Simulating the Impact of Drivers' Personality on City Transit

José António Capela Dias, Penousal Machado, Francisco Câmara Pereira
CISUC, Department of Informatics Engineering, University of Coimbra
jacdias@student.dei.uc.pt, machado@dei.uc.pt, camara@dei.uc.pt

ABSTRACT
Nowadays, simulation of urban transit is an important task for major decisions in urban planning. However, current state-of-the-art simulation frameworks do not model the driver's particular behavior or approach such task in very simplistic ways. This paper tries to overcome this limitation by introducing a set of features to reproduce several aspects of a driver's personality. We conduct several experiments to assess the impact of these features on city transit. The experimental results indicate that drivers' personality has a significant impact on the flow of city transit.

Categories and Subject Descriptors
.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence – *intelligent agents, multi-agent systems.*

General Terms
Measurement, Experimentation, Human Factors, Theory.

Keywords
Experimentation, Simulation, Traffic, Driver Personality, MAS, Agent Behavior, Artificial Intelligence, Ant Colony Optimization.

1. INTRODUCTION
The study of urban traffic is an increasingly important field given the need to explore new traffic-control strategies and to make important decisions in urban planning. However, infrastructure modifications often have high costs and the consequences of such changes must be studied thoroughly. Traffic simulators provide a cost-effective way to model traffic flow in a realistic manner, being used to predict the consequences of infrastructure modifications and to understand certain traffic phenomena.

Current microscopic traffic simulators allow for an agent-based simulation, enabling the individual modeling of vehicles and allowing us to control/influence their behavior. These tools already include important driving behaviors such as car following and lane changing. However there is room for improvement, especially regarding personality. Personality traits and emotions influence the way drivers behave and can consequently have an impact in the entire system in which the driver is involved. In order to achieve a more realistic portrayal of real life traffic we propose studying the effect of personality parameters such as distraction, stubbornness, irregularity and aggressiveness. Our main contributions are:

- the introduction of a set of features that are able to reproduce several aspects of a driver's personality;
- the study of the impact that these personal features have on city transit.

This paper is structured as follows. In section 2 we present the state of the art on driver's behavior. Section 3 describes the tool used in the development of this work. Section 4 explains the developed architecture, experiments and assumptions. Section 5 presents the results, which are discussed in Section 6. Finally, in Section 7, we present the final conclusions.

2. STATE OF THE ART
Current state-of-the-art simulation frameworks either do not model the driver's particular behavior or have a somewhat simplistic approach regarding such modeling.

For example, the work of Vaa [1] is focused on the lack of understanding of human cognition in the current state of the art and the need for a deeper understanding of risk compensation. Older theories affirm that drivers have a "target level of risk". However, Vaa believes that this concept does not grasp the varied dynamics of thinking and feeling and should not be regarded as a number, but as a feeling. So it should be replaced with "target feeling" concept. In conclusion he states that by combining risk monitoring and target feeling "the development of driver behaviour models can be put back on the right track.". This work pointed out some of the faults that the current state of the art presents. The following papers offer solutions to some of the problems of current traffic simulators and study some of the most relevant features needed in order to reproduce a more realistic driver's personality.

2.1 Simulating driver behavior
Ehlert & Rothkrantz [2] proposed a model based on reactive driving agents that can control a simulated vehicle and perform tactical-level driving. They utilized the *SHIVA (Simulated Highways for Intelligent Vehicle Algorithms)* simulator that models highway traffic. The developed agents combine traditional and reactive methods to execute their tasks but the emphasis is on the latter given that the response time is important. For every agent, sensor information that models a temporary representation of the world is stored in memory.. Each agent follows behavior rules that range from road following to respecting traffic lights and to performing a car-following behavior. All the behavior rules are influenced by subsequent behavior parameters: speed, gap acceptance and rate of acceleration or deceleration. The authors made experiments with a careful driver (having a low preferred speed, reasonably large gap acceptance, and a low preferred rate of deceleration) and a young aggressive driver in order to show that their driving agents exhibits human-like driving behavior and are capable of modeling different driving styles.

Demir & Çavuşoğlu [3] suggested a model to create a realistic urban traffic environment with hazardous situations in order to allow novice drivers to practice in a realistic environment. The tool they used was the *TRAFIKENT* driving simulator, which is used for driver training. They implemented different driving styles to create categories of urban drivers (e.g. private car, taxi, bus driver; slow, normal or fast driver) and for each of those drivers they implemented a behavior model that consists of two abstraction layers: *Decision Making Layer* (tactical level tasks such as determining the right of way or lane changing) and *Decision Implementation* (operational level tasks such as car following or speed adaptation). They have also implemented a mechanism to simulate driver errors and violations such as following too closely (tailgating) or mistakes in yielding right of way. They present results that validate their behavioral model being able to emulate various driving styles for different categories of drivers.

2.2 Aggressiveness

Tasca [4] performed a review of existing literature on aggressive driving and suggested that "a more precise definition of aggressive driving would focus on deliberate and willful driving behaviors that while not intended to physically harm another road user shows disregard for their safety and well-being" and that such behaviors "are motivated by impatience, annoyance, hostility and/or an attempt to save time." They state that in attitudes and behaviors the gender effects are negligible but there are substantial age-related differences. The conclusions they present are that the following factors appear to influence the likelihood of aggressive driving behavior: being young, male, in a traffic situation that confers anonymity, generally disposed to sensation-seeking, in an angry mood (likely due to events unrelated to traffic situation), having the belief that one possesses superior driving skills and finally, unexpected traffic congestions.

