UNIVERSIDADE DE SÃO PAULO
POLYTECHNIC SCHOOL

BRUNO SCARANO PATERLINI

Assessment of Connected and Autonomous Vehicles impacts on traffic flow through microsimulation

São Paulo

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I dedicate this work in the first place to God.

To my wife Amanda, my daughter Lívia, to my new baby Gael, my parents Ednei and Marcia, and all who gave me support from different perspectives during this journey.

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RESUMO

Veículos Autônomos e Conectados (CAVs) são parte importante do futuro das vias inteligentes ao redor mundo. Eles são objeto de interesse dos órgãos mundiais de trânsito e da sociedade por apresentarem um grande potencial para melhoria no fluxo de tráfego, redução no número de acidentes, aumento da eficiência enérgica e redução dos níveis de emissão. A indústria e a academia vêm aumentado seus esforços e investimentos para desenvolver as várias tecnologias que irão integrar o CAV assim como avaliar o seu impacto nas vias. As fases de transição apresentam maior complexidade devido a coexistência de veículos autônomos e não autônomos na mesma via, e assim necessitam ser cuidadosamente avaliadas. Esta dissertação tem como principal objetivo desenvolver uma metodologia para avaliar o impacto dos CAVs no fluxo de tráfego em vias urbanas e rodoviárias. São também focos do estudo as fases de transição que incluem o tráfego misto dos veículos dirigidos por humanos (HDVs), veículos autônomos (AVs) e veículos autônomos e conectados. Além disso, a pesquisa avaliou como estas tecnologias afetam os tempos de viagem na presença de distúrbios e também o impacto da função de comboios automatizados pra todos os cenários dentro de ambientes urbanos ou rodoviários. O estudo foi realizado por meio de microsimulação de tráfego utilizando o software PTV VISSIM, onde os modelos de *car-following* foram desenvolvidos e calibrados. Os resultados mostraram que cenários com 100% de CAVs combinados com as configurações de tamanhos ótimos de comboio levaram a redução de até 71% nos tempos de viagem em aplicações urbanas, e de 43% em aplicações rodoviárias, quando comparados com cenários onde 100% dos veículos eram dirigidos por humanos. O estudo também traz uma avaliação focada na aplicação dos comboios autônomos em cidades e rodovias. Em general, eles apresentaram um papel importante na redução do tempo de viagem. Finalmente, os estudos mostraram que os impactos medidos no desempenho do tráfego podem variar significativamente, dependendo das características da rede e da configuração da capacidade dos CAVs. O ponto convergente é que apresentam impactos positivos.

Descritores: Veículos Autônomos e Conectados. Veículos Autônomos. Tráfego autônomo heterogêneo. Microssimulação de tráfego. Comboios Automatizados.

ABSTRACT

Autonomous and Connected Vehicles (CAVs) are an essential part of the future of intelligent roads around the world. They are an object of interest to the world traffic authorities and society. They have great potential for improving traffic flow, reducing the number of accidents, increasing energy efficiency, and reducing emission levels. Industry and academia have increased their efforts and investments to develop the various technologies that will integrate the CAV and assess its impact on the roads. The transition phases are more complicated due to the coexistence of autonomous and non-autonomous vehicles on the same path and need to be carefully evaluated. This dissertation's main objective is to develop a methodology to assess the impact of CAVs on traffic flow on urban and highway roads. The study also includes the transition phases that include mixed human-driven vehicle traffic (HDVs), autonomous vehicles (AVs), and autonomous and connected vehicles. The research evaluated how these technologies affect travel times in the presence of disturbances and the impact of automated trains' function for all scenarios within urban or road environments. The study was carried out employing traffic microsimulation using the PTV VISSIM software, where the car-following models were developed and calibrated. The results showed that scenarios with 100% CAVs combined with optimal train size settings led to a reduction of up to 71% in travel times in urban applications and 43% in road applications than scenarios where humans drove 100% of vehicles. The study also shows a specific assessment platooning applied to cities and highways. In general, the platoons can place an essential role in minimizing travel time. Finally, studies have shown that the impacts measured on traffic performance can vary significantly, depending on the network's characteristics and the configuration of the capacity of the CAVs. The convergent point is that they have positive impacts.

Keywords: Connected and Autonomous Vehicles (CAV). Autonomous Vehicles (AV). Autonomous Heterogeneous Traffic. Traffic Microsimulation. Platooning.

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LIST OF ABBREVIATIONS

ABS - Anti-lock Brake System)
ACC – Adaptive Cruise Control
ADAS- Advanced Driver Assistant Systems
AI - Artificial Intelligence
AV – Autonomous Vehicles
CACC – Cooperative Adaptive Cruise Control
CAH - Constant Acceleration Heuristics
CASE – Connected, Autonomous, Shared, Electric
CAV – Connected Autonomous Vehicles
COM - Component Object Model
CV – Connected Vehicles
CVIC - Cooperative Vehicle Intersection Control
C2C – Car to Car
C2X – Car to "X" (everything)
DSRC - Dedicated Short Range Communication
EDBM - External Driver Behavior Model
ESP - Electronic Stability Program
EIDM – Enhanced Intelligent Driver Model
FOT – Field Operational Trials
GLOSA - Green Light Optimized Advisory
HDV – Human Driven Vehicle
IBGE - Brazilian Institute of Geography and Statistics
ICV - Intelligent and Connected Vehicle
IDM – Intelligent Driver Model
IoT – Internet of Things
ITS - Intelligent Transportation Systems
LTE – Long Term Evolution
MHT - Multi-lane Hybrid Theory
NCAP - New Car Assessment Programs
OEM - Original Equipment Manufacturer
PNAD - National Household Sample Survey
RSU - Road Side Units
SAE - Society of Automotive Engineers
SDM – Smart Driver Model

SIM - Subscriber Identity Module

SPTRANS – São Paulo Transportation

SSD - Stopping Side Distance

UMTRI - University of Michigan Transportation Research institute

USDOT – United States Department of Transportation

USP – Unique Selling Point

VANETs- Vehicular Ad Hoc Networks

VDOT- Virginia Department of Transportation

V2V – Vehicle to Vehicle

V2I – Vehicle to Infrastructure

V2X -– Vehicle to Everything

V2N – Vehicle to Network

WAVE - Wireless Acess in Vehicular Environments

W74 – Wiedemann 74

W99 - Wiedemann 99

WHO - World Health Organization

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1 INTRODUCTION

1.1 CONTEXT

Humans are almost 7.8 billion people globally, and United Nations estimates that this number will be nearly 10 billion in 2050 (UNITED NATIONS 2, 2019). The world urbanization prospects from the United Nations show that big cities will continue to re (UNITED NATIONS 2, 2019) despite the pace reducing. Simultaneously, Brazil's vehicle fleet almost doubled in the last ten years, from 54.5 million in 2008 to 100.7 million in 2018 (IBGE, 2019). In the same period, road infrastructure remained at the same level (CNT, 2020). These prospects reinforce the relevance of studies on Smart Cities and Intelligent Transportation Systems (ITS) context to keep the cities sustainable.

Mobility is a basic human need, and the demand is growing mainly in metropolitan areas (MEYER and SHAHEEN 2017). The decisions on how to go from “a” to “b” when you have several mobility options involve four main factors: 1) distance and time to achieve the destination, 2) cost, 3) safety, and 4) comfort (MADHUWANTHI et al., 2015). To match all those factors, including the environment, European Commission, in 2018, delivered a communication with the directives to the sustainable mobility for Europe, which they are: safe, connected, and clean c. This directive drives the main topics for overcoming current transportation challenges of reducing traffic jams and air pollution, improve energy efficiency and accessibility for all citizens (including the elderly and disabled). At the same time, changes in lifestyle, demographic changes, and the rise of the “Mobility-as-a-Service” (MaaS) concept are paving the way for a new mobility ecosystem in urban multimodal planning (MEYER & SHAHEEN, 2017).

Following this path, the traditional Original Equipment Manufacturers (OEMs) as Audi and Daimler group in the last years have set a vision for the future of mobility based on four technology pillars: connected, autonomous, shared, and electric (AUDI, 2019; DAIMLER, 2019). The automotive business will change drastically, mainly for passenger cars. Owning a completely driverless vehicle as a personal car will not be possible for most of the population due to its cost (BANSAL & KOCKELMAN, 2017). Buying a car will be much more related to an investment where during the time one is not using it, one could offer this availability as part of the mobility service. The most interested in being large fleet owners will be experts in some core aspects of vehicles or transportation as specialists on high-tech cars maintenance or logistics, energy supply/storage companies, owners of parking places, multimodal transportations companies, among others (JIA & NGODUY, 2016).

A transition period is ongoing where the traditional OEMs and new high-tech players as Uber, Tesla, and Google frequently announce their progress on public roadside testing on autonomous vehicles. In this situation, it is clear that heterogeneous traffic will provoke a complex interaction between Human Driven Vehicles (HDV) and the driverless cars that have them from different automakers (including different systems providers) merging on the same road (GE et al., 2018).

This ecosystem will make our roads a mix of different car technologies for many years. For traffic agencies, this heterogeneous environment brings new challenges widely discussed on the legislation, legal responsibilities, cybersecurity, infrastructure, and road construction (dedicated lanes, ITS corridors) aspects.

The driverless car will require the merging o many technologies. At first, the driver assistance systems replace many technologies by perceiving the environment around and acting higher performance, reliability, and safety to take the passenger to the desired destination, known as Advanced Driver Assistant Systems (ADAS). The communication technologies complement with additional features that enable the data sharing from vehicle sensors and actuators, positioning, and routes with other vehicles, infrastructure, pedestrians, or any relevant elements. It leads to the so-called Vehicle-to-Everything communication (V2X), in close relationship with the Internet-of-Things (IoT) concept (SBD, 2018; FROST & SULLIVAN, 2017; BAILEY, 2016; AISSIOUI et al., 2018).

Vehicle-to-vehicle communication (V2V) is part of V2X using a dedicated communication protocol to enable vehicles to exchange data with each other. It can develop new features as the Cooperative Cruise Control (also called platooning or automatic convoy). It brings new possibilities to improve traffic flow. The communication between is possible due to the development of Vehicular Ad Hoc Networks (VANETs) and 5G complying with low latencies, high reliability, safety, and data security requirements (FROST & SULLIVAN, 2017; CHAI et al., 2017; AISSIOUI et al., 2018; 5G Automotive Association, 2019). The communication from the Vehicle-to-Infrastructure (V2I) brings additional possibilities for merging much real-time relevant information for improving traffic efficiency. Traffic lights timing, road signs, traffic jams, road accidents, bus service management, modals integration, and weather forecast, as well as historical data, are examples of relevant traffic-related data. These are the critical interfaces between the ITS and the Smart Cities (NETO et al., 2016; C-ITS, 2017; (CHEHRI et al., 2020). The joint of ADAS and V2X leads to Connected and Autonomous Vehicles (CAVs).

This complex combination of technologies raises many questions about validation and homologation aspects and data security robustness. Either way, vehicular field testing is essential in this process, but it is important to note that it is time-consuming and expensive. A wide variety of traffic simulators are available to support this development, playing an important role in technology assessment, either individually or in their combination (SONGCHITRUKSA et al., 2016).

The traffic simulators bring relevant outputs that can clarify different actors such as the government, industries, legal entities, and the population the real benefits that CAVs can bring to the mobility ecosystem. Therefore, traffic simulation can provide a more accurate estimation of these technologies' impact on traffic flow, test varied scenarios, and evaluate the most appropriate traffic behaviors to achieve the proposed goals (ZHANG et al., 2018).

The context where many characteristics of autonomous vehicles are required to improve traffic flow and reduce accidents will demand three pillars: the components smart cities, intelligent transportation systems leading, and automotive/technology industries. The use of traffic simulators is crucial to test hypotheses and speed up development. All these components and subcomponents were used in this research, and their interaction is described in Fig. 1.

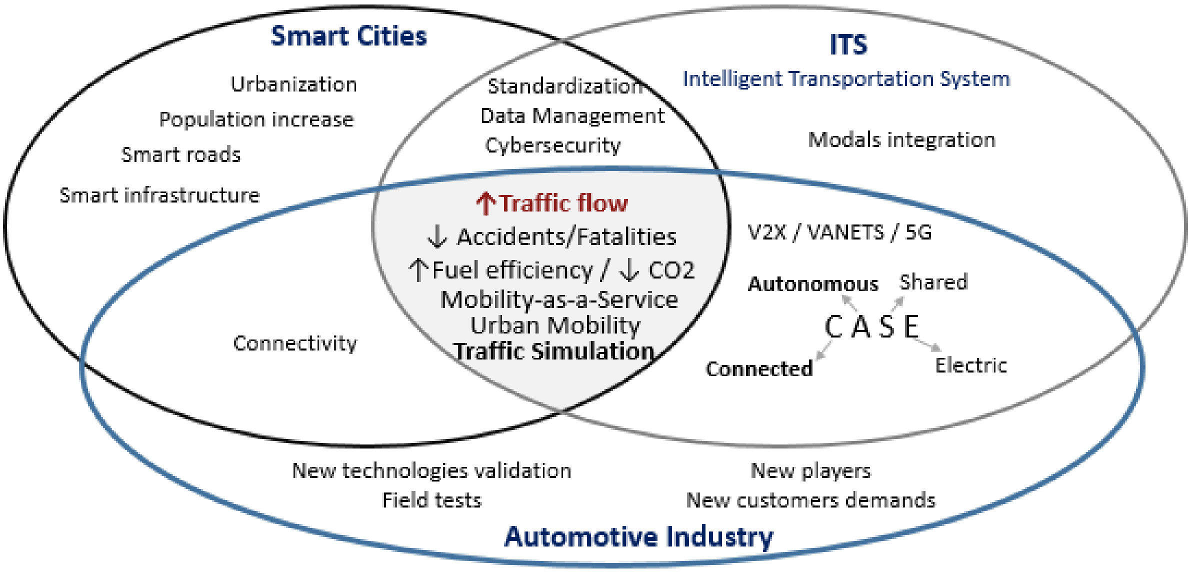


Fig. 1. Context and fields in which the research localizes.

Source: Author.

1.2 MOTIVATION

According to the Brazilian Institute of Geography and Statistics (IBGE) over National Household Sample Survey (PNAD) data from 2018 (PNAD, 2018), the average time spent from home to work in São Paulo city is around 45 minutes. More than 25% of the population spend more than 1 hour on this route. It directly affects the population’s health and the economy.

CAVs bring new possibilities to reduce travel time significantly. Delivering reliable data from CAVs benefits to Brazilian cities' context can support these technologies' deployment and speed up their introduction on the roads.

In general, the traffic behavior impacts of AVs and CAVs technologies for cities and highways are the most valuable contributions from this research. It is essential to highlight one of the key topics was to evaluate one attention point from CAVs introduction: the transitions phases. Many different aspects will occur when roads have human-driven vehicles (HDV) and vehicles with varying automation levels defined by the SAE J3016 norm (SAE, 2018).

Besides, this research can be part of a set of studies that support Brazilian government decisions to accelerate the current path on approving regulations to make safety features mandatory, as airbag and Anti-lock Brake System (ABS) in 2014 and Electronic Stability Program (ESP) that will start in 2022. It can also support the approval of regulations to allow autonomous vehicle testing on a public road.

One important topic to mention is that measuring the benefits of CAVs on traffic conditions in Brazil is a topic still few explored. A few kinds of research were released with a focus on traffic performance on national universities.

The overall motivation comes from the possibility to contribute to an emerging and trend topic that can play a critical transformation role in society.

1.3 OBJECTIVES

This research aims to analyze, identify, and quantify the benefits of traffic flow from AVs and CAVs technologies for cities and highway applications. The analysis was also extended to the heterogeneous environment where autonomous and human-driven vehicles will coexist.

The specific objectives of this research are the following.

- To understand the characteristics of traffic microsimulation and choose one that suits the model and objectives proposed in the research.
- To use a traffic microsimulation to build a model with the following characteristics:
    - High-density flow city roads in a big city in Brazil, including bus stops and the high number of motorcycles, and to measure the impacts of disturbances such as road accidents on traffic flow from that ecosystem.
    - Highway application, including merging areas and exits for mixed fleets (passenger cars, trucks, and busses).
- To assess models that describe driver behaviors: the software object of the study uses the microscopic traffic models.
- To understand which features of autonomous vehicles distinguish from those human-driven and how these characteristics interfere with traffic microsimulation models.
- To assess the impact of autonomous vehicles on travel time.
- To assess the platooning/automated convoys impact on traffic flow for city and highway traffic characteristics, including the evaluation of optimal platooning size.

1.4 RESEARCH PROPOSAL

This research looks for measuring the impacts of AVs and CAVs on the travel time for the mentioned mixed traffic environment considering big Brazilian cities' traffic characteristics. To bring new contributions, this research will evaluate for different scenarios how a disturbance (e.g., break down vehicle) affects traffic performance and proposes a rescue vehicle shared model to fasten attenuate the disturbance effects. Moreover, platooning features were evaluated to simulate CAVs characteristics. It was recently integrated into PTV VISSIM in September 2019. Fig. 2 illustrates the research gap.

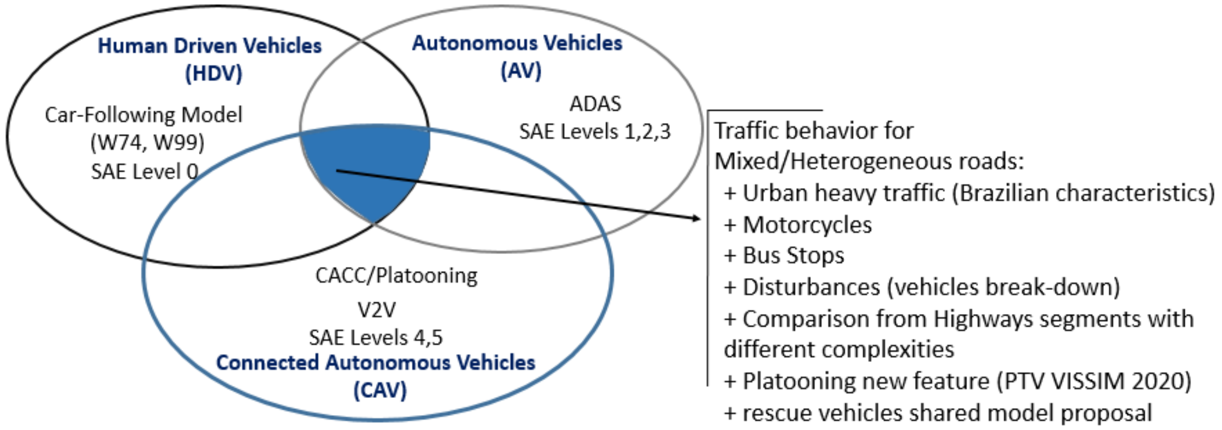


Fig. 2. The research gaps.

Source: Author.

Considering this research gap and topics that will be handled, this research aims to answer the following question:

- How will the CAVs influence traffic travel times for big cities and highways scenarios, including the transition phases?

1.5 DOCUMENT ORGANIZATION

The rest of this document is organized as follows.

Chapter 2 gives an overview of the key concepts from the automotive industry's future that drives this research, including the idea of CAVs and the tool used to develop this research: traffic microsimulation.

Chapter 3 describes and discusses the literature review from CAVs traffic simulation and the measured benefits on traffic flow.

Chapter 4 formally states the problem and the methodology to study the issue.

Chapter 5 describes the methods, materials, scenarios evaluated, and software setups to validate the study.

Chapter 6 presents experimental results, the comparison between scenarios, and the discussions.

Finally, chapter 7 describes the conclusions of this research and suggestions for further investigations.

2 KEY CONCEPTS OF CONNECTED AND AUTONOMOUS VEHICLES AND TRAFFIC SIMULATION

Connected and autonomous vehicle (CAV) research and developments are mainly focused on the following aspects: to reduce accidents, to increase fuel efficiency, to reduce emissions, and to improve traffic flow. To achieve that target, the vehicles need to be equipped with proper systems and technologies (PENDLETON, et al., 2017).

The most central concept when it comes to autonomous vehicles is to understand their classification. After many years of divergence, SAE International (Society of Automotive Engineers) released the first worldwide-adopted taxonomy and definitions for terms related to driving automation. The standard J3016 was first released in 2014 with two additional revisions in 2016 and 2018 (SAE, 2018). **Fig. 3** shows a timeline with the evolution of this definition.

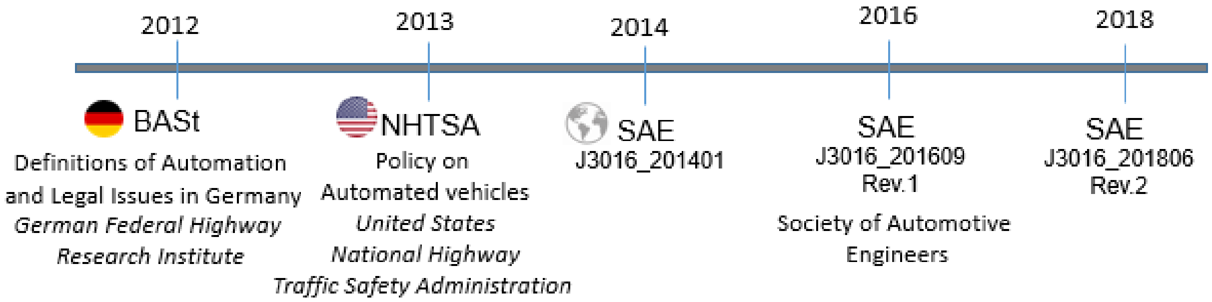


Fig. 3. Taxonomy timeline of vehicle automation level standardization.
Source: Author.

The standard classifies six different levels, from no automation to full automation. The higher the automation level is, the lower is the driver inputs dependency. Nevertheless, the higher the automation, the higher the Advanced Driver Assistance Systems (ADAS) dependency requires an incremental combination of sensors (ultrasonic, camera and LiDAR), the control of active drivability systems vehicle communication features. In fact, on SAE Level 5, the vehicles will not need a physical accelerator, brake pedals, or steering wheels; the driver will become a passenger (SAGIR & UKKUSURI, 2018).

Fig. 4 shows the definition of each automation level and ADAS examples.

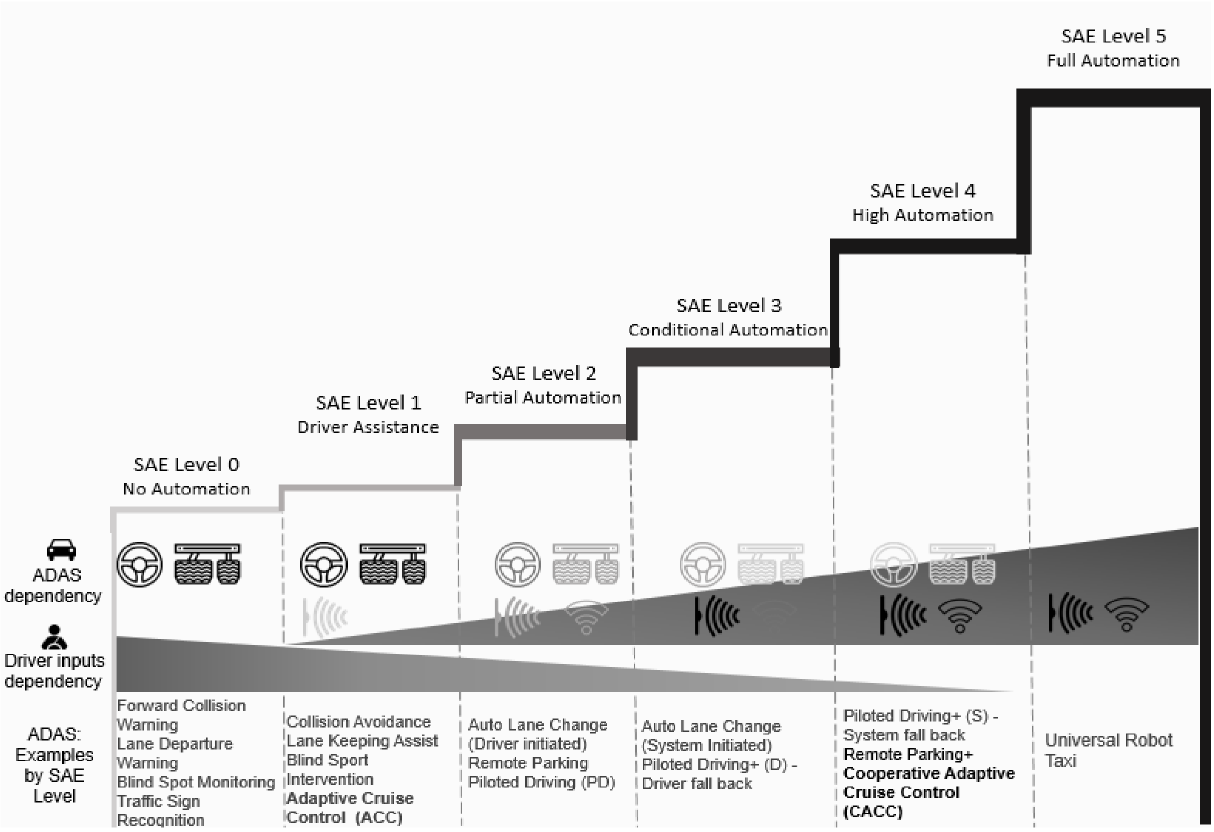


Fig. 4. SAE automation levels.

Source: Adapted from SAE J3016 (SAE, 2018).

