, It is worth to mention that we have based our investigation on only one type of anticipation, which is the anticipation by acceleration that we have considered as a major cause of rear-end collisions. However, even if this investigation has brought into the evidence interesting information about the mechanism behind the accidents occurrence, conducting extensive empirical studies to confirm our assumption seem to be an interesting field of research as far as the security and the fluidity aspects of the traffic are concerned.

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