Laagland [5] described how aggressive driver behavior can be modeled. They acknowledge that in current driver behavior models there is an important factor missing: emotion. The most influential emotion is aggression, which can be defined with this formal description: "A driving behaviour is aggressive if it is deliberate, likely to increase the risk of collision and is motivated by impatience, annoyance, hostility and/or an attempt to save time." He presented a series of aggressive behaviors (cutting, tailgating, etc.) and categories that contribute to aggressive driving: situational and/or environmental conditions, personality or dispositional factors and demographic variables. Also, according to a study he states that driving in rush-hour traffic did not correlate with driver aggression and that aggressive driving only occurred if the congestion was unexpected. They propose that the aggressiveness of vehicles can be represented by attributing weights for personality parameters (stressful drivers, high and low aggression drivers, etc.), and by varying the age factors and the anonymity levels.

2.3 Compliance with traffic guidance

Dia [6] intended to study the individual driver behavior under the influence of real-time traffic information. In order to do that he used the data from a behavioral survey of drivers, conducted on a congested commuting corridor, to define for each individual driver a set of preferences, perceptions, goals and personal characteristics. Using a *Belief Desire Intention (BDI)* agent framework and microscopic traffic simulation model (*Quadstone*), he developed cognitive agents that possess a mental state composed by the following mental elements: beliefs (representation of current state of the agent's internal and external world), capabilities (executing actions), commitments (agreement to attempt a particular action at a particular time if the necessary pre-conditions are verified) and behavioral rules (which match the set of possible responses against the current environment). In this model, each driver is assigned aggressiveness, awareness, gender, age and familiarity with the network.

Gao & Wang [7] explored the driver's route choice behavior under guidance information with a combination of decision field theory (DFT) and Bayesian theory and developed a model that describes a driver's propensity to comply with received guidance information. They state that in human's decision-making process there is a threshold parameter that regulates the trade-off between the decision-making speed and quality (cautious drivers tend to use higher thresholds and impetuous drivers use lower values – leading to shorter deliberation times that result in insufficient data processing). They also stated that route criteria can attribute more importance to total distance or total time required to complete that route. In conclusion, they suggest that the following factors critically affect drivers' response to guidance information: the confidence level of guidance information, travel experience, inherent route preference, decision-making speed/quality and route choice criteria.

3. TOOLS

In order to simulate the traffic system logic we needed a road traffic simulator. The works of Demir [3] and Ehlert [2] propose interesting approaches but the simulators used in such works are poorly documented and the *SHIVA* project is no longer active. With that in mind, we opted for the *Simulation of Urban MObility (SUMO)* [8] which is an open source, microscopic road traffic simulation package that offers the possibility to simulate how a given traffic demand moves through a given road network. It was analyzed by Krajzewicz [9] and is described as being multi-modal, which means that there can be various types of transportation vehicles besides passenger cars. It is also purely microscopic, meaning that every vehicle has their own route, and moves individually through the network. It is a space continuous, time discrete (the default duration of each time step is one second) and collision-free system. It also offers support for implementing traffic lights. Our system used *SUMO* version 0.12.3.

4. METHODOLOGIES

In this paper, we approach this theme by using a Multi-agent System (MAS) to study the influence of drivers' personality on city transit through traffic simulation. Due to the driver behavior of the simulation tool being already implemented and to the tool's constraints we decided to develop the following personality features:

- *Distraction* – Taking a wrong turn (or several) along the route.
- *Stubbornness* – Unwillingness to accept the proposed route.
- *Irregularity* – Inability of a driver to maintain a constant speed.

- *Aggressiveness* – Defining driver types according to age, gender and temper.

4.1 System Architecture

Our system is divided into five main modules:

- *Agent*: contains all the information and actions relative to each individual agent;
- *Constants*: contains global constants that are used by the other modules;
- *Controller*: the main class – it is responsible for parsing the network file, creating the network and its population, for communicating with SUMO and for saving the simulation results to a file;
- *Network*: contains the relevant information of the network in question – the layout, the distances and time step occupancies;
- *Population*: serves as an intermediate between the Controller and the Agents and is responsible for creating the agents, parsing the route files and attributing routes to the agents and for communication.

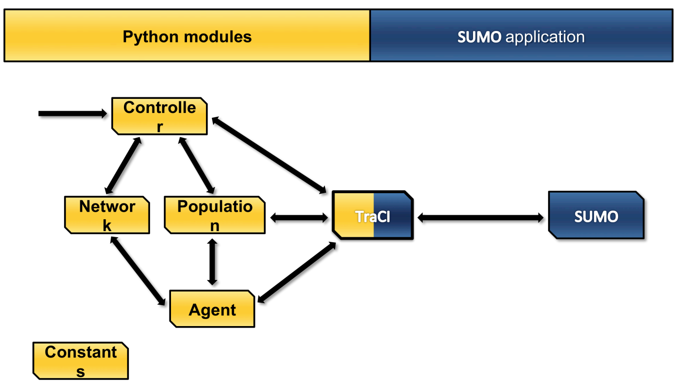

Figure 1 - Communication Process

4.2 Assumptions

The *SUMO* simulator already has the following aspects hard-coded: stopping at traffic lights, switching lanes, overtaking and applying traffic rules. So these driving parameters will not be changed. Also, *SUMO* uses a collision-free model so no traffic accidents will be considered in this work.

4.3 Personality features

The implementation of the following features intended to create a more realistic portrayal of the diversity of driver behaviors in a city. These features can be divided into two groups: the stubbornness feature which assumes the existence of an information service that provides drivers with information about traffic congestion; the distraction, aggressiveness and irregularity features which do not make that assumption.

4.3.1 Distraction

This feature represents situations in which a person is not experienced/familiar with the environment or is dealing with a high cognitive load (talking on a cell phone for example), therefore being distracted, and consequently taking one or many wrong turns along its route.

The experience/familiarity of a driver with the network in which he is traveling obviously affects the amount of wrong. A person who is very familiar with a certain route is much less prone to make a mistake along the way than a person who is traveling trough that path for the first time.