To illustrate the path of automation level development, Audi A8 was the world's first production car to have achieved Level 3 (IEEE Spectrum, 2017). Companies are focused on Level 4 automation within geographical areas or weather conditions (ANDERSON, 2020). Waymo from the Alphabet group announced their first tests on level 4 vehicles on streets in October 2017 (WAYMO, 2020). In partnership with Torq Robotics, Mercedes-Benz started the first public road test of an autonomous truck, Level 4, in September 2019 in Virginia, USA, expanding this test to new public routes (DAIMLER TRUCKS, 2020).

To understand the autonomous vehicles' benefits on traffic performance, it is essential to explore some crucial concepts from vehicle dynamics, traffic engineering, and driver behavior. Let us consider **Fig. 5** to illustrate traffic engineering parameters.

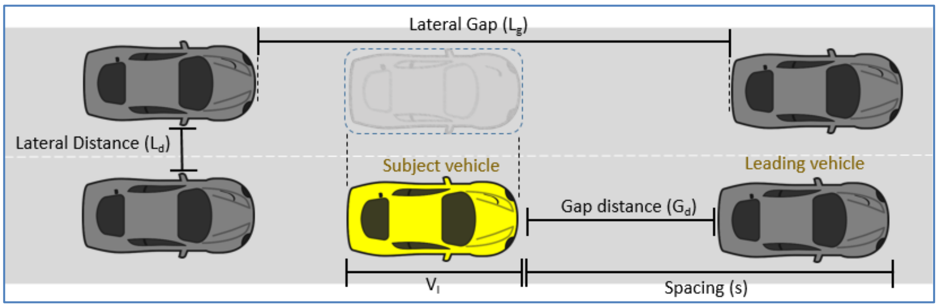


Fig. 5. Traffic engineering parameters

Source: Author.

The following is a description of the parameters shown in Fig. 5.

- **Spacing (s):** is the distance between the front bumper of two consecutive vehicles.
- **Gap distance (G_d):** is the distance between the rear bumper of the leading vehicle and the subject vehicle's front bumper, where headway focuses on front-to-front spaces.
- **Headway (h):** a measure of the temporal space between two vehicles. The front bumpers of successive cars are used as a reference.
- **Time Gap (T_g):** a measure of the temporal space between two vehicles. Anyhow the references now are the rear bumper and front bumper of successive cars. The time gap is the ratio between spacing and speed. This concept is linked to driver behavior, so-called safety distance. The higher the speed, the higher the distance a human driver maintains from the vehicle forward. It is essential to mention that this safety distance is not proportional to human drivers' vehicle brake performance. It means that independent from the brake performance one individual in a determined vehicle speed will keep the same time distance.
- **Lateral Gap (L_g):** is the front to rear bump distance between two vehicles placed at the subject vehicle's side lane. This distance affects the driver’s behavior decision of lane changing. It also affects the possibility of traveling at a higher speed if the driving condition in the target lane is better than that in the current lane (YE & YAMAMOTO, 2017). The perception of a proper lateral gap to perform the maneuver is also dependent on the speed.
- **Lateral distance (L_d):** is the distance between side-by-side vehicles. The lateral mirrors or cameras are used as a reference. This concept is especially relevant for traffic jams.
- **Driver reaction time (R_T):** usually defined on simulations as the time lag that the follower uses to react to the leader's change in driving behavior during a car following. In real traffic, it corresponds to the time delay between the brake lights lit from the leading vehicle and the brake pedals touch in the pursuing car. It is affected by several factors on a human-driven vehicle, from the driver distraction to the driver experience (ZHANG & BHAM, 2007; WERF, SLADOVER, MILLER, & KOURJANSKAIA, 2002).
- **Stopping Side Distance (SSD):** is the distance a vehicle needs to a full stop. It is a consolidated formula used in the transportation engineering field (FHWA, 1997) which the mathematical model is described as:

$$SSD = 1{,}47V(RT) + \frac{V^2}{2g[f \pm \left(\frac{G}{100}\right)]} \tag{1}$$

where *SSD* is the Stopping Side Distance (m), *V* is the vehicle speed (km/h), R_T is the driver Reaction Time (s), *g* is the gravity, *f* is the friction coefficient, and *G* the inclination or slope (%).

In Table 1, it is presented as a numerical example from equation 1. The human driver's reaction time is around 0,8s to 1s, considering an experienced driver, with no distractions or fatigue. It means that if an autonomous vehicle has a faster reaction time, the SSD can be considerably reduced**.**

Table 1: **(a)** Values used on the calculation of SSD numerical example. **(b)** A numerical example of SSD parameter

(a)		
Variable	*Unit*	*Value used on the example*
SSD: stop distance	*m*	→
V: Speed	m/s	25=90km/h
R_T: Reaction Time	s	→
g: gravity	m/s²	9.8m
f: friction coefficient		0.8
G: inclination/slope	**(%)**	0%

(b)	
R_T (s)	SSD (m)
2	104.13
1	67.38
0.8	60.03
0.6	52.68
0.4	45.33
0.2	37.98
0	30.63

Source: Author

- **Safe Speed:** the highest speed a vehicle can drive on an accident-free model where the subject vehicle can stop even on sudden braking from the leading vehicle (TREIBER & KESTING, 2013). The safe speed is defined as

$$v_{Safe} = -bR_T + \sqrt{b^2R_T^2 + V_l^2 + 2b\,(s - s_0)} \tag{2}$$

where R_T is the driver reaction time (s), b is the constant braking deceleration (m/s²), is V_l the leading vehicle speed (m/s) and $(s - s_0)$ = Gd as gap distance (m).

In Table 2, it is presented as a numerical example from equation 2. Considering a harsh deceleration (-5m/s²), a human driver can drive at 97.26 km/h on accident-free mode on a highway at 100m distance from the leading vehicle and reaction time around 1s. For lower reaction times, this speed can be 15% higher. In an urban environment, at a 10m distance from the leading vehicle, the safe speed difference can be above 50% from a usual human driver to a system with a slower reaction time. It means that it is possible to correlate a lower reaction time with higher safe speeds that could benefit the traffic flow.

This group of traffic engineering parameters presents the aspects involved in traffic, vehicle dynamics, and driver behaviors that characterize human-driven vehicles. They are the basis to discuss how CAVs technologies will affect traffic conditions.

Table 2: (a) Values used on the calculation of Safe Speed numerical example. **(b)** Results from the numerical example from the Safe Speed parameter.

(a)		
Variable	***Unit***	***Value used on example***
b: braking constant deceleration	m/s^2	5
R_T : Reaction Time (s)	s	→
V_l : Leading vehicle speed	m/s	0
(s-so): Gd - gap distance	m	→

(b)		
	Gd=100m	Gd= 10m
RT (s)	**Safe Speed (km/h)**	**Safe Speed (km/h)**
2	83.4	14.91
1	97.26	22.25
0.8	100.35	24.37
0.6	103.55	26.79
0.4	106.87	29.51
0.2	110.3	32.58
0	113.84	36

Source: Author

2.1 AUTONOMOUS VEHICLES

The first definitions of Autonomous Vehicles (AVs) were usually related to a composition of different ADAS systems that would perform the core vehicle dynamics behaviors independent from the driver (RAJESH, 2006). Anyhow, this definition became limited when the target is to transfer completely to the vehicle the responsibility to autonomously accelerate and brake and execute longitudinal and lateral movements and maneuvers. These activities are under development based on how humans perceive, plan and act over the environment during driving, replacing it with an extensive range of sensors, actuators, and artificial intelligence (PENDLETON et al., 2017; FROST & SULLIVAN, 2017; HE et al. 2019).

The subject vehicle can continually monitor vehicles surrounding, leading to deterministic behavior compared to human drivers and almost instantaneous reaction time when relevant changes in the driving environment are assessed (MAHMASSANI, 2016). AVs are in continuous development to a broader application, including covering the limits of driving domains. Humans' capabilities are limited due to environmental, geographical, time-of-day restrictions. The Operational Design Domains (ODD) is defined as the conditions a human driver or an autonomous vehicle can operate (SAGIR & UKKUSURI, 2018).

The Adaptive Cruise Control (ACC) was the first ADAS to control longitudinal vehicle motion, also referred to as the first step on AVs roadmap (RAJESH, 2006). The Intelligent Driver Model (IDM) has been developed and enhanced for several kinds of research over the years to model ACC and other aspects from AV (TREIBER et al., 2000; KESTING et al., 2010; SCHAKEL et al., 2010; SHLADOVER et al., 2012; TREIBER & KESTING, 2013; DERBEL et al., 2013;

MAHMASSANI, 2016; ZHOU et al.,2017; XIE et al., 2019). IDM considers some aspects as no exact reaction time or destabilizing effects on acceleration and braking caused by human imperfections (DO et al., 2019).

IDM specifies a subject vehicle acceleration as a continuous function of its current speed, the ratio between the current spacing to the desired spacing, and the vehicle speed difference between the leading and the subject vehicle as

$$\alpha_{IDM} = a\left[1-\left(\frac{v}{v_o}\right)^{\delta}-\left(\frac{{G_d}^{*}(v,\Delta v)}{G_d}\right)^{2}\right] \tag{3}$$

where a is the comfortable acceleration rate (m/s²), G_d are the distance from the subject and leading vehicle (m), v is the subject current vehicle speed (m/s), v_o is the desired (safety) speed (m/s), Δv is the speed difference between the subject vehicle and the leading vehicle (m/s), δ is the parameter that decides the magnitude of acceleration decrease depending on the vehicle speed, $G_d{*}$ is the desired distance (safety gap) described as

$${G_d}^{*}(v,\Delta v) = G_{d_o} + max\left[0, vT + \left(\frac{v\Delta v}{2\sqrt{ab}}\right)^{2}\right] \tag{4}$$

Where G_{d_o} is the minimum gap (m), T is a constant value representing the desired gap (m), a is the comfortable acceleration rate, and b *is* the deceleration rate (TREIBER & KESTING, 2013; DO et al., 2019).

IDM acceleration and deceleration rates are plausible for most situations other than when the gap between the subject vehicle and the leading vehicle is significantly lower than the desired interval or gap. TREIBER & KESTING (2013) combined the IDM and the Constant Acceleration Heuristics (CAH) to avoid unrealistic deceleration rates. The frameworks of CAH matches with some assumptions from CAVs, as:

i. The leading vehicle will not change its acceleration suddenly in the following seconds.

ii. Safe time headway or minimum distance do not need to be considered.

iii. Drivers reaction time is zero (no delays).

Considering the gap G_d, the subject vehicle speed v, the leading vehicle speed v_l and constant acceleration of both vehicles $\dot{v}$ and $\dot{v}_l$, the maximum acceleration max ($\dot{v}$) = α_{CAH} that prevents accidents is described as

$$\alpha_{CAH}(G_d, v, v_l, \dot{v}_l) = \begin{cases} \frac{v^2\bar{a}_l}{v_l - 2G_d\bar{a}_l}, & if\ v_l(v-v_l) \leq\ -2G_d\bar{a}_l \\ \bar{a}_l - \frac{(v-v_l)^2\theta(v-v_l)}{2G_d}\ , & otherwise \end{cases} \tag{5}$$

where $\bar{a}_l(\dot{v}_l)$=min $(\dot{v}_l, a)$ is the adequate acceleration used to outline the situation where the leading vehicle acceleration capability is higher than the subject vehicle acceleration. The condition $v_l(v-v_l) \leq\ -2G_d\bar{a}_l$ is valid if the vehicles stop until the minimum gap $G_d = 0$ is achieved. It means that negative approaching rates make no sense, and it is handled by Heaviside step function $\theta(x)$ (with $\theta(x) = 1$ if $x \geq 0$ and zero, otherwise).

IDM and the CAH acceleration models combined lead to the ACC model formulated as (TREIBER & KESTING, 2013):

$$\alpha_{ACC} = \begin{cases} \alpha_{IDM}, & if\ \alpha_{IDM} > \alpha_{CAH} \\ (1 - c)\alpha_{IDM} + c\ _{l}[\alpha_{CAH} + b\ \tanh\left(\frac{\alpha_{IDM} - \alpha_{CAH}}{b}\right) & ,\ otherwise \end{cases} \tag{6}$$

Where c is the coolness factor, for c=0, the ACC model comes to IDM, while c =1 means no speed difference exists. TREIBER & KESTING, 2013, had assumed c =0.99.

2.2 CONNECTED VEHICLES

Connected Vehicles (CV) will bring additional capabilities that humans are not able to. It will carry a complete assessment to perceive directly and instantly beyond the sensor range, as illustrated in **Fig. 6**. It will be enabled mainly by vehicle to everything communication (V2X) technology together with high-definition (HD) online mapping, analytics, and stored big data (JIA & NGODUY, 2016; FROST & SULLIVAN, 2017; UHLEMANN, 2016; SBD, 2018). CVs are based on the Cooperative Intelligent Transportation Systems (C-ITS) strategy defined by the European Commission to improve road safety and traffic efficiency (C-ITS, 2017; SINGH et al.., 2019).

The framework from connected vehicles is the ability to exchange information. For that, V2X capabilities include (for additional applications, see Annex 2):

- **Vehicle-to-Vehicle (V2V):** this technology enables each vehicle to be a gateway from its information and the whole ecosystem connected to it. It allows features as Cooperative Adaptive Cruise Control (C-ACC) or platooning (MAHMASSANI, 2016; DOLLAR & VAHIDI, 2017; LI et al., 2020).
- **Vehicle-to-Infrastructure (V2I):** this technology enables the vehicle to broadcast information with infrastructure over the Roadside Units (RSU), telecom infrastructure, radars, or traffic signs. It allows accessing and sharing real-time data from the weather forecast, road conditions, online traffic information, historical data, and traffic signals timing (GUO & BAN, 2019; SINGH et al., 2019).
- **Other V2X technologies:** Vehicle-to-Pedestrian (V2P), Vehicle-to-Network (V2N), Vehicle-to-Home (V2H) (CHEHRI et al., 2020), and additional connectivity that matches with the Internet of Thing (IoT) concepts (MIR & FITALI, 2016).

Fig. 6 shows examples of V2X capabilities.

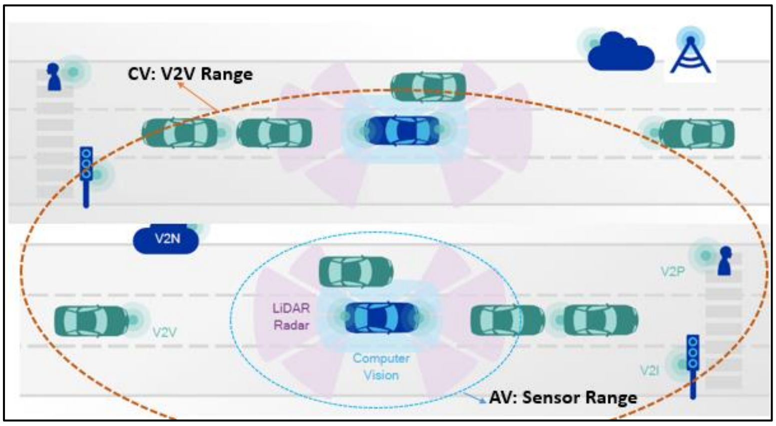


Fig. 6. V2V allows CAV vehicles to scan a broader vehicle ecosystem beyond the sensors range Source: adapted from Qualcomm (2016).

V2X network infrastructure and requirements were standardized over IEEE.802.11p/DSRC (IEEE, 2010) allows the data exchange with wireless Access's characteristics in Vehicular Environments (WAVE). It includes multiple propagation paths, high node dynamism, high bandwidth, and low latency (PENDLETON et al., 2017; VUKADINOVIC et al., 2018; HE et al., 2019).

However, in the last five years, the development of 5G brought new discussions opportunities, as it was conceived to fulfil V2X requirements (Trafic Technology International, 2017; 5G Automotive Association, 2019; LUCERO, 2016; AISSIOUI et al., 2018; HUSSAIN, HUSSAIN, & ZEADALLY, 2019; SINGH et al., 2019).

The current picture is that there is no convergent decision about adopting DSRC or 5G. Pros and cons of technologies application, time to market, and costs are under discussion (AISSIOUI et al., 2018; LUCERO, 2016; SBD, 2018).

2.3 CONNECTED AND AUTONOMOUS VEHICLES (CAV)

To achieve high dependability for higher automation levels, including reliability and safety, the interface between a connected and autonomous vehicle will merge. CAV is a terminology adopted in the last few years to vehicle clustering features as Cooperative Adaptive Cruise Control (CACC) will require the full integration between sensors and communication technologies to control the vehicle's dynamics considering overall predictability from the road environment (CALVERT et al., 2020). CAVs will merge the technologies to enable the broad application of Artificial Intelligence (AI), including being adaptive, self-learning and foresight of future events on the road (uptime), and making a historical analysis based on big data analytics. **Fig. 7** illustrates the convergent point between AV and CV technologies.

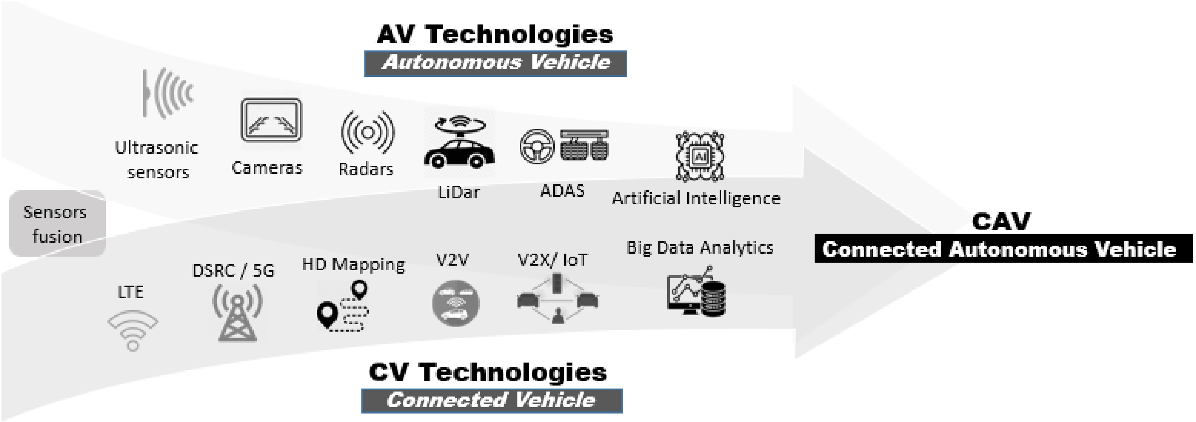


Fig. 7. CAV technologies roadmap

Source: Author.

CAVs will enable cooperative driving features that allow lower gap distances, shorter lateral distances, and optimized merging conditions. It will process a considerable amount of real-time data from vehicles around that. Simultaneously, it will make useless the former mandatory components on the human driver environment (e.g., brake lights, turn indicators, and horns). On the other hand, AI algorithms together with big data analytics will be essential players to replace distinctive human capabilities as context-sensitivity (memory effect of present and past overall traffic conditions), courtesy, and cooperation (particularly relevant for merging and lane changes situation) (TREIBER et al., 2000; DO et al., 2019, HE, et al. 2019).

The EU recently introduced legislation that requires OEMs to fit e-Call (Emergency Calls) as standard on all new vehicles. e-Call regulation could mean that all OEMs in the EU will have an embedded SIM-card (Subscriber Identity Module) in the future that enables as a fundamental feature the vehicles to send a warning to the authorities on an accident automatically. It was expected that around 60% of new cars sold in the EU and US would be equipped with embedded connectivity by 2020 (SBD, 2018). MEYER & SHAHEEN (2017) states that fully CAVs, where a driver no longer must steer or adjust speed, could be commercially available within the next 10–20 years.

Coming to the relevant concepts, CACC is frequently used to model CAVs, incorporating communication technologies into ACC (JIA & NGODUY, 2016; MAHMASSANI, 2016; ZHOU et al., 2017; GE et al., 2018; DO et al., 2019). DO (2019) presents a survey of studies of CACC that highlight benefits on traffic flow considering shorter headway (i.e., 0.5 seconds) compared to the ACC (i.e., 1.4 seconds), mainly due to V2V technologies that bring a different approach to minimum safety distance. Field tests showed the same tendency to shorten time gaps due to faster response on changing behavior from the leading vehicle (SCHLADOVER et al., 2010).

ZHAO & SUN (2013) based on previous studies by KESTIN et al. (2008), proposed acceleration equations for ACC and CACC acceleration. The acceleration model is a linear function between the subject vehicle and the leading vehicle and the current speed. The accelerations of vehicles are described by equations (7) and (8) for ACC vehicles and (9) and (10) for CACC (PARK et al., 2017) as

$$a_{c\,ACC} = k_v \cdot (v_l - v_s) + k_s \cdot (s - v \cdot t_d) \tag{7}$$

$$a = \max[a_{min}, min(a_c, a_{max})] \tag{8}$$

$$a_{c\,CACC} = \boldsymbol{a_l} + k_v(v_l - v_s) + k_s \cdot (s - v \cdot t_d) \tag{9}$$

$$a = \max[a_{min}, min(a_c, a_{max})] \tag{10}$$

where a is the acceleration in the next step of the subject vehicle, $\boldsymbol{a_l}$ is the acceleration of the leading vehicle (the only additive variable added at CACC), v_s and v_l are the vehicle speed of the subject and leading vehicles, respectively, a_{max} is the maximum allowed acceleration, a_{min} is the maximum allowed deceleration, k_v and k_s are constant gains greater than zero.

On the other hand, Van AREM et al. (2006) developed the Microscopic Model for Simulation of Intelligent Cruise Control (MIXIC), which is compatible with CACC. The first focus of the study was to assess the throughput and stability impacts of the system. Results showed better stability and average speed increase on a freeway lane drop with increasing penetration of CACC. The model can incorporate V2V by sharing relevant information from leading vehicles to subject one, like vehicle speed, acceleration, and braking, assuming that the delay is zero (SHLADOVER et al., 2012; DO, et al., 2019).

On MIXIC basic model, the safe following distance is given by

$$r_{safe} = \frac{v^2}{2} \cdot \left(\frac{1}{d_p} - \frac{1}{d}\right) = t_{system} \cdot v \tag{11}$$

where v is the subject vehicle speed, d_p and d are the deceleration capability of the leading and subject vehicles, respectively. t_{system} is the time headway (0.5 seconds if the leading vehicle has CACC function and 1,4 seconds, otherwise). It means that for CACC equipped vehicles, the safe distance can be almost three times lower. SONGCHITRUKSA et al. (2016) stated that a proper time headway for CACC could be as small as 0.6 seconds. Fig. 9 illustrates it.

TELEBPOUR & MAHMASSANI (2016) developed important concepts for CAVs based on MIXIC. The framework is that the speed of the CAV enables it to stop at the sensor detection range. The model that calculates safe speed considering it is

$$\Delta X_n = (X_{n-1} \text{-} X_n - l_{n-1})\, v_n \tau + \frac{v_{n-1}^2}{a_{an-1}^{decc}} \tag{12}$$

$$\Delta X_n = min(SensorDetectionRange, \Delta X_n) \tag{13}$$

$$v_{max} = \sqrt{-2a_i^{decc} \Delta X} \tag{14}$$

where n and $n-1$ are the subject and the leading vehicles, respectively. X_n, l_n, v_n, τ, and a_n^{decc} denotes the position, the length, the vehicle speed, the reaction time, and the maximum deceleration of the subject vehicle n, respectively.

The researchers defined the safe following distance (s_{safe}) and the following distance based on the reaction time (s_{system}) as

$$S_{safe} = \frac{v_{n-1}^2}{2} \cdot \left(\frac{1}{a_n^{decc}} - \frac{1}{a_{n-1}^{decc}} \right) \tag{15}$$

$$S_{sytem} = v_n \tau \tag{16}$$

It leads to the acceleration of CAV given by

$$a_n(t) = \min[a_n^d(t), k(v_{max} - v_n(t)] \tag{17}$$

k is a model parameter that is the same as the basic MIXIC (TELEBPOUR & MAHMASSANI, 2016; DO, et al., 2019).

YE & YAMAMOTO (2017) denotes the anticipation distance capability (based on the premise that CAVs can obtain the exact value of the distance gap). Equation 18 clearly shows the driver behavior difference when the leading vehicle is a CAV or an HDV (for mixed scenarios), given by

$$d_{anti}^{CAV} = \begin{cases} d + v_{anti}, & if\ v_l\ is\ a\ CAV \\ d + v_{anti} - b_{defense}\ , & otherwise \end{cases} \tag{18}$$

where d is the distance gap between subject and leading vehicle, v_{anti} is the leading vehicle's expected speed, and $b_{defense}$ is the randomization-deceleration rate under the defensive state. This equation is on the worst-case where a CAV is following an HDV. As HDV driving behavior is unpredictable, the CAV always needs to drive on the defensive.

YE & YAMAMOTO (2017) incorporate the connectivity characteristics of V2V on the safe speed of a CAV as

$$v_{anti}^{CAV} = \min(d_l\ , v_l + a\ , v_{max}\ , v_{li}) \tag{19}$$

where v_{li} is the average speed of leading CV within the communication distance range, v_l and d_l are the speed and gap distance from the leading vehicle, respectively.

Fig. 8 shows the evolution path of mathematical modeling of AVs, CVs, and CAVs expressed along with equations (3) (19).