According to the *World Health Organization (WHO)* [10] a percentage between 1% and 7% of drivers have been observed using mobile phones in several European countries while driving. They also report that in the United Kingdom "45% of drivers reported text messaging while driving" and that in the United States “27% of American adults report having sent or read text messages while driving”. One of the obvious implications of this are driving accidents: *WHO* [10] refer that “in Spain, an estimated 37% of road traffic crashes in 2008 were related to driver distraction”. Being driver distraction of such importance, its influence combined with network familiarity will be studied in a route selection point of view: how distraction levels contribute to make mistakes along a certain route.

4.3.2 Stubbornness

This trait refers to the unwillingness of an agent to accept the proposed route. The rejection of route suggestion might be caused by having little confidence on the system and by the belief that drivers have in their better judgment of the current state of traffic in order to define a more suitable route.

Gao [7] suggests that aggressive drivers were less prone to act in accordance with received guidance information. However, no significant proof of this correlation was found so we will assume that stubbornness and aggression are independent.

4.3.3 Irregularity

The concept of driver imperfection refers to the inability of a driver to maintain a constant velocity, causing fluctuations in speed that affect the vehicles behind. The car-following model used in *SUMO* was developed by Krauß [11]. In it, each driver computes a safe velocity, in order to be able to brake fast enough to not collide with the vehicle ahead. In addition there is a “randomization step” in which a random amount that is uniformly distributed between 0 and $\sigma*accel$ (where σ refers to driver imperfection and *accel* refers to a vehicle’s acceleration) is subtracted to that safe velocity.

4.3.4 Aggressiveness

Dukes et al. [12] claims that aggressive driving is a growing concern. They state that "64% of Americans believed that drivers were driving much less courteously and safely than five years ago." thus being an important aspect of driving behavior.

The implemented feature refers to the definition of various types of drivers according to age, gender and temper. The work of Tasca [2] initially suggests that “gender effects are negligible but there are substantial age-related differences”. Afterwards they state that the factors which increase the probability of aggressive behavior are “being young, male, in a traffic situation which confers anonymity, generally disposed to sensation-seeking, being in an angry mood (likely due to events unrelated to traffic situation), the belief that one possesses superior driving skills and finally unexpected traffic congestions.” From these stated parameters, we will not consider the anonymity factor nor the occurrence of unexpected traffic congestions.

According to Wickens et al. [13], driver aggression is greater for males (38.5%) than females (32.9%) and younger drivers (from 18 to 34 years of age) reported the highest occurrence of perpetrated driver aggression (47.3% for females, 54.5% for males). The oldest drivers (above 55 years of age) reported the lowest rates of driver aggression: 15.1% for females and 20.9% for males.

With such data in mind we decided to create the following driver types:

– *courteous young male, courteous young female, aggressive young male, aggressive young female, courteous middle-aged male, courteous middle-aged female, aggressive middle-aged male, aggressive middle-aged female, courteous elder male, courteous elder female, aggressive elder male* and *aggressive elder female*.

Each driver type will be assigned a specific value for minimum gap acceptance, reaction time, acceleration and deceleration rates and desired speed. The minimum gap acceptance parameter allows us to simulate the tailgating behavior (following someone too closely) by defining low gap acceptance values. The tailgating phenomenon is, according to Björklund [14], the driving situation that provokes most irritation. In Figures 2 and 3 we can see the effects of differentiated minimum gap acceptance values in *SUMO*:

Figure 2 – Default *minGap* values

Figure 3 – Differentiated *minGap* values

According to Holland et al. [15] one of the personality factors that influence driver behavior is *Locus of control (LOC)*. Drivers with internal *LOC* "perceive outcomes to be dependent on their own skill, efforts or behaviour" which enables them to be more responsive than externally oriented drivers, which take fewer precautions to prevent road accidents. One consequence of internal *LOC* might be a more risky driving style, caused by the drivers' belief in their better driving skills in order to avoid an accident. Given this information, the driver's reaction time will be used to simulate the influence of *LOC* and also to simulate elderly people's slower reaction capability. However, it does not seem to exist a consensus on what is the actual correlation between the driver's reaction time and factors such as gender, age, alertness or driving experience. Davis [16], Mehmood & Easa [17], McGehee et al. [18] and Triggs et al. [19] present different values for reaction time, ranging approximately from 0.7 to 2.3 seconds. Mehmood & Easa [17] states that reaction time increases with age and that females have larger reaction times. The reaction time values used in this experiment take these studies into account. Both acceleration and deceleration rates and desired speed will be a result of the aggressiveness of the driver and also of his responsiveness.

Tasca [4] considers gender effects to be almost negligible. On the other hand, Holland et al. [15] affirm that "women have more external LOC than men". Our belief regarding this matter is closer to the opinion presented by Tasca [4], so, we considered gender effects to be almost negligible by only slightly altering parameters between male and female drivers, attributing slightly more aggressive parameters to male drivers.

Regarding age, in young drivers we defined a greater percentage of aggressive drivers, in middle-aged drivers a more balanced percentage and in elderly drivers a smaller percentage of aggressive drivers. Being predisposed to sensation-seeking and believing to possess superior driving skills are also implicitly taken into account in the cautious/aggressive driver ratio.

4.3.4.1 Aggressiveness parameters

SUMO's standard parameters' values are based on the work of Krauß [11] and are defined as follows:

```
accel="2.6" decel="4.5" minGap="2.5" maxSpeed="70" tau="1.0"
```

(where *accel* corresponds to the vehicle's acceleration, *decel* refers to the vehicle's deceleration, *minGap* corresponds to the minimum gap acceptance, *maxSpeed* refers to the vehicle's maximum speed and *tau* corresponds to a driver's reaction time).

Initially, we defined young aggressive drivers as having a small *tau* value, i.e., having a reaction time smaller than one second. However, this produced unrealistic results so we opted for only using values equal or greater than one second for the reaction time parameter.

Having this in mind, we created several driver types based on the parameters described in Table 1. It should be noted that these are merely tentative values – more attention was given to the difference of parameter values between driver types than to the parameter values themselves. However, the fact that the *minGap* parameter is only configurable in the most recent versions of *SUMO* (which currently have that previously referred bug regarding the entering of vehicles into junctions) causes widespread jams and produces unrealistic results. So, as previously stated, we opted for using a previous version of *SUMO* (version 0.12.3) that does not offer the configuration of the *minGap* parameter but in which that bug is not present.

type		acceleration (m^2/s)	deceleration (m^2/s)	sigma	maxSpeed (m/s)	*minGap (m)*	tau (s)
Young	courteous male	2,5	4,5	0,5	23	*2,5*	1
	courteous female	2,4	4,4	0,5	23	*2,5*	1
	aggressive male	3,1	5,5	0,4	33	*1,2*	1
	aggressive female	3	5,4	0,4	33	*1,3*	1
Middle-aged	courteous male	2,4	4,1	0,6	21	*2,5*	1,5
	courteous female	2,3	4	0,6	21	*2,5*	1,5
	aggressive male	2,9	5	0,5	28	*1,6*	1,3
	aggressive female	2,7	4,9	0,5	28	*1,7*	1,4
Elder	courteous male	2,3	3,8	0,7	19	*2,5*	1,9
	courteous female	2,2	3,7	0,7	19	*2,5*	2
	aggressive male	2,6	4,5	0,6	25	*2*	1,7
	aggressive female	2,4	4,4	0,6	25	*2,1*	1,8

Table 1 – Aggressiveness: driver types

5. EXPERIMENTATION

The objective of this work's experiments is to evaluate the influence of the personality parameters in a network's performance. As a proof of concept we ran experiments for two different traffic networks simulating two different situations. So, the testing process was executed in two different networks: *Lattice* and *Radial and Ring*. These networks are illustrated in the following figures:

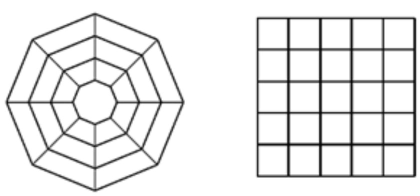

Figure 4 – Radial and Ring (left) and Lattice networks (right)

In this paper we study the overall effects that these features will have in city traffic. Therefore, the results shown in the following sections refer to the average travel time in the given scenario. For example, we do not intend to study the number of wrong turns that a distracted user makes along the way but rather the effects that those wrong turns will produce in the overall traffic.

5.1 Experimental Setup

We compare the results obtained with the developed personality features to those of a default *SUMO* population (i.e. a collection of vehicles with standard values) on the *Lattice* and *Radial and Ring*. We experimented with 5.000 vehicles and 10.000 vehicles to enable the occurrence of some congestion on the networks. The developed features were at first tested separately and afterwards simultaneously.

5.1.1 Distraction

Before beginning the simulation, we attributed a random value to each driver to represent the *distraction* and *familiarity* parameters. A distracted user who is also unfamiliar with the network will have a distorted view of the network. We simulate this error making process by tampering with each driver's perception of the network, altering the weights that a driver associates with each edge:

```
if (distraction > distractionThreshold) and (familiarity <
familiarityThreshold):
   for edge in graph:
      for sucessor in graph[edge]:
         distance = graph[edge][sucessor]
         graph[edge][sucessor] = distance +
                                 random.uniform(-distance, distance)
```

These random values follow a Gaussian distribution with mean value $\mu = 1$ and variance $\sigma^2 = 0{,}25$ so:

- value < 1 corresponds to a 50% probability;
- value > 0.75 corresponds to a 84,4% probability;
- value > 1 corresponds to a 50% probability;
- value > 1.25 corresponds to a 15,6% probability.

Given this, we decided to experiment with three different values for the distraction threshold and one for the familiarity threshold:

- <u>*high distraction*</u>*:*
  distractionThreshold > 0.75 and *familiarityThreshold* < 1
- <u>*medium distraction*</u>*:*
  distractionThreshold > 1 and *familiarityThreshold* < 1
- <u>*low distraction*</u>:
  distractionThreshold > 1.25 and *familiarityThreshold* < 1

We decided to only allow drivers who are not very familiar with the network to take a wrong path, and therefore only 50% at most can make wrong decisions. Then we varied the *distractionThreshold* to simulate different amounts of distracted drivers. In terms of probabilities, the three scenarios have the following probabilities:

- *high distraction:* 42,2%;
- *medium distraction*: 25%;
- *low distraction*: 7,8%.

Figures 6 and 7 refer to experiments with these three scenarios and the assumption that every driver uses the *IACO* [20] system.

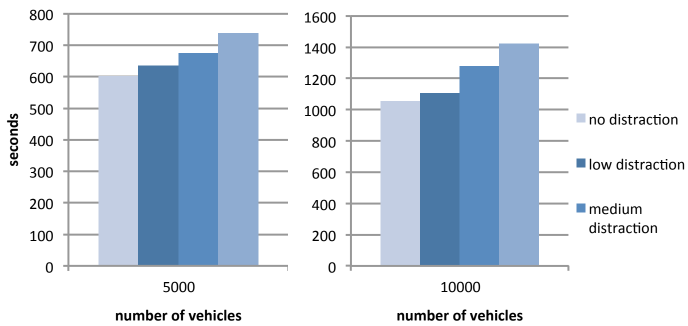

Figure 6 – Distraction: effect on trip duration with IACO algorithm (Lattice map)

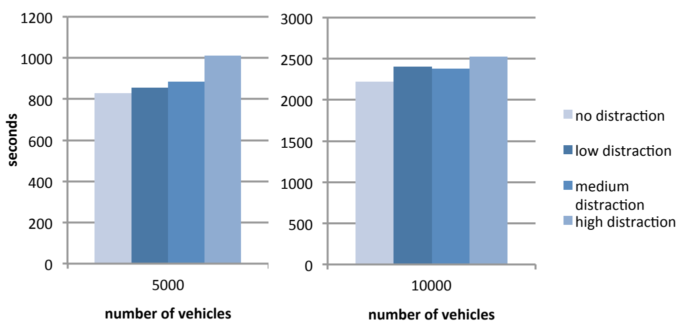

Figure 7 – Distraction: on trip duration with IACO algorithm (Radial and Ring map)

In Figure 6 we observe that in the *Lattice* map, distraction is always harmful to overall network performance. However, in Figure 7 we can observe that in the *Radial and Ring* map – which is more prone to congestion occurrence given its topology – when heavy congestion occurs, a medium distraction is the least harmful of the three levels in terms of average travel time.