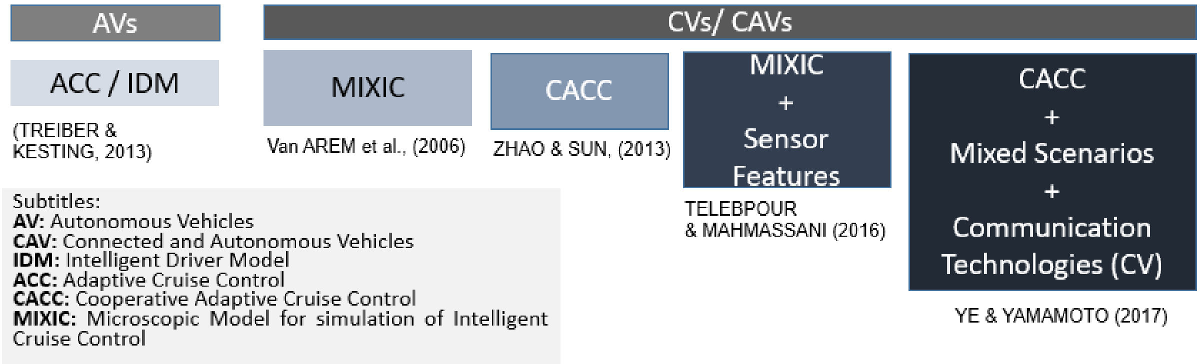


Fig. 8. Mathematical models Evolution from AVs, CVs, and CAVs
Source: Author.

2.3.1 Deep dive on CACC/Platooning

A sophisticated feature that CAVs enable is platooning, also called an automated convoy. The first public assessment of the technology dates from more than 20 years ago, in 1997 where the National Automated Highway Systems Consortium (NAHSC) conducted a public demonstration of eight fully automated cars driving in convoy in San Diego, California. The road was equipped with reference magnets for steering maneuvers, and the communication between vehicles was based on radio technologies (RAJESH, 2006).

The current approach for platooning is to use CACC as a framework. Its sensors and V2V communication technologies make it possible to create a group of vehicles electronic engaged. The first vehicle has responsibility for leading the convoy setting the speed, lane, and directions. The other vehicles act as slaves or followers (RAHMAN & ABDEL-ATY, 2017).

The vehicles at the platoons use an Identification number (ID) to represents their sequential position on the convoy. The leader ID is zero, and the other vehicles have the ID number increased by one unit (1,2,3…) sequentially until the maximum allowed platoon size. Suppose a vehicle is approaching the platoon, and the maximum platoon size is already achieved. In that case, this vehicle will start a new platoon where the inter platoon time headway should be considered. The maximum platoon size can depend on many different factors like the road type, maximum vehicle speed allowed, and vehicle models (SERAJ et al., 2018; GONG & DU, 2018).

The relevant variables that will determine the platoon's performance are the number of vehicles and their distance. One additional primary feature that affects its performance is the capability to open gaps, accept new vehicles or allow vehicles to cut-in, and close gaps from vehicles that left the convoy (HU et al., 2017; YAO et al., 2020). **Fig. 9** shows examples.

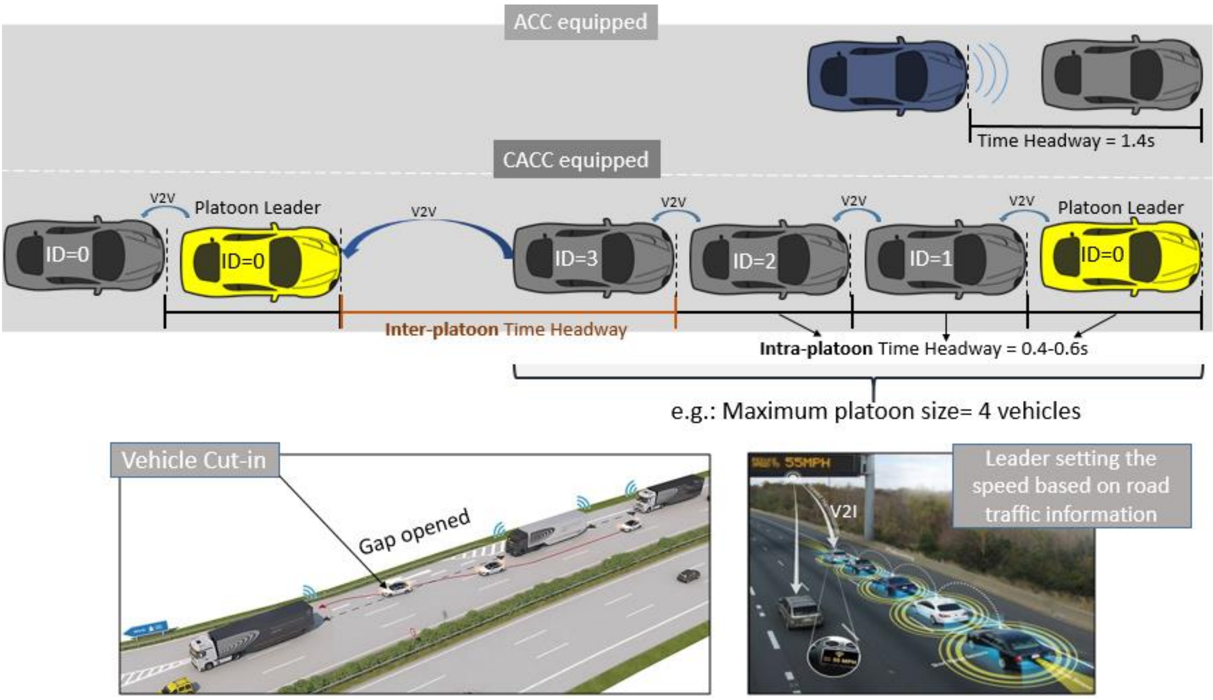


Fig. 9. Platooning/CACC key concepts
Source: Author and adaptation from DIRT (2019) and DAIMLER CASE (2019).

SERAJ et al. (2018) bring the modeling of acceleration of the subject vehicle in a CACC system, similar to proposed by ZHAO & SUN (2013) on equation (7) as

$$v(t+\Delta t) = k_1(d(t) - v(t)\cdot T - s_0) + k_2\Delta v(t) \tag{20}$$

where k_1, k_2 are control constants for relative distance and speed, respectively, higher than zero, d is the distance gap between leading and subject vehicle, and T is the reaction time.

The researchers simulated numerous scenarios with a stream of 20 vehicles following a platoon leader vehicle. The first analysis showed that creating platoons and HDV on mixed traffic configurations positively impacted the overall traffic flow (SERAJ, LI, & QIU, 2018). SONG, CHEN & MA (2019) results from numerical simulations also show positive effects of platooning on traffic flow by increasing the average speed and reducing lane change frequency. The best results were achieved for platooning dedicated lanes. The research shows that the positive effect is reduced gradually when traffic density increases. CALVERT, SCHAKEL, & VAN AREM (2019) study focused on trucks platooning also concluded that its ability is better on non-congested traffic. On the other hand, they concluded that no positive effect was found on traffic flow performance and recommended focusing on improvements in emissions and energy consumption.

Different studies state the benefits of the group's fuel efficiency and emissions by reducing the overall air drag (ALAM et al., 2015). TSUGAWA (2014) delivered the results from the field test project that tested a platoon of 3 fully automated trucks, driving along an expressway at 80 km/h with a preset distance of 10m between them. The fuel consumption measurement showed a reduction of about 14%. WANG et al. (2017) assessed an eco-friendly CACC system with cars car and got 2% higher fuel efficiency with 17% emission reductions. ALMANNAA et al. (2019) field studies showed that the proposed Eco-CACC could achieve a 31% fuel consumption reduction. DE RANGO et al. (2020) performed simulations using MATLAB and Omnet++, showed that the platoons save energy and reduce fuel consumption. They used Grey Wolf Optimization to find the best platoon configuration, limiting to a maximum of five vehicles in each platoon.

The best platoon configurations are a high point of interest. One crucial aspect studied by Van Arem et al. (2006) was the intra-platoon gap time. They projected a value as low as 0.3s for the future. SERAJ, LI, & QIU (2018) found the best platoon configuration that gives the maximum benefits to the traffic was: intra-platoon headway = 0.5s, inter-platoon headway = 2s, and maximum platoon size = 5/6 vehicles. CALVERT, SCHAKEL, & VAN AREM (2019) stated a time gap between 0.3s for 100% CAVs penetration rates until 0.7s for lower ones.

Tsugawa et al. (2016) found that using dedicated lanes for trucks platooning with sizes up to 10 could double the capacity. JO et al. (2019) analyzed 160 scenarios. They noticed that the configuration that maximized the capacity was a platoon size of 2 trucks, 6m intra-platoon, and 50m inter-platoon gap size for 25% penetration rates.

Also, a literature review showed that currently, most of the studies for CACC/Platooning focus on trucks due to the hypothesis that a better aerodynamic performance can be achieved by grouping large vehicles. A platoon survey for trucks can be found at (BHOOPALAM et al., 2018).

Finally, considering that CAVs will enable a shorter gap and lateral distance between the vehicles, one additional relevant aspect that these technologies will bring to the society comes up: the throughput capability increases using the same road area or keeps the throughput decreasing the number of lanes. Adding it to the new approach that V2X can give to sharing mobility and multi-modal transportation can dramatically change the cities architecture, avoiding the continuous necessity of roads area increase as well as open spaces for sidewalks, bicycles lanes, parks, among others (NTOUSAKIS et al., 2015; ARIA et al., 2016; HAO et al., 2017).

It is essential to mention that the minor part of the research still focuses on the traffic performance potential of CACC/platooning, as the benefits of energy consumption and emissions seem to be more evident. This study brings a contribution to evaluate further this and other aspects of platooning.

2.4 VEHICLE AUTOMATION FIELD OPERATIONAL TRIALS (FOT)

A Field Operational Trial (FOT), in terms of CAVs, is a private or government-funded project in which autonomous technologies are tested in a real-world environment. A key benefit of real-world trials is that the technology can be observed and monitored to evaluate how it reacts to random scenarios. The possibility of exposing the technology to public interaction is another positive aspect of making people aware and confirming innovations (SBD, 2018).

These CAVs field tests have many different targets as the assessment of operational systems, artificial intelligence, sensing, DSRC, 5G (MOTO et al., 2019), communication (LI et al., 2020), mobility, mapping, software and hardware development, simulation, transition phases (CALVERT et al., 2020) and coexistence between human-driven and CAVs as well as government certification and legislation relevant topics.

2.4.1 CoEXist project

Inside the FOT context, the CoEXist project must be highlighted and further explained. Some of its deliverables were used as core references for the traffic microsimulation phase developed inside this research. CoEXist was a European project (May 2017 – April 2020), aiming to prepare the transition phase where automated and conventional vehicles will co-exist on the roads. The mentioned deliverables were related to field tests in cooperation with the PTV company are described below:

- (Coexist D2.3, 2018) - Default behavioral parameter sets for Autonomous vehicles (AV): set of new features to make AV vehicles simulation more accurate (available from VISSIM 11), the numerical recommendation for the Wiedemann 74 (W74), and Wiedemann 99 (W99) following behavior, lane changing behavior, and signal control behavior.
- (Coexist D2.4, 2018) - PTV VISSIM extension new features and improvements: show the results of data evaluation in combination with the proposed concept of four different driving logics, which characteristics are:
    i. **Rail Safe**: suggested parameters characterize a mostly closed environment (e.g., no lane changes allowed), similar to driver behavior on public transportation dedicated lanes;
    ii. **Cautious**: driver that follow all rules straightly, keep a safe distance from the vehicle ahead, and change lanes when significant gaps are opened at the lateral lane;

iii. **Normal**: suggested parameters mostly based on PTV VISSIM users manual. It will represent the driver’s behavior that reproduces with more accuracy the actual human-driven vehicle;

iv. **All-knowing**: based on driver behavior and dynamic characteristics of CAV, as smaller front-rear gaps between vehicles, cooperative lane changes (vehicles at the lateral lane create the gaps), and slower reaction time. Anyhow just setting this behavior at VISSIM does not mean that any connected technology can be assessed.

- (Coexist D2.5, 2018) - Micro-simulation guide for automated vehicles: deep dive explanation on how to use the new features available at VISSIM 11, including “enforce absolute braking distance,” “use implicit stochastic,” “number of interaction vehicles,” and “increased desired acceleration.”
- (Coexist D2.6, 2018) – Technical report on data collection and validation process: details the validation process with the data collection process done in TASS international test network in Helmond Netherlands. The tests were performed using three vehicles equipped with CAVs Level 3 systems.
- (CoEXist D5.6, 2019) – Report from a CAV demonstration at ITS in European Conference 2019 (Helmond, Netherland). Simulations on PTV VISSIM and Prescan and a live demonstration showed that travel time could be reduced by 16% when V2V and V2I were used compared to scenarios with no communication.

The project results proved that using new features and adapted driver behavior parameters can simulate CAVs behavior with a satisfactory accuracy level.

2.5 TRAFFIC SIMULATION

The study of traffic for roads and urban environments is a complex science. It presents many variables and interactions that make it a challenge to find a formal general description. Researchers recognized the need to represent traffic flow in analytical terms and developed formulations, which simulation modelers could use.

That context triggered the traffic simulators that dates from the 1950s (Transportation Research Circular, 2015) . In Annex 3, a genealogy of traffic simulators is presented. They are software tools that support traffic engineers, transportation planners, system designers, authorities, and researchers to evaluate diverse traffic ecosystems and relevant topics with agility and low cost. They are used for many different purposes, from the design of sensors and algorithms to control driverless cars individually (DOSOVITSKIY et al., 2017) and evaluate the impacts of the overall traffic condition, supporting to find optimization opportunities during the design phase of new highways and urban pathways. They also can assess the effect of public transportation and pedestrian interactions (HELBING, 2002; SAIDALLAH et al., 2016). One more capability of traffic simulators was used in this research: to evaluate the impact of new technologies as V2X and CAVs vehicles on different traffic aspects.

As mentioned, the traffic complexity made it necessary to split the traffic simulators into four categories, from nanoscopic to macroscopic traffic models. The category selection depends on the focus of the study. **Fig. 10** and **Chart 1** describes the differences between these levels of simulations.

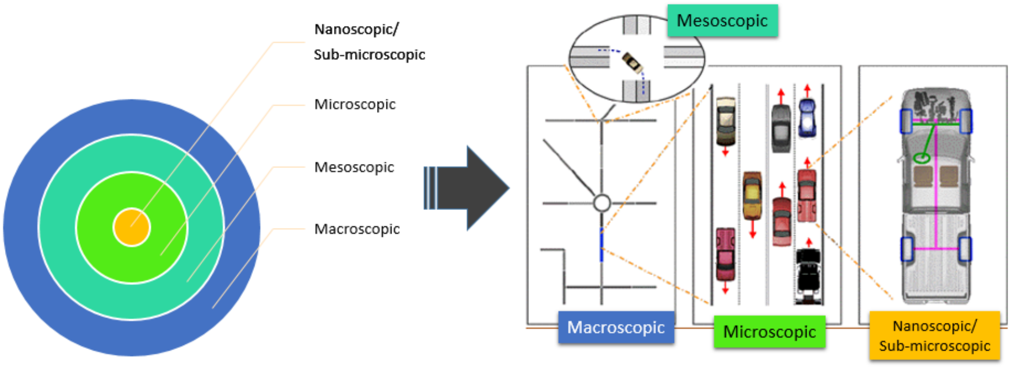
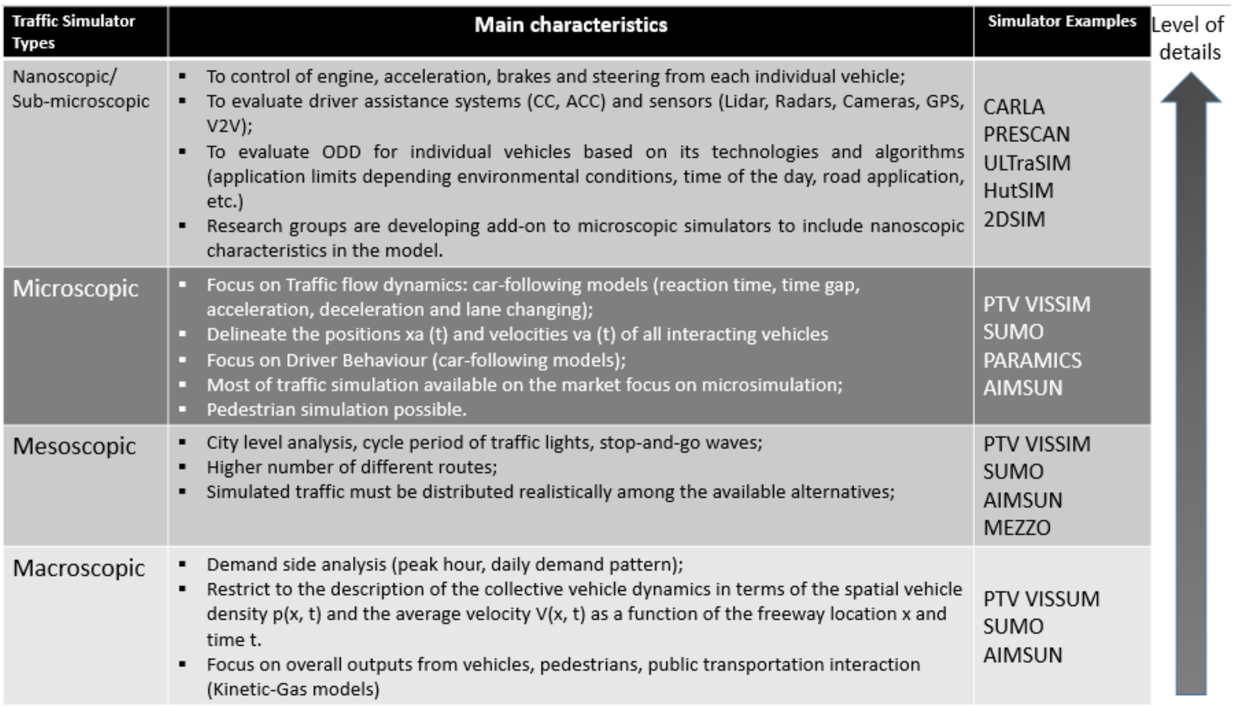


Fig. 10. Traffic simulation categories

Source: Author.

Chart 1: Characteristics of traffic simulators



Traffic Simulator Types	Main characteristics	Simulator Examples
Nanoscopic/ Sub-microscopic	▪ To control of engine, acceleration, brakes and steering from each individual vehicle; ▪ To evaluate driver assistance systems (CC, ACC) and sensors (Lidar, Radars, Cameras, GPS, V2V); ▪ To evaluate ODD for individual vehicles based on its technologies and algorithms (application limits depending environmental conditions, time of the day, road application, etc.) ▪ Research groups are developing add-on to microscopic simulators to include nanoscopic characteristics in the model.	CARLA PRESCAN ULTraSIM HutSIM 2DSIM
Microscopic	▪ Focus on Traffic flow dynamics: car-following models (reaction time, time gap, acceleration, deceleration and lane changing); ▪ Delineate the positions xa (t) and velocities va (t) of all interacting vehicles ▪ Focus on Driver Behaviour (car-following models); ▪ Most of traffic simulation available on the market focus on microsimulation; ▪ Pedestrian simulation possible.	PTV VISSIM SUMO PARAMICS AIMSUN
Mesoscopic	▪ City level analysis, cycle period of traffic lights, stop-and-go waves; ▪ Higher number of different routes; ▪ Simulated traffic must be distributed realistically among the available alternatives;	PTV VISSIM SUMO AIMSUN MEZZO
Macroscopic	▪ Demand side analysis (peak hour, daily demand pattern); ▪ Restrict to the description of the collective vehicle dynamics in terms of the spatial vehicle density p(x, t) and the average velocity V(x, t) as a function of the freeway location x and time t. ▪ Focus on overall outputs from vehicles, pedestrians, public transportation interaction (Kinetic-Gas models)	PTV VISSUM SUMO AIMSUN

Source: Author.

Due to the characteristics of this research, the microscopic model was chosen as detailed in chapter 4.1. The differences in driving behaviour between HDV and CAVs can be better explored in the microscopic environment.

2.5.1 Microscopic Traffic simulators

The Microscopic traffic simulation focuses on flow models from single vehicle drive units, where the dynamic parameters and variables represent their speed and position individually. Its models consist of several sub-models that are used to describe the driving behavior. These sub-models are referred to by GAO (2008) as the "underlying logic" of a traffic simulation model. This logic consists of car-following, lane-changing, and gap-acceptance logics, all of which are highly relevant in driver behavior modeling.

A wide range of micro simulators is available for commercial and research applications (SAIDALLAH et al., 2016). On **Chart 2**, an overview of the most used is presented.

Chart 2: Overview of most used traffic microscopic traffic simulators.

Traffic Microsimulator	Car-following model	Application Software License	Developer
PTV VISSIM	Wiedemann 1974 (W74) and Wiedemann 1999 (W99)	Proprietary	PTV (Planung Transport Verkehr AG) in Karlsruhe, Germany.
SUMO	Krauss (1997)	Open-source	German Aerospace Center (DLR), Germany.
AIMSUN	Gipps (1981)	Proprietary	Transport Simulation Systems (TSS), Spain. Acquired by Siemens in 2018.
CORSIM	Pipes or GM (1953)	Proprietary	Federal Highway Administration (FHWA), USA.
PARAMICS	Fritzsche (1994)	Proprietary	Quadstone Paramics, UK.
MOTUS	External models	Open source	Delft University of Technology, Netherlands
MovSim	Gipps (1981) Krauss (1997)	Open source	CIVITAS initiative, Europe
MATsim	Vickery model	Open source	MATsim Communiity
TransCAD	Not mentioned	Proprietary	Caliper Corporation, USA.
SimTraffic	Not mentioned	Proprietary	Trafficware (CUBISC Company), USA.

Source: Author.

During the literature review phase of this research, VISSIM, SUMO, and AIMSUM are the most used simulators in studies by traffic planners and traffic planning researchers, as shown in

Chart 5 from chapter 3. Many different studies worldwide were done based on that three software. Due to the characteristics of this research further explained in chapter 5, VISSIM was the option chose.

PTV group headed by Rainer Wiedemann at Karlsruhe University in Germany VISSIM developed the microsimulation software called VISSIM. The backbone of the microscopic simulator is driving behavior (OLSTAM & TAPANI, 2004). Fig. 11 shows the main components of the driver behavior model in VISSIM.

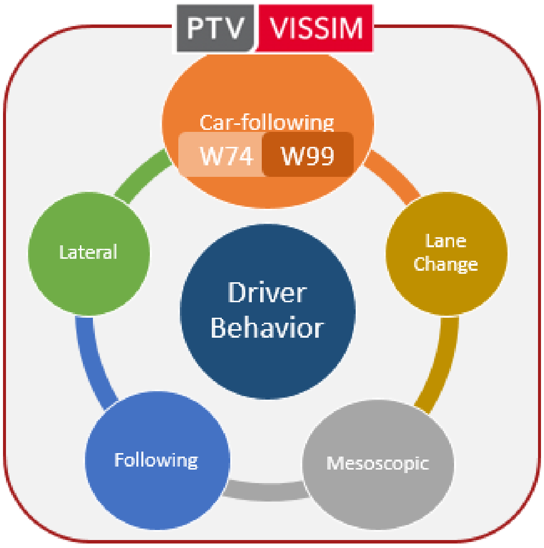


Fig. 11. Driver behavior components in VISSIM.

Source: Author.

The car-following behavior in VISSIM is based on a so-called psychophysical model. It combines human physiological restrictions as reaction times, estimation errors, perception thresholds (HIGGS, ABBAS, and MEDINA, 2011), and psychological aspects such as anticipation, context-sensitivity, and driving strategy. Wiedemann suggested this model in 1974 (WIEDEMANN, 1974) and 1999. This characteristic is why the distance a human driver keeps from the leading oscillates around a target time headway. This human driver behavior shall be adjusted to modeling the test vehicles' deterministic behavior (TREIBER & KESTING, 2013).

GAO (2008) and HIGGS et al. (2011), the Wiedemann model assumes that a driver can be in four different driving regimes:

- Free driving: no obstacles or vehicles in front of the vehicle. The driver can proceed with its desired current speed.
- Approaching: the driver identifies the leading vehicle in lower vehicle speed and brakes until it achieves the desired gap.
- Following: the driver tries to keep the desired gap from the leading vehicle. For human drivers, the distance oscillates due to acceleration and brake patterns.

- <u>Braking</u>: the leading vehicle applies the harsh brake, and the subject vehicle must also brake.

The four driving regimes are defined by the thresholds that represent the change in driver behavior. Fig. 12 shows a simplified representation of these transitions in the three-dimensional state space spanned by a gap (s), speed (v), and approaching rate (Δv: speed difference between subject and leading vehicles). The blue line with an arrow shows the trajectory of a vehicle coming from a “free flow,” changing to “approaching” and then to the “following” process where the leading vehicle is the reference. (TREIBER & KESTING, 2013; FRANSSON, 2018).

As can be seen in Fig. 12, the transition thresholds for the regimes are as follows:

- SDV: it is where the driver recognizes he is driving is a higher speed than the leading vehicle and starts approaching).
- CLDV is where a driver recognizes minor differences in speed, decreasing distances);
- OPDV: it is where the driver recognizes he is driving is a lower speed than the leading vehicle and starts to accelerate to keep following).
- ABX: it is minimum following distance).
- SDX: it is the maximum following distance during the same speed conditions as ABX.

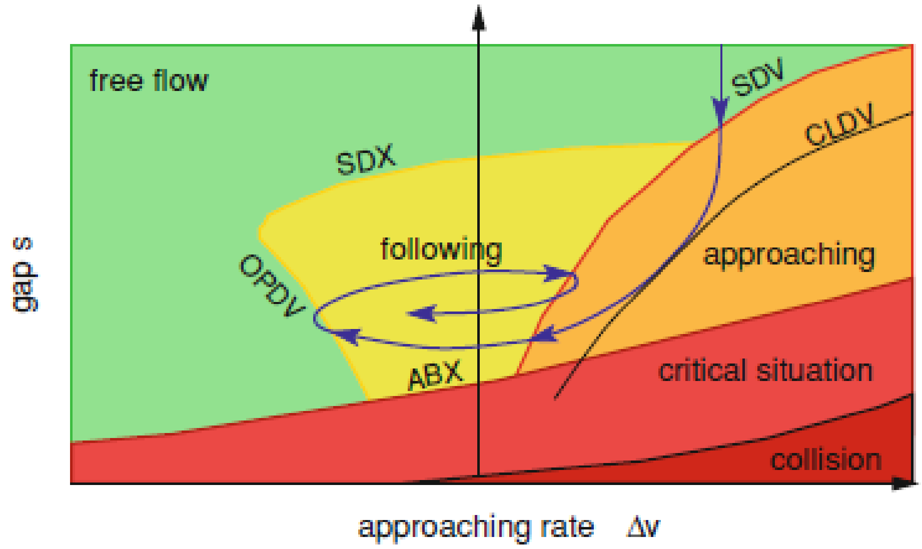


Fig. 12. Illustration of the driving regimes from the Wiedemann model.

Source: (WIEDEMANN, 1974)

According to GAO (2008) Wiedemann 74 (W74) model used in VISSIM is formulated as

$$u_n(t+\Delta t) = min \left\{ \begin{array}{l} 3.6 \cdot \left(\frac{s_n(t)-AX}{BX}\right)^2 \\ 3.6 \cdot \left(\frac{s_n(t)-AX}{BX \cdot EX}\right)^2 \end{array} \right. , u_f \tag{21}$$

where $u_n(t + \Delta t)$ is the speed update and u_f is the space-mean traffic stream free-flow speed (km/h). AX and BX are adjustable parameters expressed at

$$d = AX + BX \tag{22}$$

where AX is the standstill distance (m) and BX the safety distance (m) given by

$$BX = (BX_{add} + BX_{mult} \cdot z) \cdot \sqrt{v} \tag{23}$$

where v is the vehicle speed (m/s), BX_{add} is the additive part of the safety distance, BX_{mult} the multiplicative part of the safety distance, and z is a value from 0-1, usually distributed around 0.5 with a standard deviation of 0.15.

While Wiedemann 74 is usually applied for urban traffic interactions and merging areas, Wiedemann 99 (W99) is a refined and modified version to model the freeway traffic conditions (PARK et al., 2017; Vissim User Manual, 2019; LACERDA & NETO, 2014; SONGCHITRUKSA et al., 2016). According to GAO (2008), the W99 model used in VISSIM is formulated as

$$u_n(t + \Delta t) = \ min \ \begin{cases} u_n(t) + 3.6 \cdot \left(CC8 + \frac{CC8 - CC9}{80}\ u_n(t) \right) \Delta t \\ 3.6 \cdot \left(\frac{s_n\,(t) - CC0 - L_{n-1}}{u_n(t)} \right)^2 \end{cases} , u_f \tag{24}$$

where CC0 is the standstill distance (m), CC8 is the standstill acceleration (m/s), and CC9 is the desired acceleration (m/s) at a speed of 80 km/h. Besides CC0, CC8, and CC9, there are still additional adjustable parameters from W99 described in Annex 5 (FRANSSON, 2018).

The relation between W99 parameters and the thresholds described in Fig. 12 are the following (AGHABAYK et al., 2013):

$$AX = L + CC0, \tag{25}$$

where L is the length of the leading vehicle

$$BX = AX + CC1 \,.\, v \tag{26}$$

Where v is the subject vehicle speed if it's lower than the leading one, it is the same value from leading vehicles with random errors determined by multiplying the speed difference of them by a random number between -0.5 and 0.5.

$$SDX = BX + CC2 \tag{27}$$

$$(SDV)_i = \frac{\Delta x - (SDX)_i}{CC3} - CC4 \tag{28}$$

Where Δx is the spacing from the subject and leading vehicle (bumper to bumper).

$$CLDV = \frac{CC6}{17000}\ (\Delta x - L)^2 - CC4 \tag{29}$$

$$OPDV = \frac{CC6}{17000} \cdot \; (\Delta x - L)^2 - \zeta CC5 \tag{30}$$

where ζ is a variable equal to 1 when the subject vehicle is higher than CC5, else 0.

CC7, CC8, and CC9 are parameters not related to the threshold but to the acceleration progress that depends on the driving behavior limited to the vehicle's maximum performance. They are described in Chart 8.

Chart 3 shows manuals and research with reference values for each of those parameters.

Chart 3: References for VISSIM parameters set.

Reference	Weblink
VISSIM 11 Manual	Available inside the installation folders
Advanced Transportation Leadership and Safety Center (ATLAS Center) from the University of Michigan and Texas A&M Transportation Institute: *Incorporating Driver Behaviors into Connected and Automated Vehicle Simulation (2016)*	https://www.atlas-center.org/wp-content/uploads/2014/10/ATLAS-Research-Report-Songchitruksa-ATLAS-2016-13.pdf Access: September 2019
Oregon Department of Transportation (ODT): Protocol for VISSIM Calibration (2011)	https://www.oregon.gov/ODOT/Planning/Documents/APMv2_Add15A.pdf Access: September 2019
Wisconsin Department of Transportation (WSDOT): *Protocol for VISSIM simulation (2014)*	https://www.wsdot.wa.gov/NR/rdonlyres/378BEAC9-FE26-4EDA-AA1F-B3A55F9C532F/0/VISSIMProtocol.pdf Access: September 2019
Wisconsin Department of Transportation (WSDOT): *VISSIM Calibration Settings (2018)*	https://wisconsindot.gov/dtsdManuals/traffic-ops/manuals-and-standards/teops/16-20att6.3.pdf Access: September 2019
Deliverable 2.3 CoEXISt: *Default behavioral parameter sets (2018)*	https://www.h2020-coexist.eu/wp-content/uploads/2018/10/D2.3-default-behavioural-parameter-sets_final.pdf Access: September 2019

Source: Author.

For CAVs simulation, a recommendation from the Coexist project is to use W99 even on freeway traffic conditions (Coexist D2.6, 2018). It is recommended mainly due to the availability of more parameters to control the behaviors. Also, on the W74 model, the vehicles keep their exact desired speed on the free driving mode, when W99 allows for changing many of the parameters used and assumes a linear relationship between speed and following distance (i.e., a constant time headway plus standstill distance). In conclusion, W99 demonstrates to be more suitable for simulating CAVs independent of road characteristics.

Finally, apart from car-following parameters, more than forty-seven other parameters are available to define the driver behavior.

2.5.2 CAVs simulation

In the simulations involving CAVs, it is demanded to gather expertise in many different fields of knowledge. Including road traffic simulation, network simulation, and V2X application. According to (GOEBEL, 2017) simulating it in a single simulator would have many disadvantages of consuming a significant amount of time for planning, programming, and verifying the combined simulator. He states that the approach to couple well-established simulators of the different domains is much more promising. At least three sets of simulators need to be coupled to allow realistic simulations of V2X applications communicating via cellular networks:

i. Well-established road traffic simulator to simulate the traversal of vehicles on the road network.

ii. Network simulator with cellular network simulation capabilities (MUSSA et al., 2016);

iii. V2X application simulator.

Fig. 13 shows an overview of possible settings for CAVs simulation with SUMO and VISSIM. (GÁLVAN, 2016). Moreover, GOEBEL (2017) describes in detail the co-simulators compatible with SUMO. On the website from Open-Source Application Development Portal (OSADP) from USDOT, it is available some co-simulators developed to be compatible with VISSIM (e.g., for CACC feature) (ITS Forge, 2019). It is essential to mention that some tries to use OSADP co-simulators were performed unsuccessfully due to a lack of documentation.

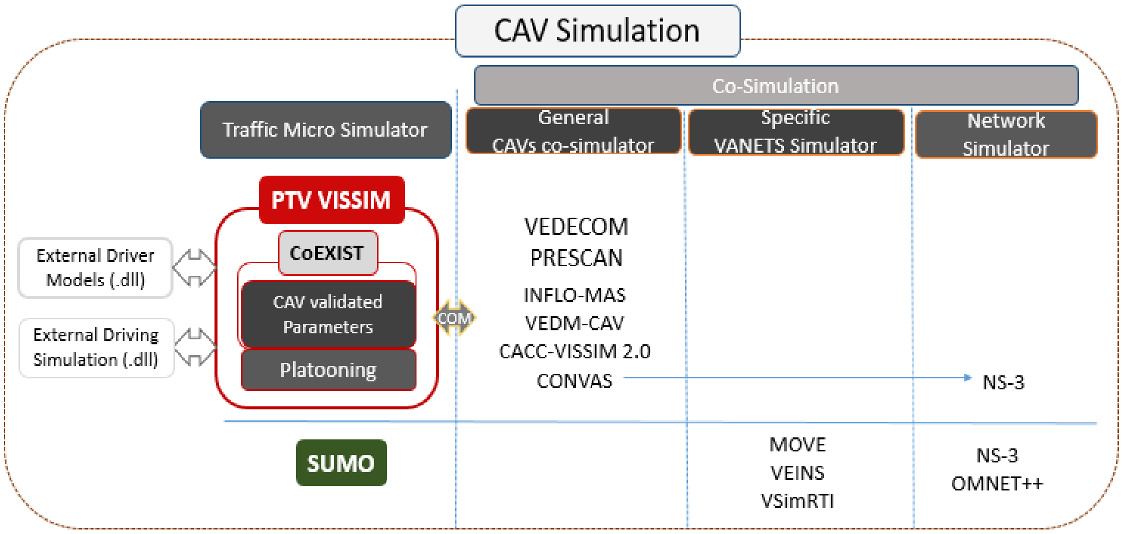


Fig. 13. Overview of simulators combinations for CAVs simulations.
Source: Author.

On the VISSIM version 11, new features were added to support CAVs characteristics and mixed traffic situations, as described in Chart 4.

Chart 4: New features released at VISSIM to enable AVs and CAVs traffic simulation.

Feature	100% HDV environment	CAV/ mixed environment
Use implicit stochastics	Stochastic: the imperfection of human driving	Deterministic machines & computers
Class dependent safety distance in the following behavior	Headway is fixed for all vehicle classes	Headway dependent on followed vehicle class: possible to set different following distances to conventional vehicles, automated vehicles, connected and automated vehicles, and cyclists
Number of interaction objects & vehicles	Humans can see many vehicles ahead independent of sensors but have limited capacity to interact with many objects	AVs can detect objects and interpret visual information inside the sensor's range. CAVs can interact with more objects due to communication capabilities.
Increased acceleration in following possible	Humans have limited capacity to keep following the leading vehicle closely. During the following behavior, the acceleration rates are not highly increased to keep the distance.	Higher acceleration rates are necessary for CAVs in a platoon formation to maintain the headway even when the leading vehicle's speed increases slightly. Therefore, to simulate platoon behavior, the “Increased acceleration” parameter must be set above 100%.
Zero passengers	It will be every time at least the driver inside the vehicle	It allows to setting vehicles with zero passengers (for SAE J3016 Level 4 and 5)

Source: Adapted from PTV (2019) and Coexist D2.6 (2018).

VISSIM did the first try on having a connected vehicle integrated tool in September 2019. VISSIM 2020.00-0 beta version released the feature platooning (PTV, 2019). Before launching platooning, all the material that the PTV released for testing CAVs was done using external coding (python script and COM interface).

On VISSIM 2020, it is possible to set five different parameters related to platooning, as follows:

- Maximum number of platoon vehicles: maximum number of vehicles in a single platoon.
- Maximum platoon approach distance (m): a vehicle that intends to join a platoon should be at a smaller distance from behind than set in this parameter.
- Maximum platooning desired speed (km/h): when a vehicle is inside a platoon, this becomes the new desired speed. When a vehicle leaves the platoon, its individual desired speed is automatically back. Reduced speed areas are considered and respected.

- Maximum platooning clearance (m): minimum standstill distance between two vehicles in a platoon.
- Minimum gap (s): refers to the minimum time gap between two vehicles in a platoon (PTV VISSIM 2020 USER MANUAL, 2019).

This feature was developed inside the software to evaluate the effects on overall traffic, and it was modeled considering the following characteristics:

- The entire platoon uses the same lane. Vehicles inside a platoon do not change lanes.
- Only vehicles with the same driver behavior can form a platoon.
- A platoon can be split if a vehicle inside needs to take a different route. If the conditions are met, the split platoons can join again.
- To safely leave the platoon, the following vehicle must increase the distance downstream to its preceding vehicle and upstream to its following vehicle.
- A platoon can be split during a red traffic light if there is not enough time for the whole convoy to pass through.
- A platoon can be disabled depending on the link configuration; it is possible to set at the same network area where platoon is enabled or disabled.
- PTV VISSIM software running alone do not consider the communication between vehicles and their possible influence on driving behavior nor other platoon-internal dynamics (PTV VISSIM 2020 USER MANUAL, 2019).

As platooning is a new feature focusing on V2V, and there are still few kinds of research worldwide that delivered results using that software capability, it will be used in that research on scenarios with CAVs.

3 LITERATURE REVIEW

This chapter presents different aspects of the CAVs concept that evolved over the years, focusing on microscopic simulation. The review is presented chronologically with the most relevant studies related to the topic to explore the art state in that research field. This review aims to answer four central questions:

i. How will CAVs impact the traffic performance of the cities and roads,
ii. How will be the traffic performance and which are the most relevant aspects to be evaluated during transition phases where different vehicle automation levels will share the same road?
iii. Any of those studies cover Brazilian city traffic situations?
iv. Which technologies are more relevant? Bearing those questions in mind, this research its relevance can be further comprehended.

The literature about traffic microsimulation for CAVs is mostly condensed in the last four years due to the topic's increasing prominence. Simultaneously, the simulator's capabilities to model the characteristics of this environment have been improved. RIOS-TORRES & MALIKOPOULOS (2017) brings a collection of studies starting from the end of the 1960s with different approaches to achieve safe and efficient vehicle coordination to improve the traffic flow. TIAN et al. (2018) and DO et al. (2019) published surveys with many different research types related to the simulation of CAVs. Those surveys and a further active literature search on leading journals, books, and congress proceedings are presented in the following.

Along with the 90s, the first system on the roadmap to the AV's most used terminology was Autonomous Intelligent Cruise Control (AICC). It was defined as a vehicle-installed system that automatically adapts the speed to keep a safe distance from the vehicle ahead. The vehicle's communication technologies were still not part of those research. KING et al. (1993) and BJORNBERG (1994) presented the control algorithm's description to define the system that years later would be so-called ACC. CHIEN & IOANNOU (1993) showed that the AICC system outperformed the human driver model due to its faster and better transient response, resulting in smoother traffic and faster traffic flow. CARREA & SAROLDI (1993) explored in a testing vehicle the integration between AICC and anti-collision systems. Other studies, as ERIKSSON & AS (1995) and AOYAGI et al. (1997), had the focus on radar development for AICC systems.

After the 2000s, the terminology ACC and CACC become more used. WERF et al. (2002) developed a simulation based on the Monte Carlo algorithm to estimate ACC's impacts in different proportions and HDVs. AREM et al. (2006) developed a microsimulation model dedicated to studying the impact of CACC on traffic flow. The authors evaluated its impacts on a highway scenario, focusing on merging spots compared to non-equipped vehicles. They reported an improvement in traffic flow stability. Anyhow, it was not found relevant improvements on travel times. On the other hand, KESTING et al. (2008) developed a microscopic traffic simulator and used the IDM to propose an ACC with an active jam-avoidance system. They noticed that a proportion of 5% of ACC vehicles already improved the traffic flow, and 25% of ACC reduced the cumulated travel time by approximately 75%, mainly because ACC avoided the breakdown of traffic flow in the model.

Many research types focused on ACC, IDM models, and CACC impact on traffic performance in the current decade. SCHAKEL et al. (2010) used a modified version of IDM, so-called IDM+ and CACC algorithms, to evaluate traffic flow stability on field tests with 50 vehicles (FOT). In mixed traffic scenarios with 50% of CACC equipped vehicles, the shockwave duration was five times lower than 100% HDVs. KESTING et al. (2010) proposed an Extended IDM (EIDM) using a constant-acceleration heuristic (CAH) as a performance index. They found a direct relation between ACC penetration rate on traffic performance: each 1% more ACCs increased road capacity by about 0.3%. (LIU et al., 2018) also developed a variation of Extended IDM that considers V2V technologies. A stability analysis is performed where EIDM shows a broader stability region when compared to IDM. LU et al. (2019) proposed a model for CAVs in a platoon based on an ecological control strategy so-called Ecological Smart Driver Model (EcoSDM), considering IDM as the base model (100% HDVs). The simulation results show that the model is superior in fuel efficiency (at fully CAVs scenarios, EcoSDM was 10% better for the platoon than EIDM) and stabilization effects compared to SDM and EIDM. A topic to highlight in this study is that the platoon's position has interference on fuel consumption as expected. A non-trivial output was that the platoon leader was almost 2% better fuel efficiency than the base scenario, and the vehicle on position 16 of the platoon was near to 0%.

In parallel, several researchers used microsimulation tools to assess their studies in the same fields. PLOEG et al. (2011) simulated CACC systems and showed evidence that the smaller gaps achieved with the vehicles' platoon increased the road throughput. PARK et al. (2011) used VISSIM to explore a lane change advisory algorithm for CAVs on-road merge conflicts, considering V2V capabilities. As the vehicles on the road open gaps for vehicles entering the merging areas, they measured a 6,4% higher average vehicle speed in the freeway and a 5.2% reduction in emissions with 100% of CAVs compared to the merging area with 100% HDVs. On the other hand, SHLADOVER et Al. (2012) simulated ACC and CACC with AIMSUM traffic simulation. They tested different market penetrations, and results showed that ACC has low impacts on increasing road capacity (veh/h), even in higher penetration rates. Although CACC showed a low penetration of 20% already increased the capacity by 7%, it doubled the lane capacity for 100% of CACC. It is essential to mention that the better results came with CACC penetration rates above 80%. (ZHAO & SUN, 2013) used VISSIM to simulate a mixed freeway with vehicles with no ADAS together with vehicles equipped with ACC and CACC (platoon mode). ACC and CACC were simulated using the External Driver Behavior Model (EDBM) coded in C/C++ coding. Results showed that traffic capacity almost doubled from 0% CACC market to 100%. One relevant outcome was that the platoon's size (from 2 to 6 vehicles) did not significantly impact traffic capacity.

Other research had a focus on the interface between vehicles and infrastructure. Their studies were assessed on micro simulators. LEE & PARK (2012) developed a V2I system for Cooperative Vehicle Intersection Control (CVIC), and simulation results revealed a reduction of 99% of stop delays and travel time, which impacted on 44% reduction of fuel consumption when compared to the same intersection with 0% vehicles equipped with V2I technology. KATSAROS et al. (2011) reported a 7% reduction in fuel consumption in a scenario with 100% of vehicles equipped with Green Light Optimized Advisory (GLOSA) when compared to standard vehicles. STEFANOVIC et Al. (2013) also evaluated GLOSA with high penetration rates that presented a reduction of 52% vehicle stop delay, a 46% reduction on vehicles stop, although just 0,5% higher fuel efficiency. A few years later, GLOSA focused on CHOUDHURY et al. (2016) that developed a simulation setup with VISSIM, MATLAB, and NS-3 (network simulator) to test this application. The authors obtained a 7.4% reduction in fuel consumption and a 20% higher network throughput in the scenario where GLOSA was applied to 100% of vehicles. An extensive report from FROST & SULLIVAN (2017) shows that intelligent traffic system applications can reduce travel time by 23% for emergency vehicles (hospital ambulances, fire engines) and 27% for other vehicles.

Studies with mixed or heterogeneous traffic topics got attention from the researchers during the last few years. When human-driven AVs and CAVs coexist on the same road, YANG et al. (2016) further explore the aspect. Simulations resulted in an evident decrease in the total number of stops and delays when using an algorithm for CVs relative flows above 50%. BAILEY (2016) modeled a mixed flow with autonomous, based on modifications on IDM (presented in chapter 2, so-called Enhanced Intelligent Driver Model (EIDM). ZHOU et al. (2017) also proposed modifications on IDM, so-called Cooperative IDM (CIDM), and evaluated the average travel time for AVs percentage from 0-25%. Results showed that for safe time gaps between 0.4s to 0.8s, the average travel was reduced by 15% when a 25% percentage of AVs was achieved. It was also concluded that an increase in urban traffic network capacity and a decrease in average delay as CVs penetration rate is increased (on 100% and 20% CVs penetration a reduction in travel time of 80% and 53%, respectively, was achieved). RIOS-TORRES & MALIKOPOULOS (2017) made a comparison with an optimal control scenario considering 100% of CAVs penetration and reached a 60%-time reduction for heavy traffic.

ARIA et al. (2016) used VISSIM (W99 model) to simulate AVs based on parameter adjustments. At the simulated autobahn with 100% of AVs, the authors reported improvement by 9% on travel times and 8.48% higher average vehicle speed when compared to the base scenario (0% AVs). PARK et al. (2016) used VISSIM running with the COM (Component Object Model) interface that makes it possible to anticipate the information from the next step of the simulation. They concluded that the CV environment reduces the congestion in proper traffic volume because of eliminating the perception-reaction time gap. YE & YAMAMOTO (2017) focus was also on heterogeneous traffic flows, showing more significant improvement when the penetration rate o CAVs is above 30%. DOLLAR and VAHIDI (2017) show different algorithms to compare platooning performance and reports a potentially significant fuel efficiency benefit when the proposed Model Predictive Control (MPC) algorithms are used. HAAS & FRIEDRICH (2017) developed a microscopic simulation with SUMO and Plexe (extension for SUMO to implement platoon functionality) for CAVs platoons, used in city logistics with the focus on the travel time issue. The main results show that an increase in the number of vehicles per platoon (from 2 to 6) decreases the travel time. This result was achieved mainly during peak hours (network crowded).

The pace of studies on the related kept increasing in the last two years. RIOS-TORRES & MALIKOPOULOS (2018) simulated based on Gipps car-following model and optimal control, including V2V and V2I, to evaluate its impacts CAVs on fuel consumption and a traffic flow from 0% to 100% penetration. The results for low traffic volumes were the fuel-saving achieved 55% increasing proportionally from 0 to 100% CAVs. One conclusion was that for medium and high traffic demand, a significant fuel saving was achieved just near 100% CAVs penetration. BAZ (2018) used VISSIM and game theory concepts to propose improving delay times on roundabouts and intersections. The results show that the proposed system reduces the total delay by more than 65% on the roundabout and about 85% percent on a signalized intersection. TILG et al. (2018) developed a variation of the multi-class hybrid model (MHT) based on multiple vehicle classes for CAVs mixing traffic in weaving sections. The model was developed using MATLAB and calibrated with field data from the city of Basel, Switzerland. Results show that growing shares of CAVs can increase up to 15% traffic flow capacity by optimizing the spatial lane change distribution compared to scenarios with no CAVs. OLIA et al. (2018) simulated the CAVs under mixed-traffic conditions with the assumption of increasing a 10% gap of CAVs. The result shows that a 100% penetration rate of CAVs could increase road capacity from 2,046 to 6,450 vehicles/hour/lane. LIU et al. (2018) simulated the impacts of a CACC multi-lane freeway with mixed traffic highway simulations by increasing CACCs' gap by 20%. The results show that the freeway capacity could be approximately 90% higher with a 100% CACC penetration rate, compared to 0%.

CHEN et al. (2019) simulated with VISSIM to assess the impact of ACC and CACC increasing penetration rates among HDVs. For both ACC and CACC increasing penetration rates, the most significant impacts were found on travel time. For a 90% penetration rate, there was a 9% and 11% reduction of travel time ACC and CACC, respectively. XIE et al. (2019) propose a generic car-following model for HDVs and CAVs. Results shoes that increasing penetration of CAVs can suppress traffic waves (using information from ADAS for penetration above 80%, the variation on vehicle speed could be almost neglected) stabilize traffic, therefore, increasing the traffic flow. ZHOU et al. (2019) modeled four-lane cellular automata traffic on mixed traffic with ACC/CACC and manual vehicles. The numerical results indicated that the CACC strings presented considerable stability while the ACC strings show instability. The CACC penetration rate evaluation showed that the capacity per lane almost doubled from 2000 veh/hr (0% CACC) to approximately 3900 veh/hr (100% CACC), where the higher impacts came from penetration rates above 60%. GHIASI (2019) presented a speed harmonization algorithm to harmonize traffic for HDVs and CAVs in mixed traffic situations. The numerical experiment results indicate that the algorithm could smooth CAV movements and harmonize the following human-driven traffic.

CALVERT et al. (2019) simulated platoons for trucks in congested highways using PTV VISSIM. They considered an extreme scenario with no maximum platoon size and intra-platoon time headway of 0,3s, where they found a small benefit of 2,9% travel time reduction for penetration rates above 80%. In general, the authors justified the results because longer platoons outperformed the lane changed from vehicles around and suggested the application of platoons in non-congested traffic, then larger platoons with short time headways can perform better. The following year, CALVERT et al. (2020) released a new study from an FOT and simulation experiment of CACC for city environments. The authors found important savings in travel time on heavy traffic, mainly when applied to the V2I feature (traffic lights green extension). For penetration rates smaller than 50%, no positive effects were found because CACC vehicles turned to normal ACC when the following vehicle does not have the technology. The results for a 100% penetration rate were a 5% reduction in travel time that was increased to 11% when V2I was applied. Their settings for CACC were time headway of 0,6s plus 5m, considering no communication delays, and 0.8s plus 5m for ACC. One important contribution was to release the calibrated W99 most relevant parameters for HDVs after field tests presented also on Chart 8: CC1 = 0.9s, CC7= 1.0m/s^2, CC8=4.5m/s^2 and CC9=1.5m/s^2. For CACC, CC1 was considered as 0.6s.