We also experimented varying the user percentage in the *Lattice* scenarios, in which the distraction effects seem to be more consistent.

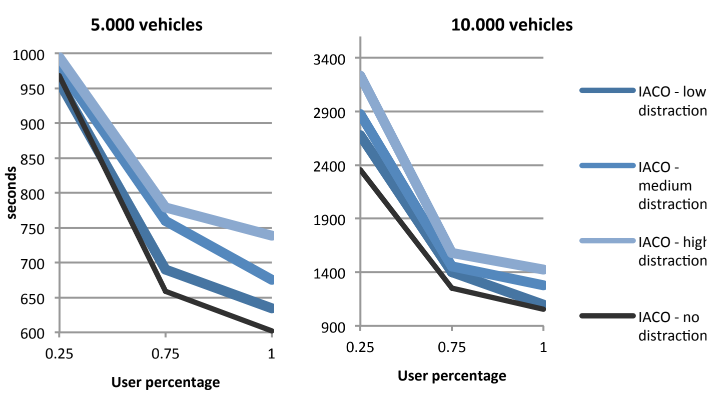

Figure 8 – Distraction: effect on trip duration with IACO algorithm (Lattice map)

As it can be observed in Figure 8, in the *Lattice* map distraction always has a detrimental effect on performance, independently of the percentage of users that adopted the system. It appears to be particularly harmful with a high traffic load and low user percentage – in that scenario, the few drivers that are using the system are evaluating the network incorrectly and therefore are not always choosing the correct path, greatly diminishing the system's accuracy. However, as user percentage rises, this effect seems to be mitigated.

5.1.2 Stubbornness

The work of Bonsall & Joint [21] suggests that there are numerous factors that affect the credibility of received guidance information, including “the extent to which it is corroborated by, or in conflict with, local evidence about the alternatives”, a “drivers’ familiarity with the local network” and “the drivers’ predisposition to accept advice”. Given this information we defined the following driver parameters:

- *experience:* the drivers’ familiarity with the local network;
- *stubbornness:* the drivers’ predisposition to accept advice.

Similarly to the distraction feature, prior to the start of simulation, we attributed random values to each driver to represent the *stubbornness* and *experience* parameters. Bonsall & Joint [21] also states that experienced drivers are more likely to reject advice. We simulate the rejection process by assigning a random value that follows the same Gaussian distribution:

```
if stubbornness < stubbornnessThreshold
   and experience < experienceThreshold:
         route = newRoute
```

Chen & Jovanis [22] introduces another factor that influences route choice: the effects of a subjects’ experience regarding the usage of the guidance information – an estimation of the system's accuracy by their temporal and spatial experiences. However, these parameters result from a sequence of travels along the same path, which will enable drivers to gain knowledge about how the network operates. Our work does not support this evolution given that it pertains to a single run in which driver’s choices are modified in real time.

These random values follow a Gaussian distribution with mean value $\mu = 1$ and variance $\sigma^2 = 0{,}25$. So we defined three different acceptance values:

- *high acceptance: stubbornnessThreshold* < 1.25 and *experienceThreshold* < 1.25;
- *medium acceptance: stubbornnessThreshold* < 1and *experienceThreshold* < 1;
- *low acceptance: stubbornnessThreshold* < 0.75 and *experienceThreshold* < 0.75.

These acceptance values have the following probabilities:

- *high acceptance:* 71,2%;
- *medium acceptance:* 25,0%;
- *low acceptance:* 2,4%.

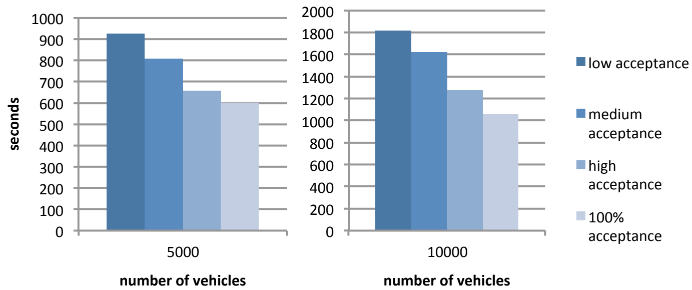

Figure 9 – Stubbornness: effect on trip duration with IACO algorithm (Lattice map)

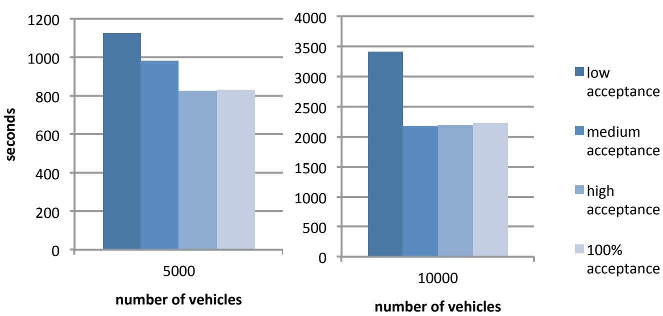

Figure 10 – Stubbornness: effect on trip duration with IACO algorithm (Radial and Ring map)

Figures 9 and 10 refer to experiments with these three scenarios. In Figure 9 we observe that in the *Lattice* map, as the acceptance levels increase, so does the system's performance. However, Figure 10 shows that in the *Radial and Ring* map (more prone to congestion), when heavy congestion occurs, the rejection of some of the proposed routes might even be advantageous in terms of average travel time.