CHANG et al. (2020) studied the platoons (CACC) for their alternative taxonomy to CAVs, so-called Intelligent and Connected Vehicles (ICVs), keeping the focus on mixed traffic flows. Their assessments were done based on IDM and CACC described in equation 20. The first analysis was on time headways for 100% CAVs penetration, where the traffic capacity decreased by 26% comparing time headways from 0,6s to 1,1s. For a 50% penetration rate, the reduction in traffic flow was much lower, by 7%, comparing headways. The second analysis kept the time headway in 0.6s, where the capacity increased by 64% from 10% to 100% CAVs penetration rates and increased by 45% from 50% to 100% penetration rates. Their third analysis was changing platoon size from 2 to 8 vehicles. For CAVs penetration rates up to 30%, the impacts on capacity were insignificant, independent of platoon size. When it comes to 50% or higher, the capacity is increased by 7% comparing 2 to 8 vehicles platoon size and 55% for a 100% penetration rate compared to the same platoon sizes. Collating the worst to the better results means a 10% penetration rate with two vehicles platoon size to 100% penetration rate and eight vehicles platoon size, the capacity increased by 75%. Therefore, they concluded that CAVs could effectively improve the throughput of existing road traffic systems. The increase in the maximum platoon size is advantageous for improving the mixed flow capacity.

YAO et al. (2020) used SUMO and OMNET++ to simulate a simple urban network. In their model, even on 100% CAVs penetration rates, all the vehicles could be driven by a human, where only platoon followers were considered to be autonomously driven. The results showed a reduction of 19% and 27% in travel delays for 60% and 100% CAVs penetration rates compared to 0%, respectively. One other remarkable result was that the merging requests for joining platoons increased up to 31% and 70% compared with 60% to 80% and 100% CAVs penetration rates, respectively.

Chart 5 shows a summary table with the major studies on CAVs microscopic simulation research that presented numerical results related to its impacts on traffic flow, fuel efficiency, and emissions. As the impacts on traffic flow focus on this research, those results are used to assess the results found during the simulation scenarios proposed.

Besides the mentioned CAVs impacts, it worth mentioning additional studies on road safety focus. VALIDI et al. (2017) use SUMO and “Scene Suit” to show the impact of CAVs on road safety. For the scenarios evaluated, the overall results show that even the lowest penetration rate (40%) of V2V resulted in a dramatic improvement in road safety by preventing all types of accidents. One additional valuable reference from GE et al. (2018) shows an experimental validation done with retrofitted vehicles equipped with V2X devices at the University of Michigan Mobility Transformation Center. The experiments demonstrate that both safety and fuel efficiency can be significantly improved for CAVs and nearby human-driven vehicles. They conclude that CAV may bring additional societal benefits by mitigating traffic waves.

Chart 5: Summary table with results comparison between references and author

Reference	Simulator	Application	Results
H. PARK et al. (2011)	VISSIM	Merging Highway	↑ 6,4% average vehicle speed ↓ 5,2% emissions
KATSAROS et al. (2011)	SUMO	City	100% GLOSA equipped vehicles → ↓ 7% fuel consumption
STEVANOVIK et al. (2011)	VISSIM	City	100% GLOSA equipped vehicles → ↓ 50% stop delays
SHALODER et al. (2012)	AIMSUM	Highway	100% CACC → 2x lane capacity
ZHAO & SUN (2013)	VISSIM + C++ DLL	Highway	100% CACC → ↑ 95% traffic capacity
ARIA et al. (2016)	VISSIM	Highway	↑ 8.48%: average vehicle speed ↓9.00%: travel time
CHOUDHURY et al. (2016)	VISSIM NS-3/Matlab	City	100% CACC → ↓ 7,4% fuel consumption 100% CACC → ↓ 7% emissions
BAILEY (2016)	AIMSUM	City	20% AVs → ↓ 53% travel time 100% AVs → ↓ 80% travel time
RIOS-TORRES et al. (2017)	AIMSUM	City	100% AVs → ↓ 60% travel time
EVANSON (2017)	VISSIM + Platooning (external)	Highway	100% CAVs → ↓ 11% travel time
BAZ (2018)	VISSIM	City	↓ 65% total delays in roundabouts ↓ 85% total delays on signalized intersections
OLIA et al. (2018)	Not mentioned	Highway	100% CAVs → ↑ 315% veh/hr/lane capacity
TILG et al. (2018)	MATLAB + Not mentioned	Highway	100% AVs → ↑ 15% traffic capacity
LU et al. (2019)	Not mentioned	Highway	100% AVs → ↓ 16% fuel consumption
ZHOU et al. (2019)	Not mentioned	Highway	100% CACC → ↑ 95% lane capacity
GOÑI-ROS et al. (2019)	Not mentioned	Highway	50% CACC → ↓15% travel time ↓55% average veh delay 100% CACC → ↓20% travel time ↓64% average veh delay
CHEN et al. (2019)	VISSIM	Highway	90% ACC → ↓ 9% travel time 90% CACC → ↓ 11% travel time.
CALVERT et al. (2019)	Not mentioned	Highway (Trucks)	≤80% CACC → no positive effect 100% CACC → 2.9% travel time reduction
CHANG et al. (2020)	Not Mentioned	Highway	Platoon size=8; Time Headway=0,6s: 50% CACC → ↓ 13% travel delays 100% CACC → ↓ 75% travel delays
YAO et al. (2020)	SUMO/ OMNET++	City	60% CACC → ↓ 19% travel delays 100% CACC → ↓ 27% travel delays
CALVERT et al. (2020)	VISSIM	City	≤50% CACC → no positive effect 100% CACC → ↓ 11% travel time.

Source: Author.

Other critical aspects for CAVs evaluated by FERNANDES & NUNES (2012); OSMAN & ISHAK (2015), BIDÓIA (2015), MIR & FITALI (2016), CHAI et al. (2017), HE, et al. (2017), NANAJI et al. (2017) and TAKAHASHI, (2018), NAUFAL et al. (2018) and HUSSAIN et al., (2019), are the connectivity robustness, cyber/data security, network performance and functional safety (ISO 26262, adapted for the automotive industry from IEC61508). They discuss topics related to the effects of the position error, communication delay, received signal strength, packet delivery ratio, number of nodes, and reliable communication range for the given data rate settings.

Besides, apart from the already mentioned BIDOIA (2015), it is essential to cite other research in Brazil related to CAVs. It was not found studies related explicitly to CAVs traffic microsimulation impacts on traffic flow; anyhow, other essential topics from their ecosystems were on the scope. MATEUS (2010) provided new directions to design efficient routing protocols performance for vehicular networks. CARIANHA (2011) also focused on vehicle networks assessing a cryptographic “mix-zones” model to improve location privacy information. GÁLVAN (2016) used the combination of SUMO and OMNET++ to study the vehicle's wave propagation modes from VANETs in the urban environment.

In conclusion, a wide range of research in CAVs, from simulation to field tests, shows that these technologies positively impact highway traffic flow, lane capacity, and fuel efficiency and emissions. On many different studies based on microscopic traffic simulation among different assumptions about car-following behavior, lane changing behavior, and connectivity, there is a common trend showing that increased penetration of autonomous vehicles leads to increased capacity and flow. The increasing penetration of technologies enabled by CAVs (as CACC/platooning, GLOSA, and modified version of IDM) impacted better results from all the aspects evaluated on the challenging mixed traffic conditions. It shows that the technologies should continue to be developed, and the implementation path accelerated.

The gaps found to be explored in this research are: The simulation research explores highways or city conditions with aspects that do not cover Brazilian metropolitan areas' roads and streets reality as the high number of motorcycles, buses, and trucks, non-dedicated public transportation lanes. Another topic that is not explored in many types of research is to add disturbance as vehicle breakdown and how to recover the normal traffic conditions in less time. Also, for highways, a gap was found on comparing, based on the same inputs data, variations of baseline network adding complexity as new entrances and exits. In this study, a different approach was made on highway networks, splitting them into segments to analyze individually the impacts of platoons being enabled or not for distinct vehicle interaction characteristics.

4 METHODOLOGY

This research aims to develop a methodology that makes it possible to carry out studies to assess the impacts of AVs and CAVs on traffic. The simulation or an FOT (Field Operational Trial) can be used as the framework, making the following methodology steps different. If the simulation is the option, then the proper traffic simulator's choice takes the central role. In this research, the possibility the simulation was chosen to make it possible to assess and compare many different scenarios and features from HDVs, AVs, and CAVs, including the interaction among a considerable quantity of vehicles from different autonomous levels.

So, the simulation network model should be built. The input data and proper parameters should be collected according to the tool characteristics leading to a crucial phase: the calibration and complete definition of the baseline model. The scenarios derived from the baseline can be developed according to the simulator features and the research targets. When the collection of scenarios is defined, many different outputs can be used to compare the relevant aspects assessed during the research leading to the conclusions. The detailed steps are described as follows.

4.1 TRAFFIC SIMULATOR

The first step of the methodology is to define the research targets clearly (step “a” from Fig. 14). The second step is to define the desired outputs to find the appropriate conclusions (step “b). Then, the level of details that the simulation network requires, and the demanded features will support to define of the simulator category from nanoscopic to macroscopic (step “c” described in). Each simulator has its characteristics: features capabilities, co-simulation compatibility, required skills from the user who builds up the model, and minimum computer processing capacity to run the simulation. An exhaustive search on the simulators and a first contact considering tutorials is essential to assure the proper choice (step “d”). At that point, it is crucial to evaluate the question from (step “e”). If the research targets cannot be covered with the current choice, including co-simulators, it is necessary to go some steps to ensure the proper choice.

In this research, the driver behavior comparison among HDVs, AVs, and CAVs took the central role of microscopic simulation. The simulator defined for this research was PTV VISSIM due to the more straightforward configuration of different scenarios than other simulators, and the built-in platooning feature enabled the assessment of the same algorithm framework for the different convoys configuration. It Included the possibility to apply the convoys in specific segments of the road, lanes, or vehicle types. Even though it is commercial software, PTV Group offers a thesis license to students. PTV provided VISSIM 11 student licenses for ten months and VISSIM 2020 for additional six months. It is also available at the university labs.

Fig. 14 shows a workflow with the steps to define the appropriate simulator.

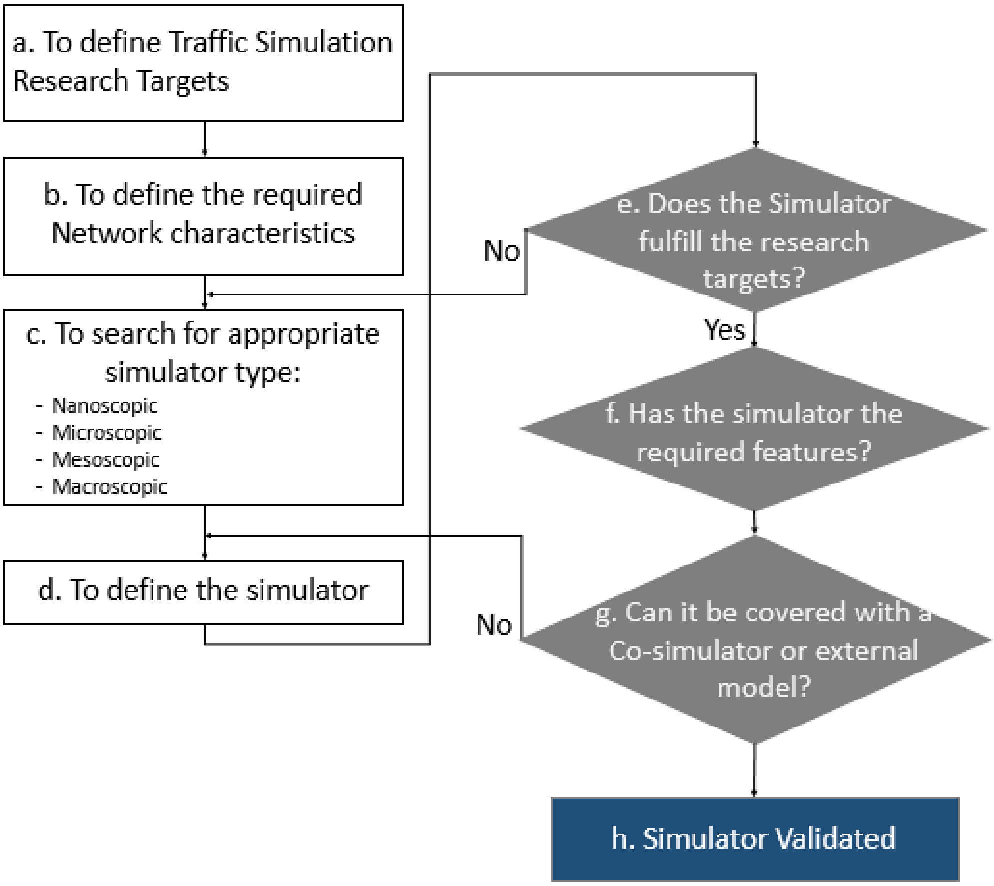


Fig. 14. Workflow to define the appropriate simulator.

Source: Author.

Once the simulator is defined, a new phase starts by building up the simulation network model, including all the required details to reproduce the base scenario described in step I from **Fig. 15**. Broad research to find all the required input data is demanded. It can include field studies, transportation entities report, or web-based data (step II). The most important part of this new phase is to perform the correct calibration to make the simulation valid. Usually, the calibration is an interactive process that is refined until the point that the result compared to a reference is acceptable (step IV). When it is finished, real-world networks with 100% of HDVs in São Paulo city, including the specific day's traffic characteristics. Besides that, three more networks were built and calibrated to assess the segment of highways.

As the purpose is to evaluate the AVs and CAV's introduction, a proper model of each automation level needs to be built. It includes the driver behavior models, parameters, and demanded features that reproduce AVs and CAVs, including how they interact with others (step

VI). Finally, all the demanded inputs to the simulator are ready. They can be used in different combinations to generate the results and use them according to the research objectives (step VII). In this research, the travel time comparison (step VIII) among the different scenarios and sub scenarios (step IX) was the primary output assessed to come to the conclusions. **Fig. 15** shows the workflows to validate a baseline scenario and to assess the results based on a comparison.

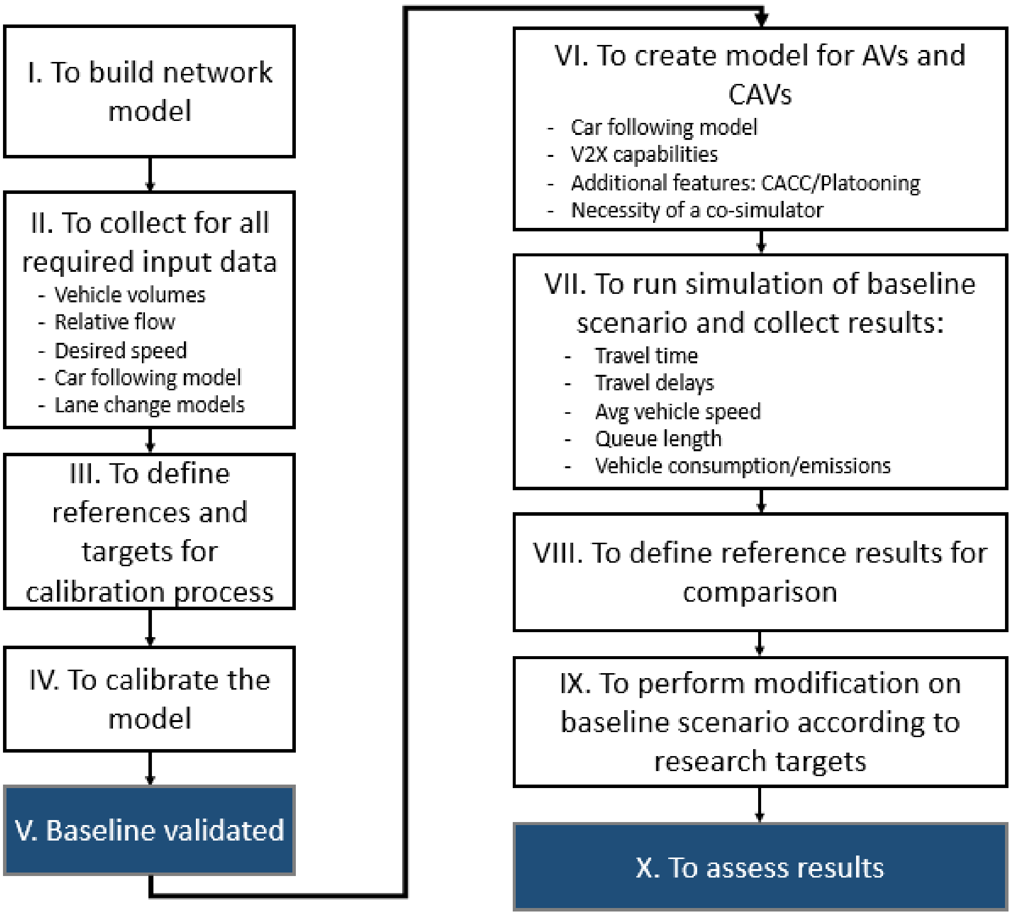


Fig. 15. Workflows to validate a baseline scenario and assessed the results
Source: Author.

4.2 MODEL CALIBRATION

The model calibration is crucial for establishing a reliable framework that makes the data assessment scientifically valid. The theory of traffic model calibration is addressed in section 2.5. The main characteristics used to the calibration from all the networks in this research are listed below:

- The base scenario 1.1 was used to calibrate the simulation model.
- Simulation time 1800s (30 minutes).
- Starting of valid data from 300s simulation time on recommended waiting time for simulation traffic loading.
- All the parameters described in section 0 were fixed: CoExist's "Normal" driving logic.

The primary output data used as a reference was the average vehicle speed. This is the only scientifically validated data found on that specific network. Fig. 16 shows a flow chart with the calibration process.

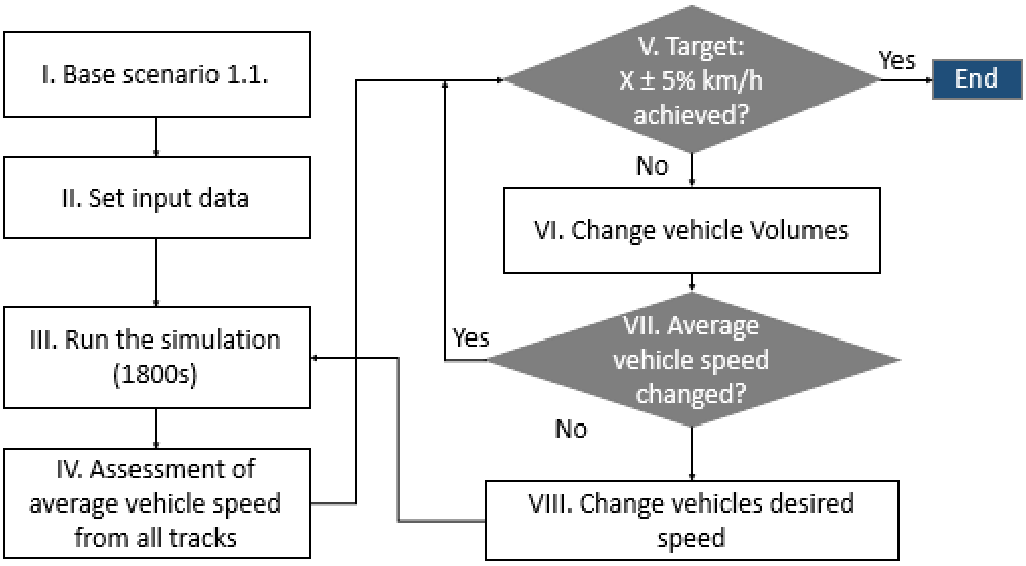


Fig. 16. Flow chart from the calibration process

Source: Author.

This interactive process was performed to define the baseline scenario for all three networks. Annex 5 is listed the vehicle's desired speed and volumes for each vehicle model after calibration.

4.3 EVALUATED SCENARIOS

Seventeen scenarios were built combining different elements as driver behaviors, external disturbance, and an additional new proposal. For every scenario, each driver's behavior's penetration rate was predefined to make it possible to measure the benefits of the incremental introduction of the autonomous and connected vehicle. **Chart 6** shows the overview.

Chart 6: Evaluated scenarios overview

Scenarios	***Subcenarios***	***Driver Behavior Model***	***Pen Rate***
1.1 (Baseline)	1.2 (Baseline)	*Human Driven (HDV)*	100%
2.1	2.2	*Human Driven (HDV)*	50%
		AV	50%
3.1	3.2	*AV*	100%
4.1	4.1.1 and 4.2	*Human Driven (HDV)*	33%
		AV	33%
		CAV	33%
5.1	5.1.1 and 5.2	*AV*	50%
		CAV	50%
6.1	6.1.1; 6.1.2; 6.1.3 and 6.2	*CAV*	100%

Source: Author.

Details from scenarios composition:

- **Scenarios X.1:** base scenarios reproduce real-world models from the modeled network. Scenario 1.1 is the baseline, and its calibration process is described in chapter 4.2. These scenarios do not include disturbances.
- **Scenarios X.2 –> adding a disturbance:** they vary from scenarios X.1, including an external disturbance. The disturbance is a vehicle break down a situation that is always placed in the same position on the network, and it starts at the same simulation time step. To simulate the broken vehicle, it was inserted a bus stop and the open-door time was defined with a value higher than the total simulation time. **Fig. 17** shows how the disturbance was added to the simulation.

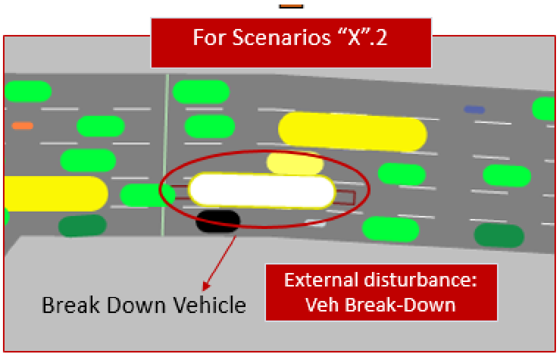


Fig. 17. The disturbance was added to the model on scenarios X.2.

Source: Author.

During the highway's simulations with platooning features, there was a need to create sub scenarios based on Scenarios X.1. They were created to support additional evaluations as described below:

- **Sub scenarios X.1.1:** they differ from X.1 as just vehicles with similar dynamic behavior can perform a platoon, i.e., a passenger car cannot join a platoon with trucks and busses. It was assessed for scenarios 4.1, 5.1, and 6.1.
- **Sub scenario 6.1.2:** the target was to enable setting different driver behaviors along with the same network. The highways from network 3.2 and 3.3 were split into segments where platooning was allowed or not. The details of these networks are in item 5.2.1.3. It was assessed only for scenario 6.1.
- **Sub scenario 6.1.3: a** combination of X.1.1 and X.1.2. It was assessed only for scenario 6.1.

The following sections will detail the simulated networks model, data input, data output, and calibration. Three different networks were selected to evaluate the aspects involved in vehicle automation for city and highway applications. Combining those networks could bring a wide range of simulations leading to a comprehensive evaluation of travel time impacts from CVs and CAVs.

5 EXPERIMENTATION

In this chapter, it is presented the methods and materials used during the research development. The input data and simulator calibrations are described as soon as the description and background of the scenarios.

5.1 MATERIAL

As this research was done based on computer simulations, the details of the materials used are described in **Chart 7**.

Chart 7 - List of materials

Item	Hardware and Software	Destination	Specification
1	Ultrabook LG	Used on scenarios configurations and first simulations	Model U46 Processor: Core i5 RAM: 4GB HD: 512 GB Dedicated graphics board: no
2	Desktop Computer	Used for multiple parallel simulations	Intel i7 Processor 3.2GHz SSD 480GB DATA 6GB Memory DDR$ 16GB 2400MHz Video card (GPU) Geforce RTX2070 HD 2TB
3	PTV VISSIM Software	Simulation	Thesis license Versions: 11.00 -06 to -10 (64 bits) 2020.00.00 to -09 (64 bits)

Source: Author.

It is important to remark that for all simulated networks, it was possible to run the traffic simulator used in this research properly even with a medium performance computer without a dedicated graphics board (item 1, **Chart 7**).

5.2 DRIVER BEHAVIORS SIMULATED MODELS

The research's main goal was to investigate vehicle automation's benefits on different networks for both city and highway applications.

Some scenarios were built based on three different driver behaviors to achieve the goal. Mind that two of them (HDV and AV) were based on the CoEXist project model validated in partnership with PTV mentioned in chapter 2.4.1. CAV driver behavior was modeled based on AVs-based settings adding the platooning feature.

The parameters validated for each driver's simulation during the CoEXist project (Coexist D2.3, 2018) are presented in **Chart 8**. Specific platooning related parameters available on VISSIM 2020 are listed. The comparison to default parameters recommended at the VISSIM user manual (PTV VISSIM 2020 USER MANUAL, 2019) is presented on column denominated “def” as well as the comparison to studies from TIBLJAS et al. (2018) and CALVERT et al. (2020).