The previous experiments were executed using the *IACO* algorithm. We decided to also experiment the *ST* algorithm in these same scenarios, in order to analyze if the effects of the stubbornness feature were similar.

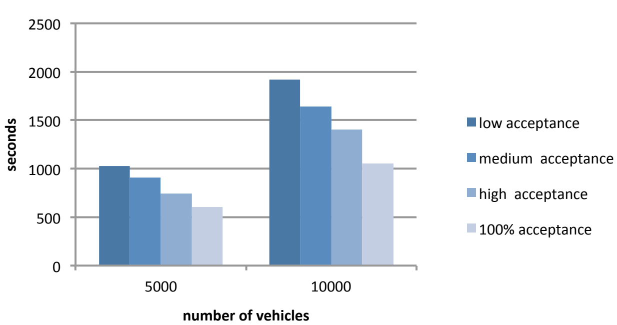

Figure 11 – Stubbornness: effect on trip duration with ST algorithm (Lattice map)

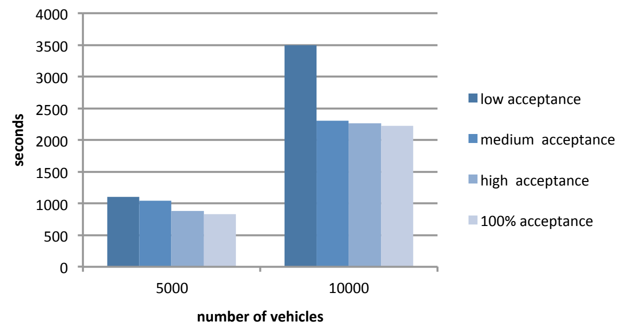

Figure 12 – Stubbornness: effect on trip duration with ST algorithm (Radial and Ring map)

In Figures 11 and 12, the results confirm that there is a similarity between the performance of the *IACO* algorithm (Figure 7 and 8) and the *ST* algorithm regarding the stubbornness parameter. The main difference is that the rejection of some of the proposed routes is never advantageous in terms of average travel time, not even in the *Radial and Ring* map with heavy congestion.

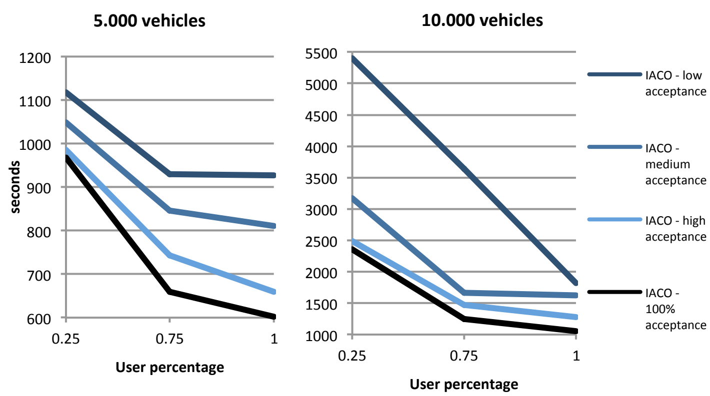

Figure 13 – Stubbornness: effect on trip duration with IACO algorithm (Lattice map)

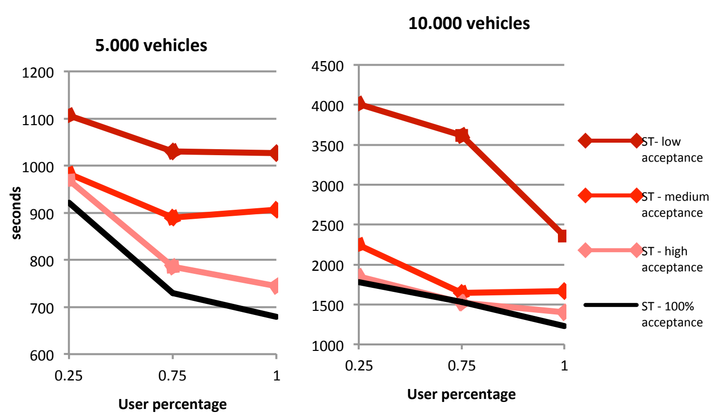

Figure 14 – Stubbornness: effect on trip duration with ST algorithm (Lattice map)

We also experimented varying the user percentage in these scenarios. Figures 13 and 14 demonstrate that in both algorithms the overall performance of the network increases with the acceptance level of the system. They also show that, for both algorithms, the efficiency deteriorates for high user percentages – it seems to stagnate in most cases.

5.1.3 *Irregularity*

According to Triggs and Harris [19], the structure of the model dynamics, such as overreactions **(**where drivers deliberately slow down to velocities lower than necessary) or reduced outflow from jams, "is mediated exclusively by the fluctuations that are introduced ad hoc through the randomization step. If these fluctuations are eliminated, none of the properties of traffic flow is modeled correctly anymore."

Experimentations were performed for high (σ = 0,8) and low (σ = 0,2) values of σ. The results are presented in figure 13.

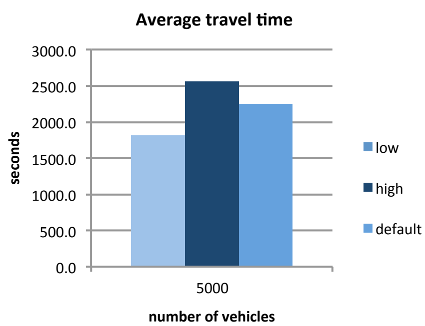

Figure 15 – Effects of irregularity

As we can observe in Figure 15, a greater *driver imperfection* leads to a worse performance in terms of travel time. On the other hand, a low value of *driver imperfection* allows for a significant decrease in the average travel time.

5.1.4 *Aggressiveness*

To experiment the created driver types we executed separate simulations for each age group. A study by the United States Department of Transportation [23] based on data from 2007, shows that there are no significant differences in driver population as far as gender is concerned. So, we established the following population distribution:

Type	Probability		
	Young Population	Middle-aged Population	Elder Population
courteous male	20%	30%	40%
courteous female	25%	35%	45%
aggressive male	30%	20%	10%
aggressive female	25%	15%	5%

Table 2 – Driver populations: type distribution

The study by the United States Department of Transportation [23] also reveals that, on a population of over two hundred million American drivers, the age distribution is approximately as presented next:

- from 16 to 39 years of age ≈42%;
- from 40 to 64 years of age ≈45%;
- above 64 years of age ≈13%.

Therefore, and in order to experiment all the driver types simultaneously, we established the following population distribution:

Type	Probability			
	Young	Middle-aged	Elder	Total
courteous male	8%	12%	8%	28%
courteous female	10%	14%	9%	33%
aggressive male	12%	8%	2%	22%
aggressive female	10%	6%	1%	17%
Total	40%	40%	20%	100%

Table 3 – Aggressiveness: mixed population distribution

Figures 16 to 19 show a comparison between population containing these age groups and a default SUMO population for 5.000 and 10.000 vehicles.

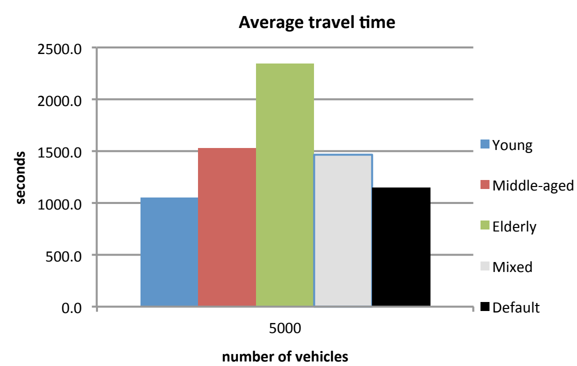

Figure 16 – Aggressiveness: effect on trip duration (Lattice map - 5.000 vehicles)

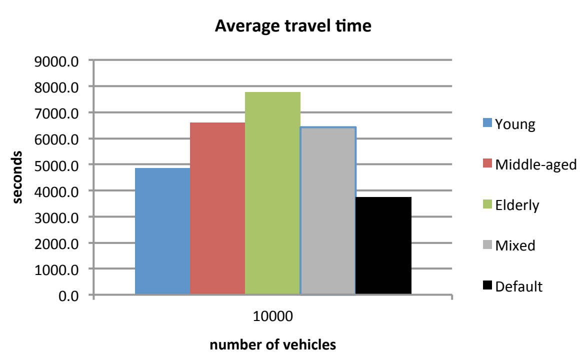

Figure 17 – Aggressiveness: effect on trip duration (Lattice map - 10.000 vehicles)

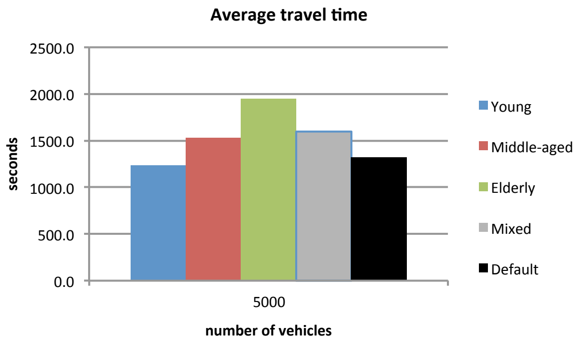

Figure 18 – Aggressiveness: effect on trip duration (Radial and Ring map - 5.000 vehicles)

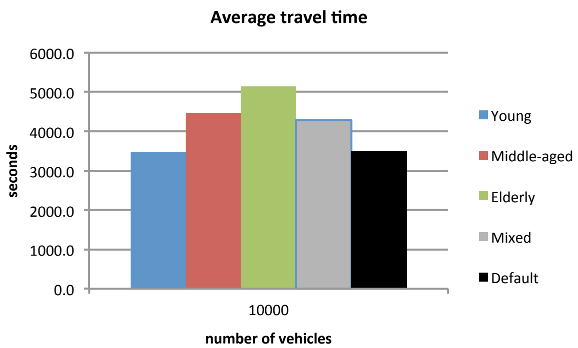

Figure 19 – Aggressiveness: effect on trip duration (Radial and Ring map - 10.000 vehicles)

As it can be observed the faster and more aggressive driving style performed by young drivers achieves a better performance than other alternatives in both maps. The groups that integrate middle-aged or elderly drivers in its population obtain worse results due to their poorer acceleration capabilities, lower maximum speed and higher reaction time. The elderly group attains the worst results for both maps, given their slower driving approaches. As the traffic load increases the difference in performance shortens, although young drivers still achieve better results than the other population groups.

Regarding the *Lattice* map, we can observe that for a smaller traffic load, the young population achieves a slightly better performance than the default population. However, when the traffic load increases its performance deteriorates, obtaining poorer results than its default counterpart. This might be due to the fact that the more aggressive driving style performed by young drivers only makes them reach the congested areas sooner, consequently increasing congestion and waiting times.

In relation to *Radial and Ring* map, and similarly to the Lattice map, we can observe that for a smaller traffic load, the young population achieves a slightly better performance than the default population. With the increase in vehicles in the network, young driver's higher speed and acceleration do not seem to make any difference, suggesting that congestion is so great that there is not enough space available for these parameters to have a positive influence. On the other hand, the other driver groups approximately maintain their performance.