Chart 8: Parameters for following behavior validated inside CoEXist project

		Human Driven (HD)	Autonomous Vehicle (AV)	Connected Autonomous Vehicle (CAV)	Default PTV VISSIM	TIBLJAS et al. (2018)	CALVERT et al. (2020)
W74	Ax – Average Standstill Distance	2	1	1	2	-	-
	Bxadd – Additive part of Safety Distance	2	1,5	1,5	2	-	-
	Bxmult – Multiplicative part of Safety Distance	3	2	2	3	-	-
W99	CC0 – Standstill distance (m)	1,5	1	1	1,5	1	8
	CC1 – Spacing time (s)	0,9	0,6	0,3	0,9	0,5	HDV:0,9 CAV: 0,6
	CC2 – Following variation (m)	0	0	0	4	1	Not mentioned
	CC3 – Threshold for entering “following” (s)	-8	-6	-6	-8	-8	Not mentioned
	CC4 – Negative „following“ threshold (m/s)	-0,1	-0,1	-0,1	-0,35	-0,1	Not mentioned
	CC5 – Positive „following“ threshold (m/s)	0,1	0,1	0,1	0,35	0,1	Not mentioned
	CC6 – Speed dependency of oscillation (10^{-4} rad/s)	0	0	0	11,44	0	Not mentioned
	CC7 – Oscillation acceleration (m/s^2)	0,1	0,1	0,1	0,25	0,4	HDV:1
	CC8 – Standstill acceleration (m/s^2)	3,5	4	4	3,5	4	HDV:4,5
	CC9 – Acceleration at 80 km/h (m/s^2)	1,5	2	2	1,5	2	HDV:1,5
Add relev. parameters	Inc Acc	100%	110%	110%	100%	Not mentioned	Not mentioned
	Safety Distance Reduction factor (m)	0,6	0,5	0,5	0,6	Not mentioned	HDV: 0,2
Platooning	Max Number of Vehicles	-	-	Not fixed	7	Not mentioned	Not mentioned
	Max Desired Speed (km/h)	-	-	90	80	Not mentioned	Not mentioned
	Max distance for catching up to a platoon (m)	-	-	250	250	Not mentioned	Not mentioned
	Gap Time [Similar do CC1] (s)	-	-	0,6s (Sc.4 and 5) 0,3s (Sc.6)	0,6	Not mentioned	Not mentioned
	Minimum Clearance (m)	-	-	2m (Sc 4 and 5) 0,5m (for Sc.6)	2	Not mentioned	Not mentioned

Source: adapted from (Coexist D2.3(2018); PTV VISSIM 2020 USER MANUAL (2019); TIBLJAS et al. (2018); CALVERT et al. (2020)).

5.2.1 Description of Simulated networks

5.2.1.1 Network 1: São Paulo city (Bandeirantes x Nações Unidas ave.)

To select a proper network for the simulation, extensive research was performed. The target city was São Paulo in Brazil due to the well-known traffic jam issues and the proximity to the university, and the possibility to do evaluations "*in loco.*"

The starting point was to find trustworthy and scientific information from the traffic situation to be a robust framework. Then it was found the annual Mobility Road System report was released for CET (abbreviation in Portuguese to Traffic Engineer Company) (CET, 2018). This report delivers information from traffic volumes and average vehicle speed from distinct main roads in the city. It is a reference used by public and private traffic management entities to report the networks' improvements and critical points requiring further attention. This report presents a robust statistics and measurement methodology to acquire data and a complete set of detailed results.

From the CET's report, a particular network was chosen. It is the intersection between Bandeirantes Avenue and Nações Unidas Avenue, as shown in **Fig. 18**.

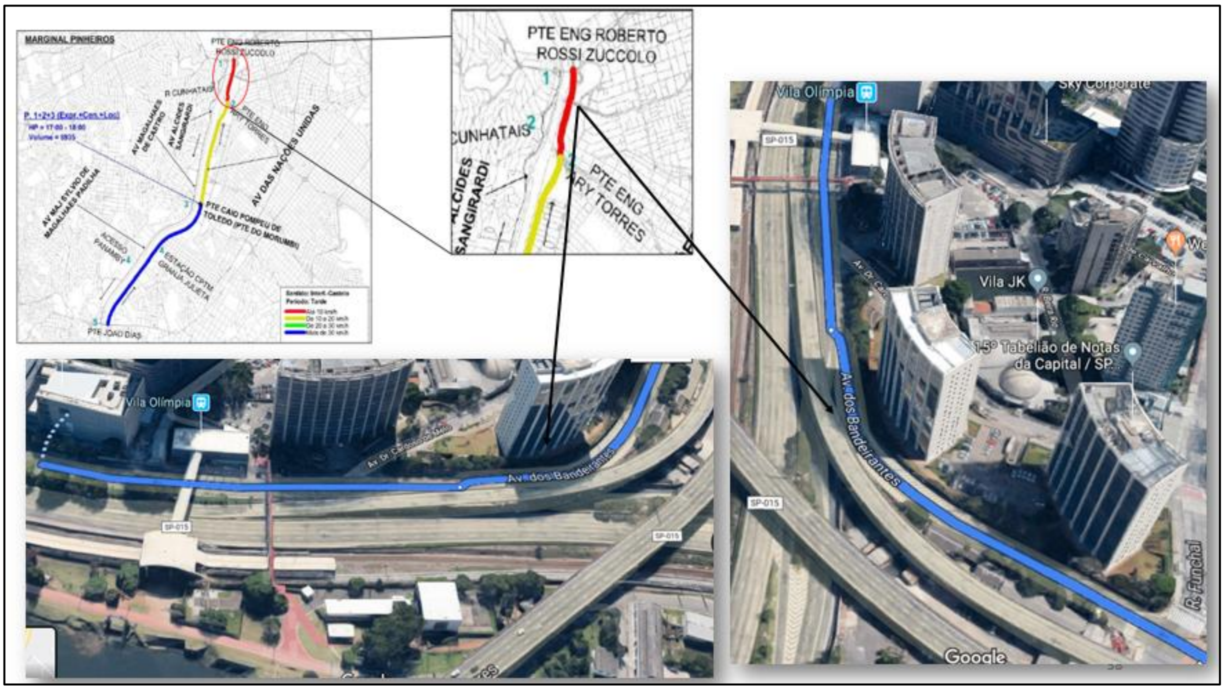


Fig. 18. Top view of simulated network

Source: Adapted from CET (2018) and Google Maps.

This network was chosen between the options due to the following reasons:

- The Highly congested area on rush time: <10km/h average speed.
- Intersection from two large traffic flow roads (pointed as I and II on **Fig. 18**).
- The Bus stop with several lines: two busses together at the bus stop most of the time leading almost to a lane blocking.

- Higher than 10% motorcycles relative flow: typical from large avenues in São Paulo city.

After choosing the network, the first step was to reproduce the streets inside PTV VISSIM software. It offers many resources to make the network as near as possible to reality. The primary resources and the ones used in the model in this research are in italic. They are: *Number of lanes and the total length; Intersections; Reduced speed areas; Bus Stops; Priority rules;* Sidewalks and crosswalks; Lane marks and road signs; Traffic sign.

It is important to remark that the HERE® mapping source company's background is an additional resource to make it easier to draw the network. On Fig. 19, it is shown the simulation test Network 1 built inside PTV VISSIM.

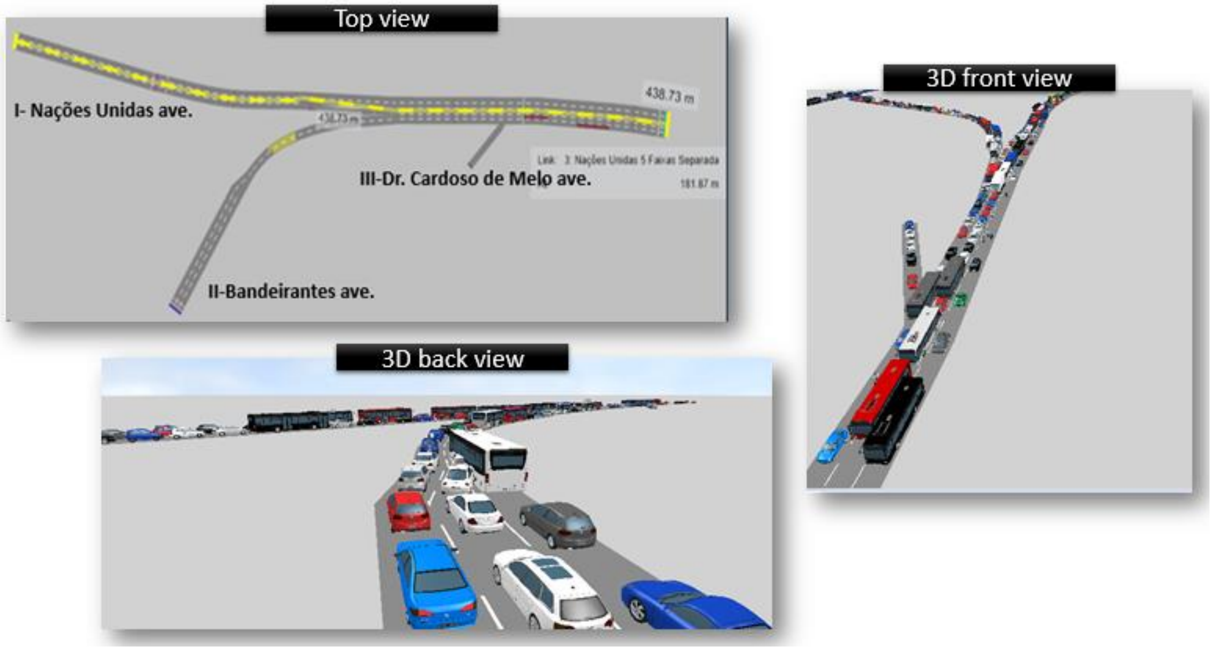


Fig. 19. Simulation Network 1 on PTV VISSIM

Source: Author.

5.2.1.2 Network 2: São Paulo City (Cardeal Arco Verde St.)

Network 2 is also in São Paulo city. Anyhow, the main characteristics are significantly different from Network 1, as:

- The high density of traffic lights: in total, three signal heads in 520m. No communication with traffic lights (V2I) considered.
- Lower volumes of vehicles: better traffic conditions.
- No relevant volume of motorcycles.

These differences are relevant to understand better the autonomous vehicle's impacts on the city environment's traffic performance. As in Network 1, the calibration was also done based on the Mobility Road System report (CET, 2018), and traffic light times were measured.

Empirically in place. On **Fig. 20**, it is shown the simulation test Network 2 built inside PTV VISSIM.

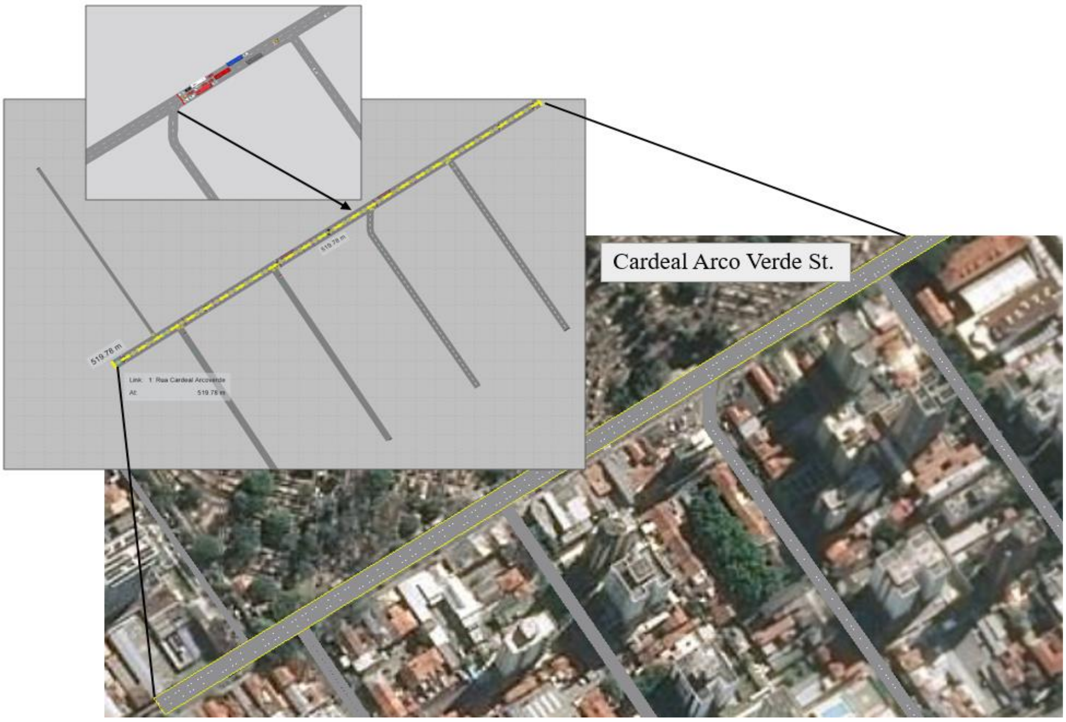


Fig. 20. Simulation Network 2 on PTV VISSIM

Source: Author.

5.2.1.3 Networks 3.X: Highways

Networks 3.X was not built based on a specific highway, but they have a combination of their main characteristics. The target was to evaluate the autonomous vehicles on a highway's different segments and mainly study the platooning feature.

At first, Network 3.1 is a straight segment from a highway without an entrance or exit. To make it comparable, Networks 3.2 and 3.3 have the same length; however, they have more complex interaction among vehicles, as they have exits that obligate cars to change lanes.

On Networks 3.2 and 3.3, 15% of vehicles leave the highway over exit one and more 10% on exit 2. Specifically, on 3.3, one additional entrance was added to increase vehicle volumes and enhance vehicle interactions.

Some essential characteristics from Brazilian highways were used as:

- High penetration rates of trucks.
- Trucks and busses maximum allowed speed of 80km/h, passenger cars 100km/h;
- Trucks and busses can drive only on the last two lanes.

In **Fig. 21**, it is shown the simulation test Networks 3.X built inside PTV VISSIM.

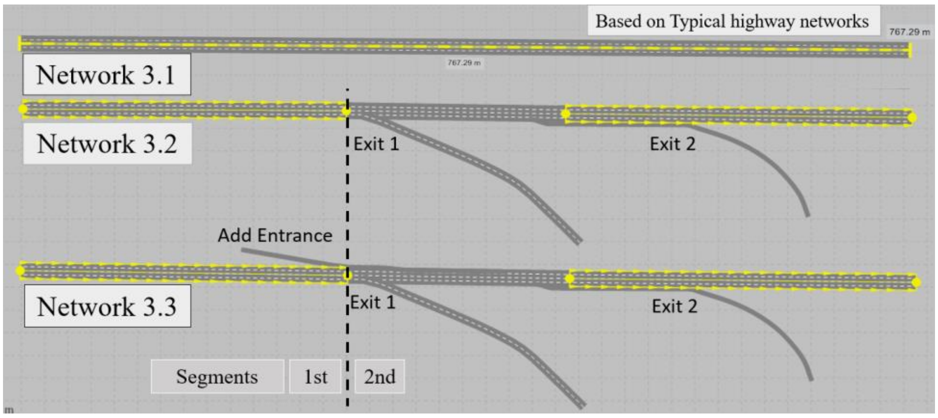


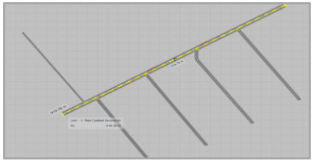
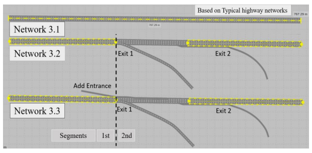
Fig. 21. Simulation Networks 3.X on PTV VISSIM

Source: Author.

5.2.1.4 Comparison between simulated networks

Chart 9 presents the overview and comparison among the simulated networks.

Chart 9: General networks comparison

	Network 1	Network 2	Networks 3.X
Simulation Top view			
Application	City (marginal areas)	City (central area)	Highway
Framework	São Paulo City	São Paulo City	Combination of highways main characteristics
Assessed Driver Behaviors	W74 and W99	W74 and W99	W99
Main Characteristics	▪ The highly congested area on rush time: <10km/h average speed. ▪ Intersection from two large traffic flow avenues ▪ A bus stop with several lines: two busses together at the bus stop most of the time leading almost to a lane blocking. ▪ >10% motorcycles relative flow: typical from large avenues in São Paulo city.	▪ The high density of Traffic lights: in total, three signal heads in 520m. ▪ Lower volumes of vehicles: better traffic conditions. ▪ No relevant volume of motorcycles. ▪ One dedicated lane for busses.	▪A high percentage of Trucks ▪Trucks and busses maximum allowed speed of 80km/h, passenger cars 100km/h. ▪Trucks and busses can drive only on the last two lanes.
Evaluation targets	Impacts of autonomous vehicles different penetration rates on cities with high-density traffic conditions	Comparison to network one on cities with lower traffic jams considering traffic lights	Impacts of autonomous vehicles different penetration rates on Highways with focus on Platooning

Source: Author.

5.2.2 Data input

Many different data are required to input in a microscopic traffic simulator to have a robust simulation. The most important are:

i. Vehicle volume by time interval: number of vehicles in volume/hour for each avenue/street.
ii. Vehicles relative flow by model: percentage split between passengers cars, trucks, buses, bikes/motorcycles a train.
iii. Desired vehicle speed for each vehicle model.
iv. Driver behavior parameters.
v. Bus stops: bus lines, volumes, number of passenger and parameters related to the time the bus stay in a standstill at the bus stop.

In the following sections, it is described how these data were obtained.

5.2.2.1 Vehicle volume and Relative flows

There are different ways to get information about volumes of relative flows for the calibration process. In a city like São Paulo, the most usual ways used by traffic planners are official reports from government traffic agencies, e.g., from CET (CET, 2018), real-time public buses with networking system data available on public APIs from the government, e.g., from SPTrans (SPTrans, 2019), and empirical measurements and even google traffic information.

The specific part of the city chosen to build Network 1 was part of the CET report's measured data (CET, 2018), as it presents a clear and robust data collection methodology. In the simulation model, there are three avenues. For each one, a vehicle input (vehicle volume by time interval) was added, as illustrated in Fig. 22.

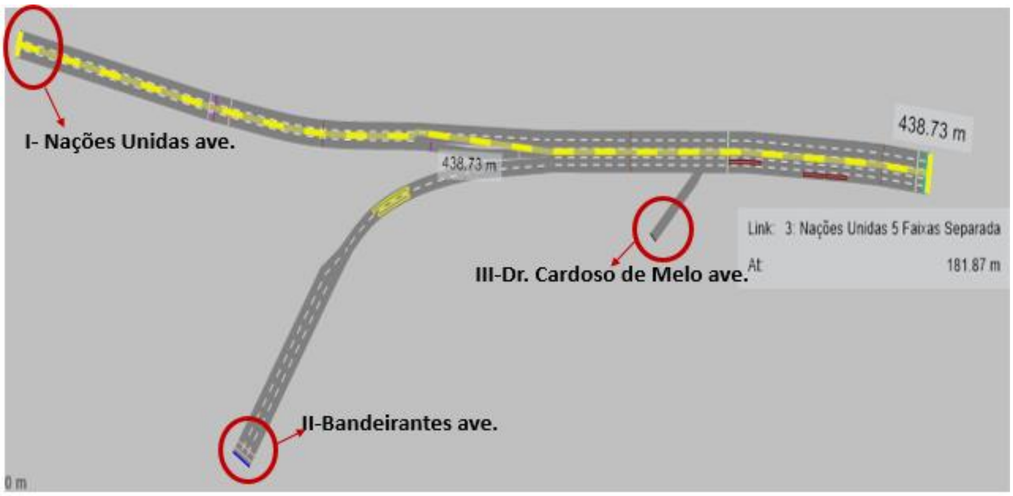


Fig. 22. Vehicles data input Network 1

Source: Author.

On Network 2, the volumes and relatives' flows were empirically measured by students from Civil Engineer (graduate course at the Universidade de São Paulo).

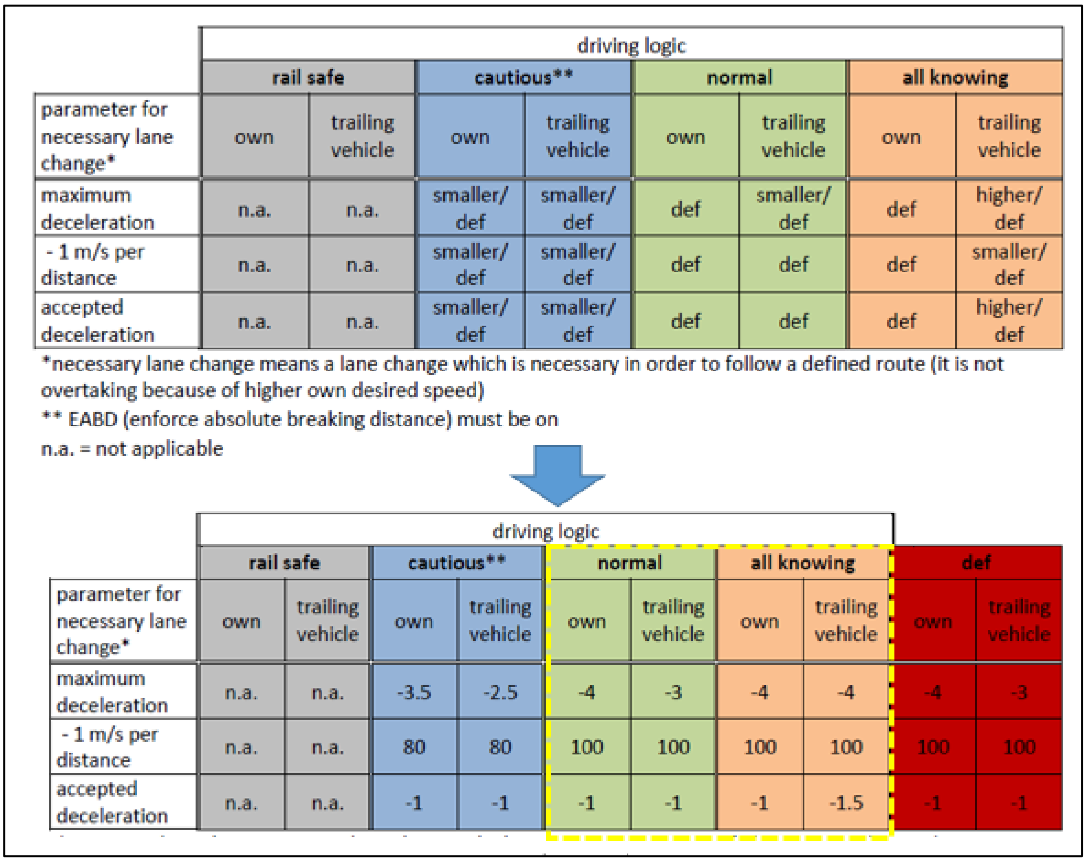
On both Networks 1 and 2, the bus lines' inputs were based on SPTRANS itinerary plan (SPTans 2, 2019).

On Network 3, the inputs were done interactively based on observation and average vehicle speed until the highways achieved the desired traffic flow, enough to study the driver behavior phenomena and the platoon formation.

The volumes, relative flows, and desired vehicle speeds used for the calibration process are detailed for all networks on Annex 5.

5.2.2.2 Driver Behavior parameters

In this research, Wiedemann's parameters for driver behaviors are in **Chart 8**. Lane change-related parameters and their driver logic are described in **Fig. 23** and **Fig. 24** following CoEXist references.