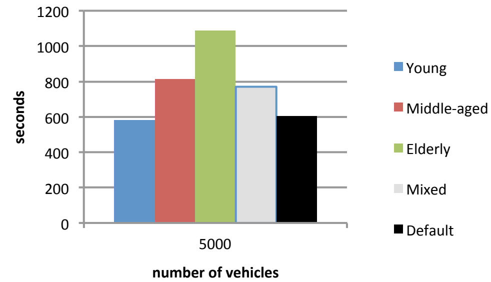

Figure 20 – Aggressiveness: effect on trip duration with IACO algorithm (Lattice map)

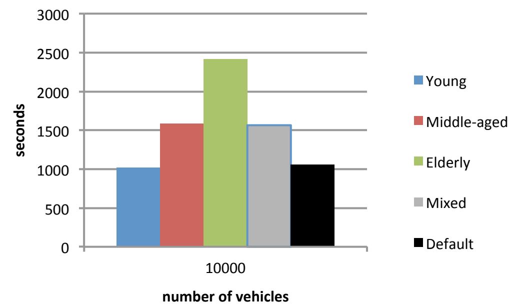

Figure 21 – Aggressiveness: effect on trip duration with IACO algorithm (Lattice map)

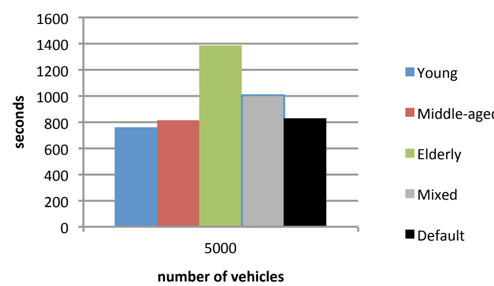

Figure 22 – Aggressiveness: effect on trip duration with IACO algorithm (Radial and Ring map)

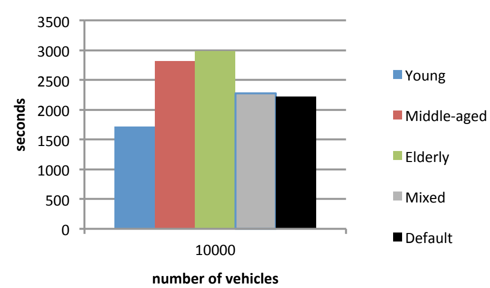

Figure 23 – Aggressiveness: effect on trip duration with IACO algorithm (Radial and Ring map)

Figures 20 to 23 show a comparison the same populations as before but now using the *IACO* algorithm. We can observe that, similarly to the previous experiments, the young drivers achieve a better performance than other alternatives in both maps and that the elderly group attains the worst results in both maps.

The main difference resides in the fact that in *Radial and Ring* map, the young population obtains a slightly better performance that the default population, especially with a higher traffic load. This suggests that now, unlike in the previous scenario, there is enough space available for these parameters to have a positive influence. Given that the *IACO* distributes vehicles more evenly through the network, congestion is diminished and therefore there is room for greater acceleration and speed. Also in the *Radial and Ring* map, it should be noted that there seems to be an irregularity regarding the *middle-aged* group – with 5.000 vehicles, its performance is similar to the *young* group and with 10.000 vehicles to the *elderly* group. We believe that with further testing, the results obtained in this map would become more normalized.

Regarding the *Lattice* map, we can also observe a great improvement in the performance of the young population with a high traffic load – it now achieves results equivalent to the default population, while previously it had an inferior performance.

6. DISCUSSION

The results concerning the distraction parameter indicate that this feature only has negative effects on the network's performance because a distracted user who is also unfamiliar with the network will have a distorted view of the network. Therefore individual trips will be longer unnecessarily increase the amount of vehicles on the road at any given time. The results show that distraction is always harmful to overall network performance. However, when heavy traffic traverses a more congestion prone map, the fact that some drivers do not take the optimal route might disperse traffic and improve performance.

The stubbornness parameter can produce a negative impact on the network's performance given that rejecting the service provider's suggested route is essentially the same as not using the system, making individual trips longer and consequently deteriorating the network's throughput. The results show precisely that, demonstrating how the overall performance of the network increases with the acceptance level. However, and similarly to what happens with the distraction parameter, when heavy traffic traverses a more congested prone map, the fact that some drivers reject the suggested route might disperse traffic and improve performance.

Regarding the irregularity parameter, the results indicate that this parameter greatly influences the average travel time. However, and as previously referred, significant modifications to these values produce an unrealistic vehicle behavior. So, it was decided to only slightly alter this parameter's values. Also, we decided to incorporate this parameter into the definition of the driver population in order to differentiate precise drivers from those who are more error prone, while maintaining the validity of the properties of the traffic flow model.

The aggressiveness feature shows the influence of differentiating between age groups. The results show that when heavy congestion occurs, a more aggressive driving style by young drivers achieves a worse overall performance given that they reach the congested areas sooner, consequently increasing congestion and waiting times. So, an aggressive style is not always the most appropriate approach in order to minimize travel times.

7. CONCLUSIONS

In this paper, we presented a set of features that are able to reproduce several aspects of a driver's personality in order to overcome the fact that most frameworks do not pay special attention to the driver's particular behavior.

We developed features to simulate various driving factors such as driver distraction, which can for example be caused by mobile phones; driver aggressiveness, which varies with age, gender and temper; and driver irregularity, which allows us to differentiate good from bad drivers. Also, with the growing demand and diffusion of route planning mechanisms, we developed a feature that simulates a driver's stubbornness, i.e., his/hers unwillingness to accept the proposed route

In conclusion, this work shows how personality traits and emotions can influence driver's behavior and consequently have an impact on the whole network's performance. The developed features allowed us to achieve a more realistic portrayal of real life traffic.

8. ACKNOWLEDGMENTS

The authors are grateful for the support and advice provided by João Oliveirinha. This work was partially funded by the Portuguese Foundation for Science and Technology (FCT) under project COSMO with reference PTDC/EIA-EIA/108785/2008. It is also supported by CISUC, financed by FEDER through the POFC - COMPETE and by FCT, project FCOMP-01-0124-FEDER- 022703 and by the iCIS project (CENTRO-07-ST24-FEDER-002003) which is co-financed by QREN, in the scope of the Mais Centro Program and FEDER.

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