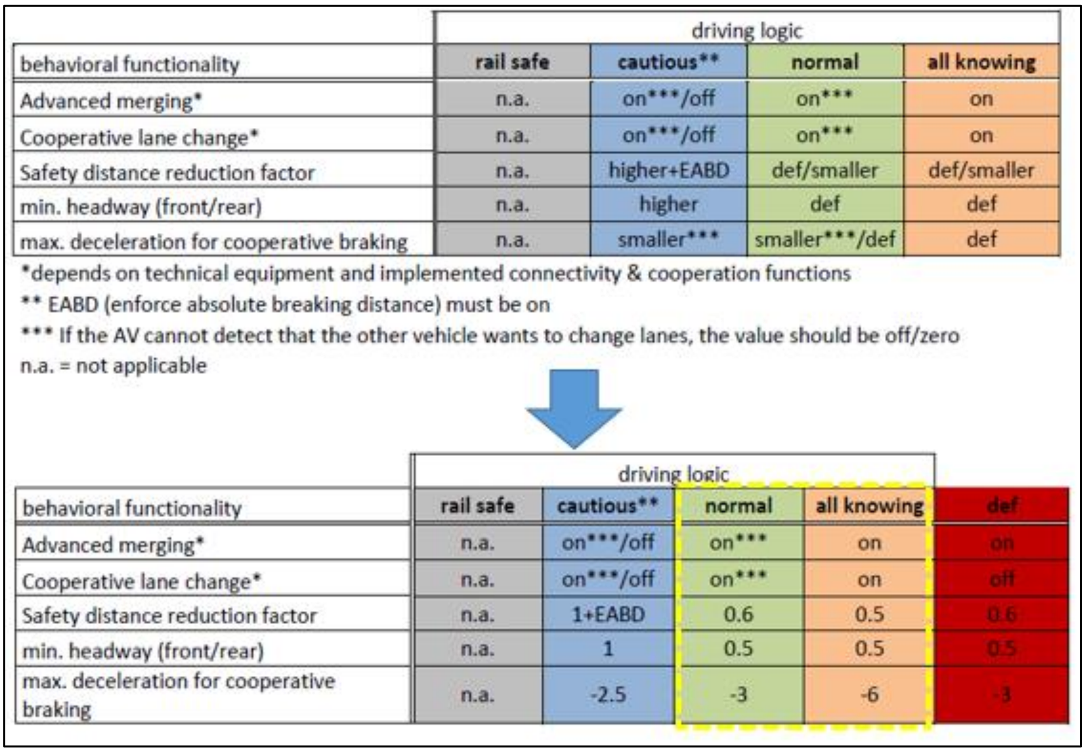


	driving logic							
	rail safe		**cautious****		**normal**		**all knowing**	
parameter for necessary lane change*	own	trailing vehicle	own	trailing vehicle	own	trailing vehicle	own	trailing vehicle
maximum deceleration	n.a.	n.a.	smaller/ def	smaller/ def	def	smaller/ def	def	higher/ def
- 1 m/s per distance	n.a.	n.a.	smaller/ def	smaller/ def	def	def	def	smaller/ def
accepted deceleration	n.a.	n.a.	smaller/ def	smaller/ def	def	def	def	higher/ def

*necessary lane change means a lane change which is necessary in order to follow a defined route (it is not overtaking because of higher own desired speed)
** EABD (enforce absolute breaking distance) must be on
n.a. = not applicable

	driving logic									
	rail safe		**cautious****		**normal**		**all knowing**		**def**	
parameter for necessary lane change*	own	trailing vehicle	own	trailing vehicle	own	trailing vehicle	own	trailing vehicle	own	trailing vehicle
maximum deceleration	n.a.	n.a.	-3.5	-2.5	-4	-3	-4	-4	-4	-3
- 1 m/s per distance	n.a.	n.a.	80	80	100	100	100	100	100	100
accepted deceleration	n.a.	n.a.	-1	-1	-1	-1	-1	-1.5	-1	-1

Fig. 23. Recommended parameters related to lane change behavior
Source: adapted from (Coexist D2.3, 2018)



	driving logic			
behavioral functionality	rail safe	cautious**	normal	all knowing
Advanced merging*	n.a.	on***/off	on***	on
Cooperative lane change*	n.a.	on***/off	on***	on
Safety distance reduction factor	n.a.	higher+EABD	def/smaller	def/smaller
min. headway (front/rear)	n.a.	higher	def	def
max. deceleration for cooperative braking	n.a.	smaller***	smaller***/def	def

*depends on technical equipment and implemented connectivity & cooperation functions
** EABD (enforce absolute breaking distance) must be on
*** If the AV cannot detect that the other vehicle wants to change lanes, the value should be off/zero
n.a. = not applicable

	driving logic				
behavioral functionality	rail safe	cautious**	normal	all knowing	def
Advanced merging*	n.a.	on***/off	on***	on	on
Cooperative lane change*	n.a.	on***/off	on***	on	off
Safety distance reduction factor	n.a.	1+EABD	0.6	0.5	0.6
min. headway (front/rear)	n.a.	1	0.5	0.5	0.5
max. deceleration for cooperative braking	n.a.	-2.5	-3	-6	-3

Fig. 24. Recommended parameters related to lane change functionalities
Source: adapted from Coexist D2.3 (2018).

As shown in 2.4.1, autonomous vehicles' characteristics were done based on CoEXist validated driver behavior parameters. Combining these parameter sets, and the platooning enabled, it is possible to simulate some aspects of CAVs, including the impacts on traffic performance.

5.2.3 Data Output

PTV VISSIM delivers many kinds of output data based on three main tools:

I. Data Collection Points
II. Vehicle Travel Times
III. Queue Counters

In this research, I. and II. were used as described below.

5.2.3.1 Data Collection points

The data collection points can be distributed at any position of the network. For example, on network 1, four collection points were added, as illustrated in Fig. 25. The position from each of them was chosen to bring more meaningful results to be analyzed. The same logic was applied for the other networks.

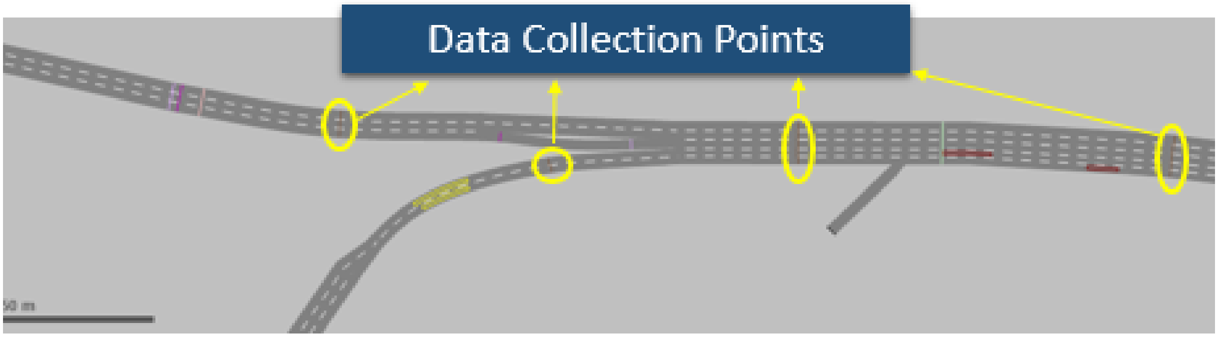
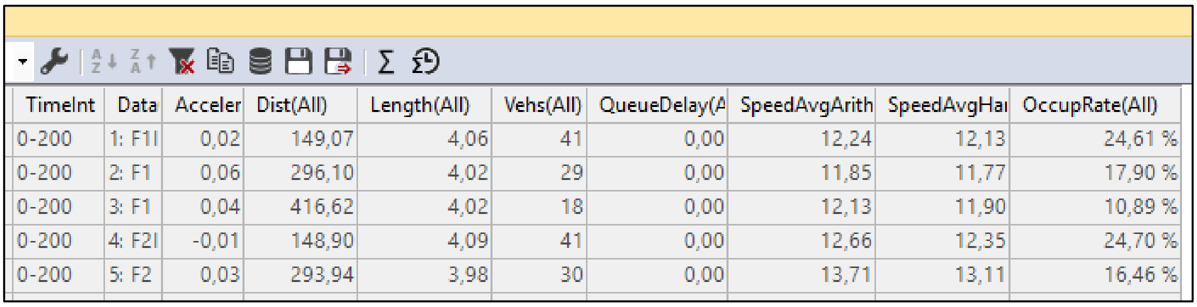


Fig. 25. Data collection points on Network 1

Source: Author.

This tool takes much information from each lane, as **Fig. 26** shows. This research's critical output element is harmonic average vehicle speed, queue delay, and occupation rate.



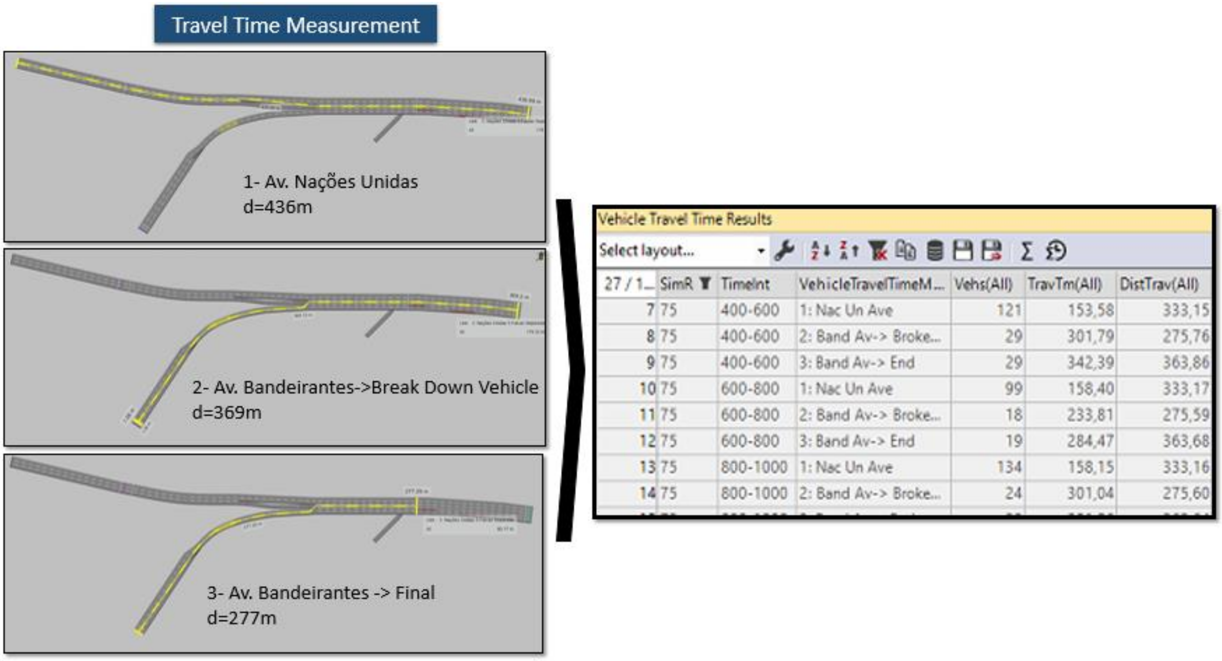
TimeInt	Data	Acceler	Dist(All)	Length(All)	Vehs(All)	QueueDelay(A	SpeedAvgArith	SpeedAvgHa	OccupRate(All)
0-200	1: F1I	0,02	149,07	4,06	41	0,00	12,24	12,13	24,61 %
0-200	2: F1	0,06	296,10	4,02	29	0,00	11,85	11,77	17,90 %
0-200	3: F1	0,04	416,62	4,02	18	0,00	12,13	11,90	10,89 %
0-200	4: F2I	-0,01	148,90	4,09	41	0,00	12,66	12,35	24,70 %
0-200	5: F2	0,03	293,94	3,98	30	0,00	13,71	13,11	16,46 %

Fig. 26. Data collection results example at PTV VISSIM

Source: Author.

5.2.3.2 Travel time measurement

Travel time measurement is a tool that makes it possible to measure delta values in time between two points in the network. Fig. 27. illustrates this tool for network 1, where three travel time measurements were configured. The same logic was applied to other networks.



27 / 1...	SimR	TimeInt	VehicleTravelTimeM...	Vehs(All)	TravTm(All)	DistTrav(All)
7	75	400-600	1: Nac Un Ave	121	153,58	333,15
8	75	400-600	2: Band Av-> Broke...	29	301,79	275,76
9	75	400-600	3: Band Av-> End	29	342,39	363,86
10	75	600-800	1: Nac Un Ave	99	158,40	333,17
11	75	600-800	2: Band Av-> Broke...	18	233,81	275,59
12	75	600-800	3: Band Av-> End	19	284,47	363,68
13	75	800-1000	1: Nac Un Ave	134	158,15	333,16
14	75	800-1000	2: Band Av-> Broke...	24	301,04	275,60

Fig. 27. Travel time measurements for Network 1 at PTV VISSIM.

Source: Author.

5.3 ADDITIONAL MODEL ELEMENT: VEHICLE BREAK DOWN

As described in Fig. 28, all the scenarios have a variation “X.2”. This variation is a disturbance added to evaluate how the traffic is affected when a vehicle breaks down occurs. To simulate that, a bus stop was added to the model on a specific position where the traffic performance was most affected, as **Fig. 28** shows. To keep the bus at a standstill for the complete simulation, the time that the doors remain opened was increased to a value higher than the total simulation time.

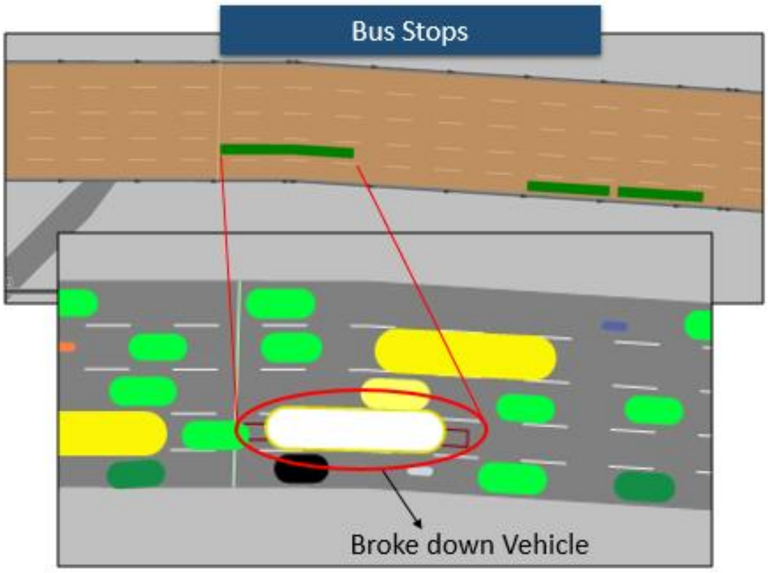


Fig. 28. Simulation of a broken-down vehicle on the network

Source: Author.

6 RESULTS AND DISCUSSION

This section details the results from this study considering the scenarios described Chart 6 for three different networks.

The comparison between W74 and W99 is evaluated based on results evaluation from networks 1 and 2 (city application). Then a comparison between the scenarios is detailed for both networks. Additionally, an evaluation of disturbance effects for each scenario and network is described. Moreover, network 3 (highway) results are assessed based on W99 driver behavior for each scenario. A dedicated section is then used to assess results from the platooning (CACC) feature applied to simulate CAVs behavior at all networks. Finally, a general comparison between the networks and scenarios is presented.

6.1 WIEDEMANN 74 X WIEDEMANN 99 COMPARISON

As described in section 2.5.1, the PTV VISSIM software manual, as other references, recommends using the W74 model for network simulations with urban areas characteristics. However, as mentioned in the same referred section, the primary reference used in this study (Coexist D2.3, 2018) recommends using the W99 model for autonomous vehicles simulation due to the higher number of driver behavior parameters, which could make it more precise.

The results from Network 1 supported better to understand the differences between those two driver behaviors models. The calculation presented in Fig. 29 is presented in **Fig. 30**, the results comparing the travel time average ratio between W99 and W74. Travel time measurements were considered just after 300s of simulation time to guarantee that the interactions and inputs were already stable.

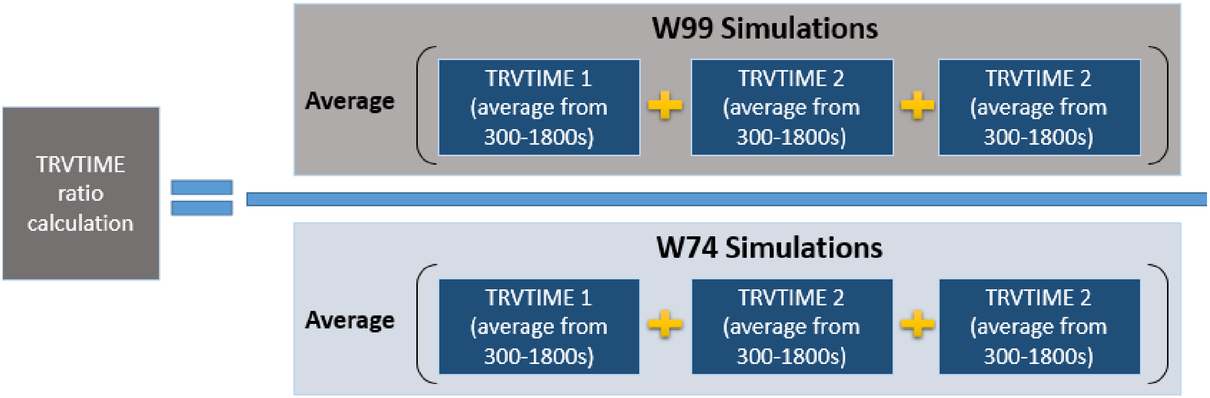
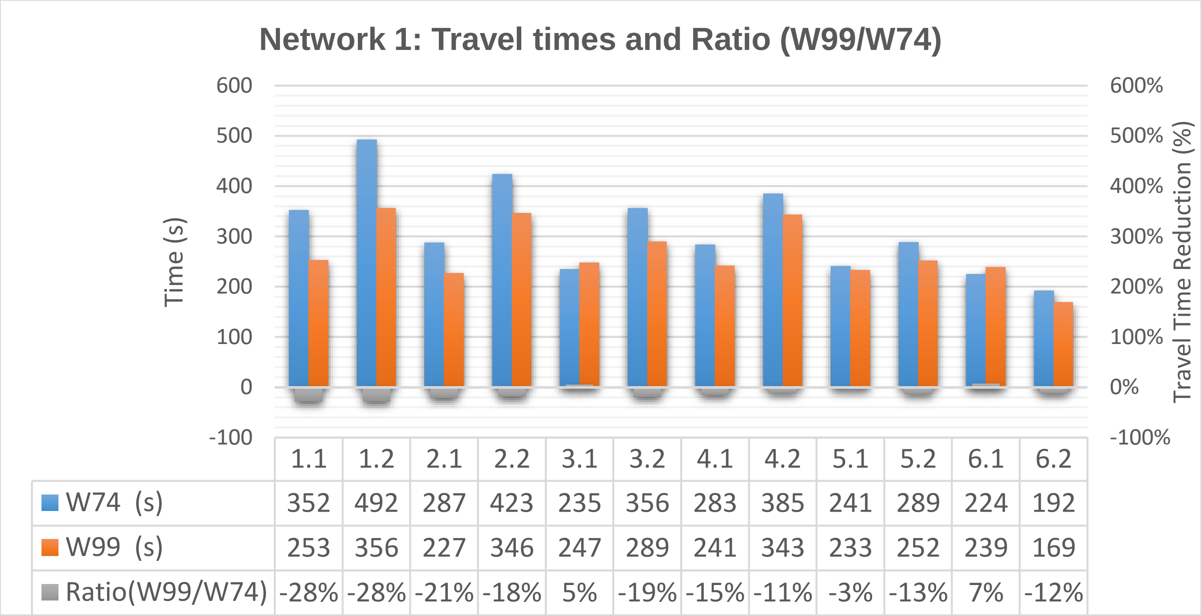


Fig. 29. Travel Time ratio calculation between W99 and W74

Source: Author.



	1.1	1.2	2.1	2.2	3.1	3.2	4.1	4.2	5.1	5.2	6.1	6.2
🟦 W74 (s)	352	492	287	423	235	356	283	385	241	289	224	192
🟧 W99 (s)	253	356	227	346	247	289	241	343	233	252	239	169
■ Ratio(W99/W74)	-28%	-28%	-21%	-18%	5%	-19%	-15%	-11%	-3%	-13%	7%	-12%

Fig. 30. Graphic from travel times and Relation between W99 and W74 simulations for Network 1. Source: Author.

In the analysis of the above results, the first general conclusion is that for the same scenario, the W99 driver behavior model presents lower travel time when compared to W74, but for scenarios 3.1 and 6.1. The tendency shows that the more significant is the percentage of AVs and CAVs, the lower is the difference. Scenarios 3.1 (100% AVs) and 6.1 (100% CAVs) bring interesting insights: they are the only fully autonomous, and the tendency is the opposite; W99 shows a slower travel time.

As those facts bring intrigues but non-concrete conclusions, a complimentary evaluation was done in the next section. On Networks 1 and 2, all the scenarios were simulated for both W74 and W99 models. It is essential to state that the next section's target is primarily to evaluate the impacts of AVs and CAVs on traffic performance, anyhow, as both models are evaluated. It supports bringing additional data to compare W74 and W99.

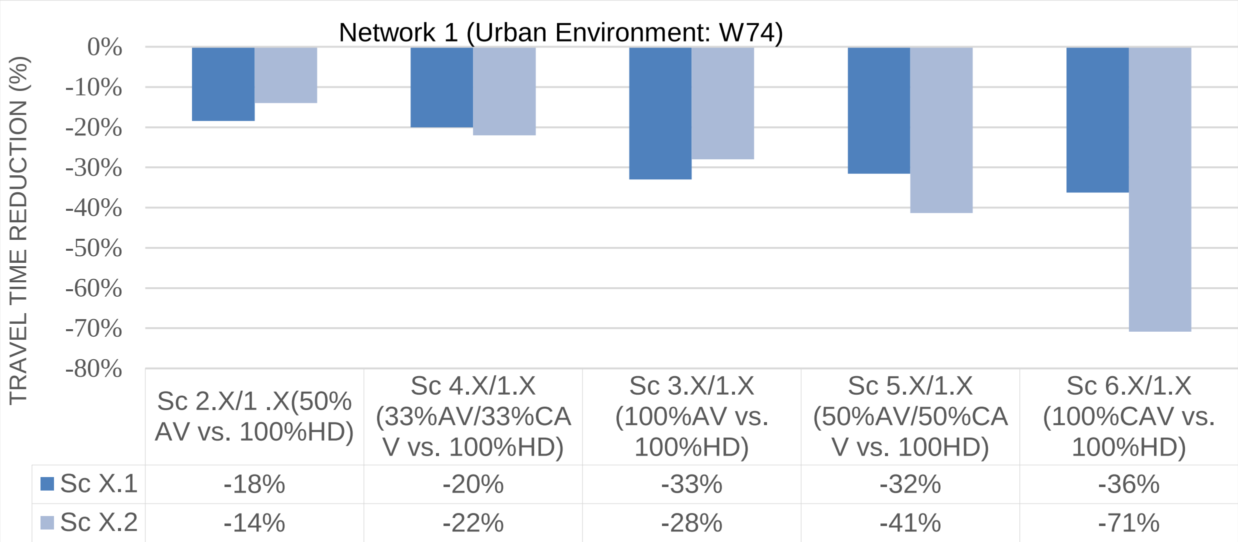
6.2 NETWORKS 1 AND 2 (URBAN): COMPARISON BETWEEN SCENARIOS

As Networks 1 and 2 were built based on city characteristics, they are assessed together. Although they are city networks, they differ in that Network 1 is a broad avenue with heavy traffic, while Network 2 is a typical downtown avenue, including a sequence of traffic lights. Once the base scenario 1.1 was calibrated, all the other scenarios were simulated for both W74 and W99 models. The additional relevant parameters are described in section 5.2.

To better understand the possible gains that the vehicle's automation can have on traffic conditions, a comparison from scenario 1.X to all the other ones was performed.

6.2.1 Network 1

Fig. 31 presents the results from all scenarios with and without breakdowns for the W74 model on Network 1.



	Sc 2.X/1 .X(50% AV vs. 100%HD)	Sc 4.X/1.X (33%AV/33%CAV vs. 100%HD)	Sc 3.X/1.X (100%AV vs. 100%HD)	Sc 5.X/1.X (50%AV/50%CAV vs. 100HD)	Sc 6.X/1.X (100%CAV vs. 100%HD)
■ Sc X.1	-18%	-20%	-33%	-32%	-36%
■ Sc X.2	-14%	-22%	-28%	-41%	-71%

Fig. 31. Graphic for Travel Time Scenarios Comparison for W74 Model on Network 1
Source: Author.

The results from Network 1 for scenarios X.1 are in sequence of better travel times. It shows that scenarios 3.X had a higher reduction on time than scenarios 4.X. It leads to the first conclusion that the hybrid scenarios brought the lower-traffic performance to the network. In general, the scenarios with 100% AVs and CAVs got better results on reducing travel time. Moreover, it is important to emphasize that mixed scenarios bring benefits to travel time. Anyhow, adaptation to traffic rules during this phase could still bring higher impacts, such as dedicated autonomous lanes. It should be highlighted because this kind of scenario (as 4.X) will probably be the most like reality for a long time.

One more point to notice is that the same conclusion can be extended to scenarios X.2 (with disturbance). There is also a substantial difference in travel time reduction between full CAVs scenarios 6.1 and 6.2, from -36% to -71%, respectively. These results lead to the conclusion that the capability of AVs and CAVs to keep smaller safety distances and faster acceleration on stop-and-go brings clear benefits in travel time for urban applications, mainly for worst traffic conditions (scenarios X.2).

6.2.2 Network 2

Fig. 32 presents the results from all scenarios with and without breakdowns for the W74 model on Network 2.

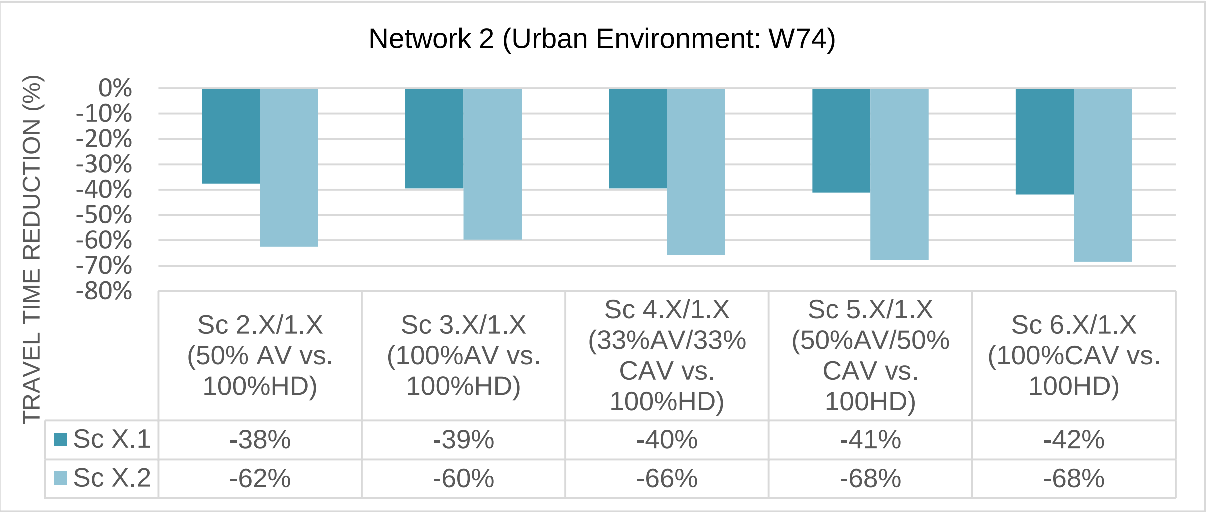


Fig. 32. Graphic for Travel Time Scenarios Comparison for W74 Model on Network 2
Source: Author.

Fig. 32 shows that there is an essential improvement in reducing travel time in scenario 2. There is little variation concerning other scenarios. This result is mainly due to the different characteristics of the network and the fact that it was calibrated for low traffic volumes. Therefore, in general, in traffic situations where there is no restriction for the driver to maintain the desired speed, there is no significant impact on travel time for higher percentages of AVs and CAVs. Looking specifically at scenarios X.2, a situation with a disturbance does not cause dramatic traffic jams due to vehicle volumes. In this situation, AVs and CAVs showed much better group performance on travel times due to reacting faster to the disturbance. It comes with the capability of keeping lower safety distances and improved reacceleration to the desired speed. Also, concerning Network 1, the Network 2 results follow the same tendency of improved travel times for scenarios where there is partial or total vehicle automation. Besides that, as expected, the results do not have many similarities due to the essential differences in traffic volume characteristics. These differences were essential to delineate how situation AVs and CAVs will benefit travel times or cities.

6.2.3 City application: Comparison to the literature

In the literature review, many studies were found showing the impacts of AVs and CAVs on traffic performance. For city application, mainly three of them show higher similarities with this one: BAILEY (2016), RIOS-TORRES et al. (2017), and CALVERT et al. (2020). BAO (2018) and YAO et al. (2020) also assessed urban environments with exciting results. Nevertheless, they measured only travel delays. In **Chart 10**, a summary of the references studied the urban environment compared with this one.

Chart 10: Results comparison with references for urban application

Reference	Simulator	Application	Results	This study
BAILEY (2016)	AIMSUM	City	20% AVs → ↓ 53% travel time 100% AVs → ↓ 80% travel time	Network 2, Sc.3.1: 100% AVs → ↓ 39% travel time
RIOS-TORRES et al. (2017)	AIMSUM	City	100% AVs → ↓ 60% travel time	Network 1, Sc.6.1: 100% AVs → ↓ 36% travel time
BAZ (2018)	VISSIM	City	↓ 65% total delays in roundabouts ↓ 85% total delays on signalized intersections	-
YAO et al. (2020)	SUMO/ OMNET++	City	60% CACC → ↓ 19% travel delays 100% CACC → ↓ 27% travel delays	-
CALVERT et al. (2020)	VISSIM	City	≤50% CACC → no positive effect 100% CACC → ↓11% travel time	Network 2, Sc.3.1: 50% AVs → ↓ 38% travel time 100% CAVs → ↓ 39% travel time

Source: Author.

In the BAILEY (2016) study, a simulation was done in the signalized intersection, not considering communication technologies. It is a framework like network two in scenario 3.1. The BAILEY (2016) obtained an 80% reduction in travel time for 100% AVs. In his study showed that a reduction in 39% in travel time was measured. The network setup's main difference is that BAILEY (2016) considers only one intersection with traffic lights and higher average vehicle speed limits than Network 2, which is longer with three.

In comparison with Network 2, CALVERT et al. (2020) simulated an ITS corridor in Amsterdam with five traffic lights equipped with V2I technology to extend the green-time. CAVs vehicles can join in platoons. As mentioned in Chapter 3, it was broad research, including an FOT. Their simulation setup can be compared to Network 2, considering that V2I was not part of this study. CALVERT et al.'s (2020) results showed benefits to the traffic only in percentages higher than 50% of CACCs. It differs from the results of this research Network 2, where since 50% AVs, the improvements were up to 39% reduction in travel times. It shows that urban applications with signalized intersection should be studied case by case to measure the effect of autonomous vehicles and their technologies.

RIOS-TORRES et al. (2017) focused on a merging zone to measure how CAVs can affect the travel time in this situation of conflict to the traffic. It is more like Network 1 on scenarios 6.1.

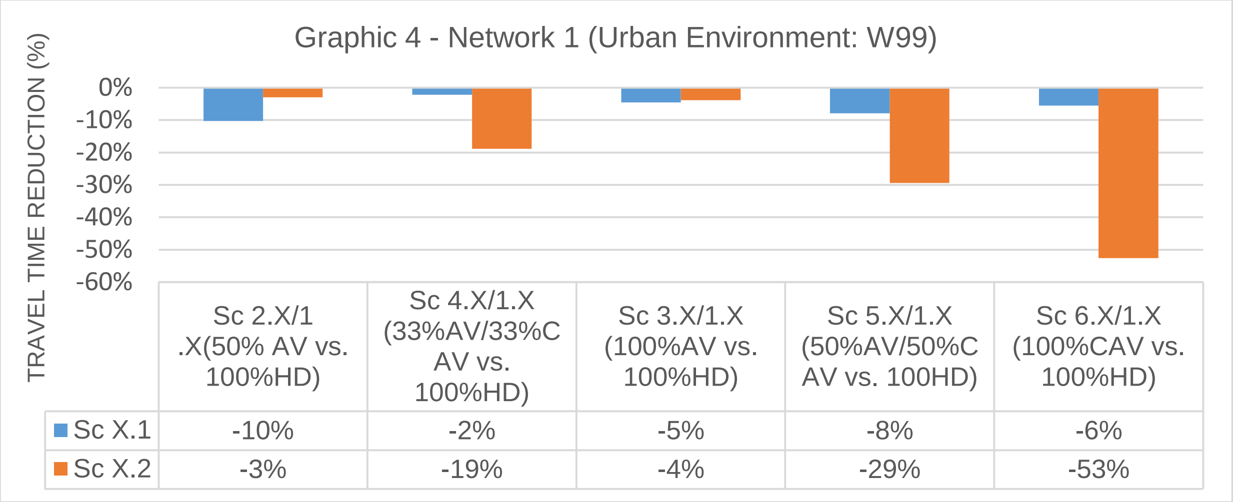
In the merging zone, the authors proposed a V2I communication to a controller that implemented the first-in-first-out (FIFO) logic and achieved until 60% reduction in travel time. The current study did not consider a specific strategy for merging and achieving the complete Network 1, reducing 36% in travel time. It shows an opportunity to achieve even better results in implementing the V2I merging controller in future studies.

As these other studies show, traffic performance's measured impacts can vary significantly, depending on the network's characteristics and CAVs capability configuration. The convergent point is that they show positive impacts.

Additional evaluations considering the platoon feature focus are described in chapter 6.4.

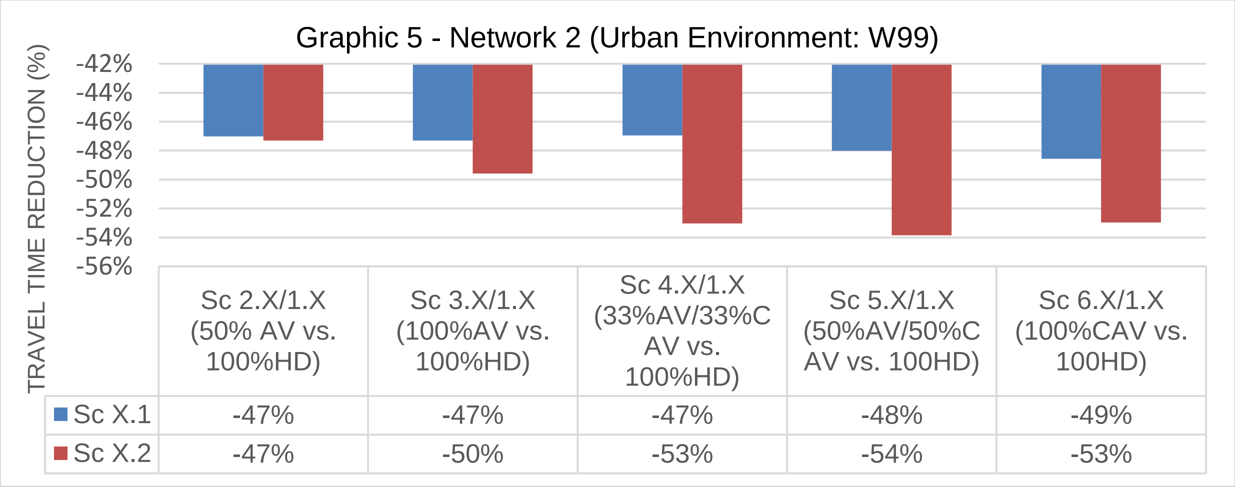
6.2.4 Comparison W74xW99:

The experiment results of Networks 1 and 2 (based on the W99 model) are presented on graphics from **Fig. 33** and **Fig. 34** to enable the comparison.



	Sc 2.X/1 .X(50% AV vs. 100%HD)	Sc 4.X/1.X (33%AV/33%CAV vs. 100%HD)	Sc 3.X/1.X (100%AV vs. 100%HD)	Sc 5.X/1.X (50%AV/50%CAV vs. 100HD)	Sc 6.X/1.X (100%CAV vs. 100%HD)
🟦 Sc X.1	-10%	-2%	-5%	-8%	-6%
🟧 Sc X.2	-3%	-19%	-4%	-29%	-53%

Fig. 33. Graphic for Travel Time Scenarios Comparison for W99 Model on Network 1
Source: Author.



	Sc 2.X/1.X (50% AV vs. 100%HD)	Sc 3.X/1.X (100%AV vs. 100%HD)	Sc 4.X/1.X (33%AV/33%CAV vs. 100%HD)	Sc 5.X/1.X (50%AV/50%CAV vs. 100HD)	Sc 6.X/1.X (100%CAV vs. 100HD)
🟦 Sc X.1	-47%	-47%	-47%	-48%	-49%
🟥 Sc X.2	-47%	-50%	-53%	-54%	-53%

Fig. 34. Graphic for Travel Time Scenarios Comparison for W99 Model on Network 2
Source: Author.

After evaluating all scenarios, the comparison from W74 to W99 on city networks leads to the following points:

- General conclusions from chapter 6.1 are confirmed.
- The travel time variation along the scenarios is more meaningful for the W74 model:
    - Based on general characteristics set in the simulator for higher autonomous levels, the results from W99 shows low coherence, and it does not contribute to getting relevant conclusions.
    - W99 model on a graphic from **Fig. 34** shows no clear tendency, as found on W74.
    - For Network 2 (**Fig. 35**), the reduction in travel times along the scenarios is remarkably similar and even lower for higher autonomous penetration.
- Network 2 does not support this assessment as it has very similar results between the scenarios for both W74 and W99.

It leads us to the following statement: once the correct software configuration and parameters for autonomous vehicles are set, the W74 model showed to be more appropriate than W99 for city traffic simulation regarding travel time evaluation, even for high penetration of CV and CAVs.

6.2.5 Platooning for city application

The overall conclusion is that the CAVs in platooning mode do not bring relevant travel time improvements for city network characteristics. Only Network 1 scenarios with disturbance brought satisfactory results. Platooning gets more meaningful, looking at highway application, explored still inside this chapter.

However, some aspects are relevant to be assessed, as the platooning size. The results for scenarios 4, 5, and 6 presented on graphics from Figs. 31 to 34 were based on the best travel time results. It means that these results were found after evaluating a range of maximum vehicles allowed in each platoon, configured as a parameter mentioned in chapter 2.5.2. All the other parameters related to platooning were fixed to perform this evaluation.

As scenarios 6.X have full penetration of vehicles with platooning capability, it was evaluated with a broader range, from 2 to 25 vehicles. **Fig. 35** and **Fig. 36** show the travel time results for each configuration.

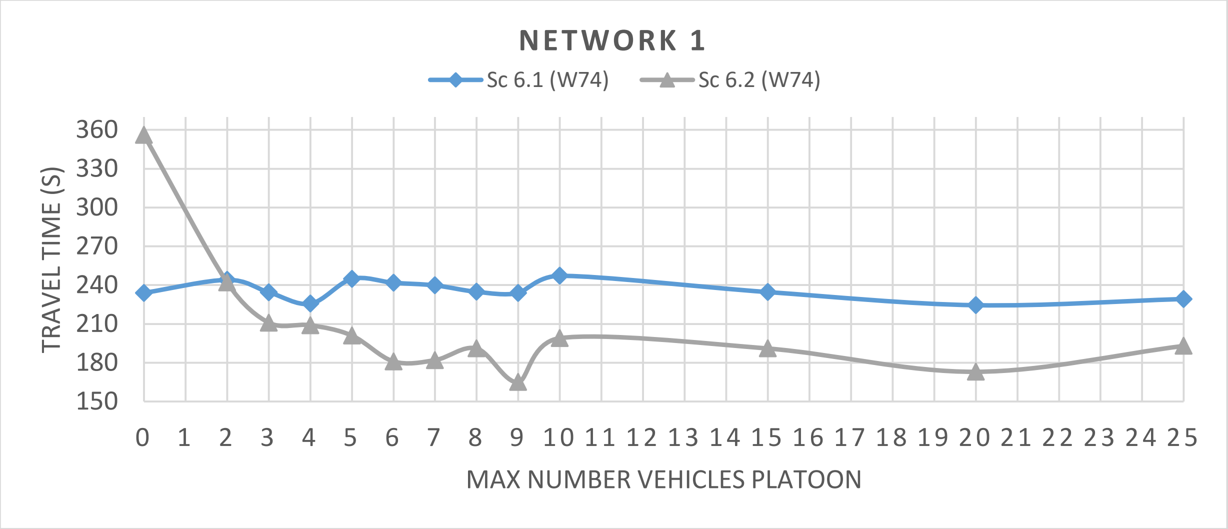


Fig. 35. Graphic for Travel time variation for a different maximum number of vehicles in a platoon on scenarios 6.X for network 1

Source: Author.

From **Fig. 35**, it is noticed that the traffic conditions affect the results of travel time optimization through platoon size for the same network. In scenario 6.2, with the worst traffic conditions, the variation was higher. It is essential to highlight that platoon showed substantial improvements compared to the platoon disabled. In scenario 6.1, the results had a lower variation when compared to the platoon disabled.

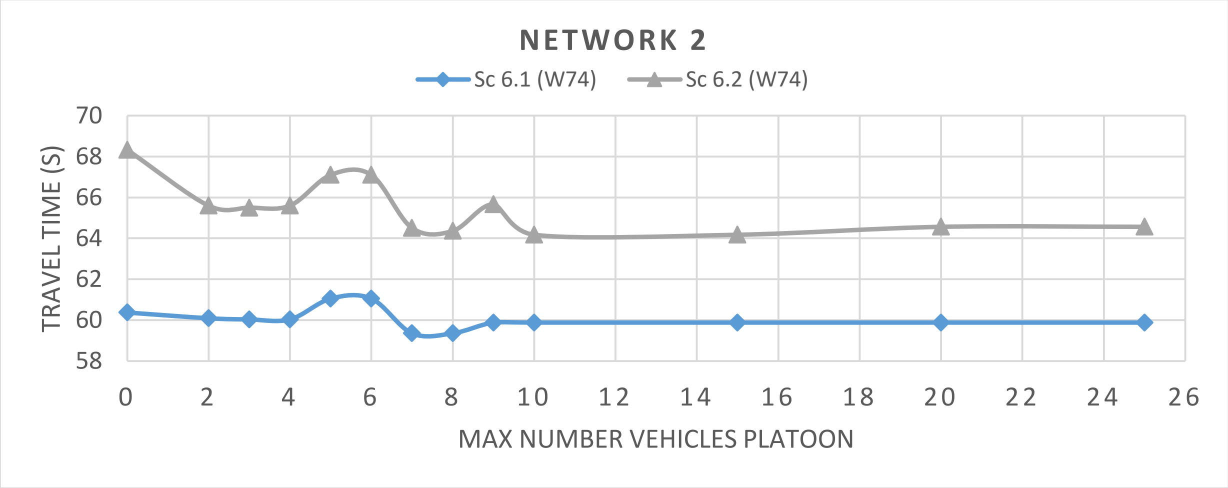


Fig. 36. Graphic for Travel time variation for a different maximum number of vehicles in a platoon on scenarios 6.X for network 2

Source: Author.

Network 2 is that setting the maximum platoon size for ten or more vehicles leads to remarkably similar results. It was hardly verified platooning with more than ten vehicles, mainly due to low volumes of traffic. The best results were found for 7 and 8 vehicles maximum platoon size for W74.

In general, it is noticed that the number of vehicles in a platoon affect the travel time, even more for scenarios with disturbance. It is an essential input for traffic planners' studies of the future urban environment. The optimal platoon size for scenarios with CAVs that enables the platoon is presented in chapter 6.4.

A broader evaluation based on a highway network is described in section 6.3.

6.2.6 Additional evaluation on Network 1

One additional point is looking more specifically at segments of the Network 1 model for all scenarios and driver behavior types described in **Fig. 37**. Two behaviors are explicit:

i. Bandeirantes Avenue presents the worst traffic conditions (orange bars);

ii. Nações Unidas Avenue (blue bars) presents lower travel time variation between the scenarios than Bandeirantes Avenue. An additional conclusion is that the simulation with break down affected more Bandeirantes avenue than Nações Unidas Avenue due to the breakdown vehicle's position at lane 2 (as described in **Fig. 28**).

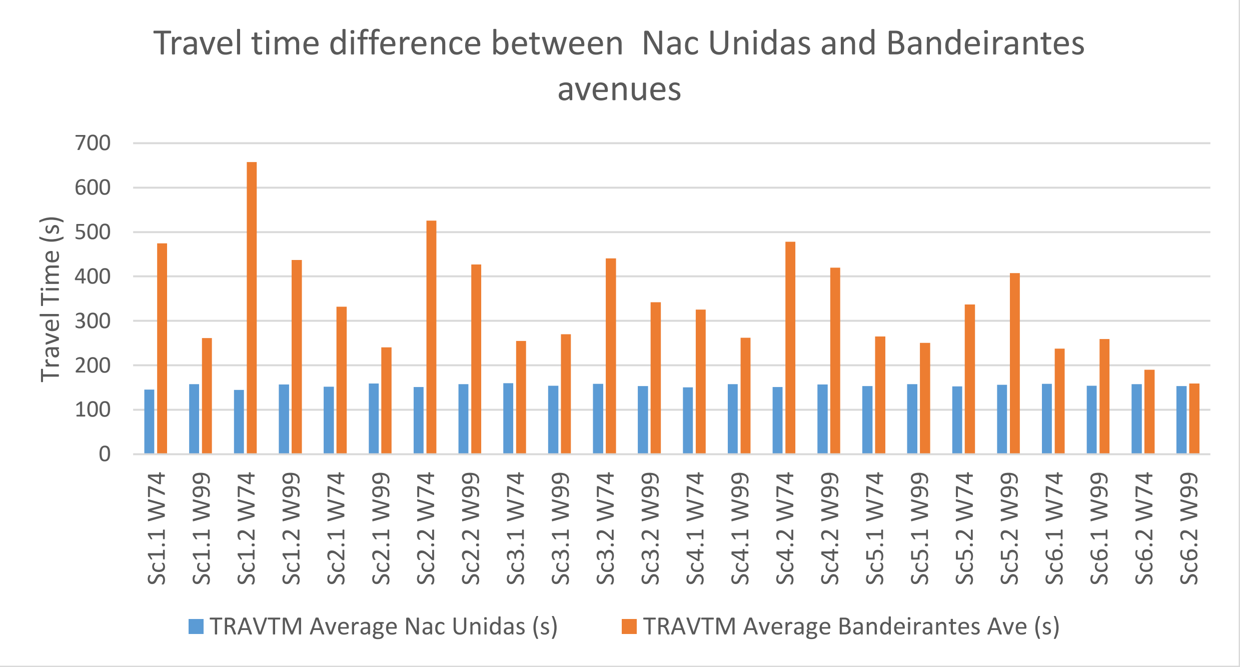


Fig. 37. Graphic for Travel time comparison between Nações Unidas and Bandeirantes avenue

Source: Author.

6.2.7 The proposition to faster overcome a disturbance

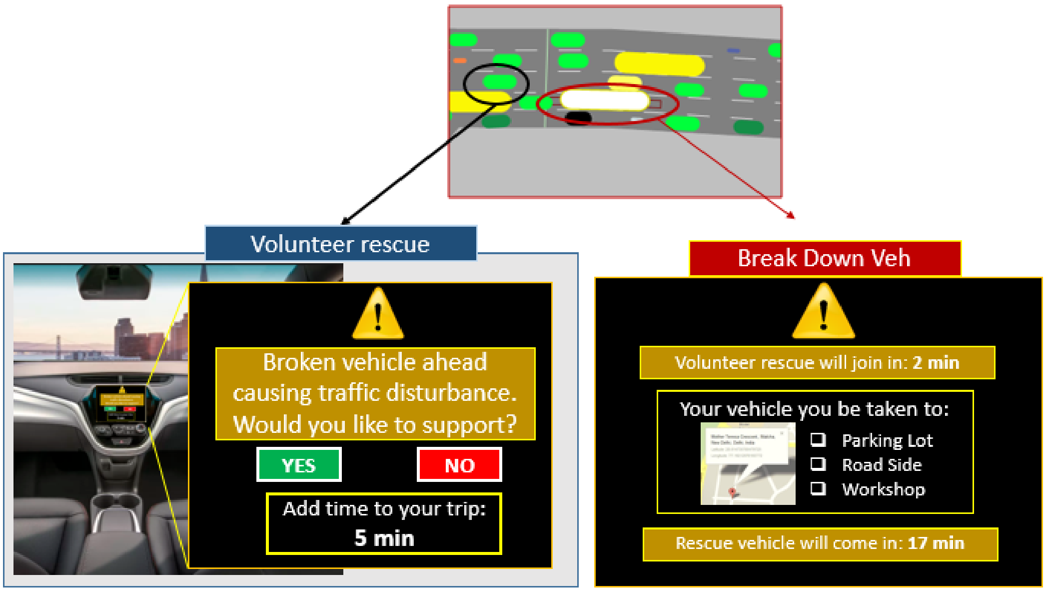
A new proposition is presented with these based on X.2 scenarios. On the premise that the faster a disturbance is overcome, the faster the traffic flow, normal conditions are recovered. It is composed of two elements: a broken vehicle and a rescue vehicle.

A mandatory requirement is that both elements should be equipped with the V2X communication feature. When a breakdown happens, an emergency condition is triggered, and this status is sent to surrounding vehicles and infrastructure.

If one of the surrounding vehicles can act as a rescue car supporting the breakdown vehicle, it will receive a display message. The rescue vehicle should move the other one out of the network to a safe point. The message on display should have the following content:

- Information of broke down vehicle ahead.
- Question asking permission to support.
- Additional travel time: to make it transparent how long it will take and motivate rescue vehicles to accept the request.

Fig. 38 and Fig. 39. describes the proposal from scenarios “X.3”.



Broken vehicle ahead causing traffic disturbance. Would you like to support?

Add time to your trip: **5 min**

Volunteer rescue will join in: **2 min**

Your vehicle you be taken to:

Rescue vehicle will come in: **17 min**

Fig. 38. Proposal for scenario “X.3’ (step 1).

Source: Author.

Both should be equipped with trailer sockets to make an automatic trailer connection between the vehicles, as described in Fig. 39.

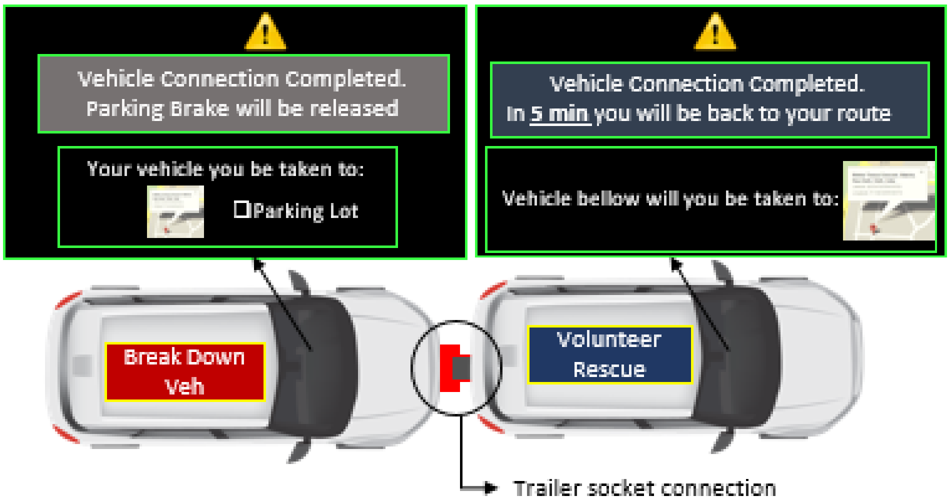


Fig. 39. Proposal for scenario “X.3 (step 2)”

Source: Author.

A reward can be offered in different ways to motivate even more the vehicles around to accept the request: cashback, reward programs like credit card, points for ranking (e.g., as used on the Waze app).

Considering that the faster the disturbance is overcome; the faster scenarios X.2 travel times will be close to scenarios X.1.

6.2.8 The general conclusion for city application

After all the considerations and assessments described in chapter 6.2, the general conclusions from Networks 1 and 2 studies are:

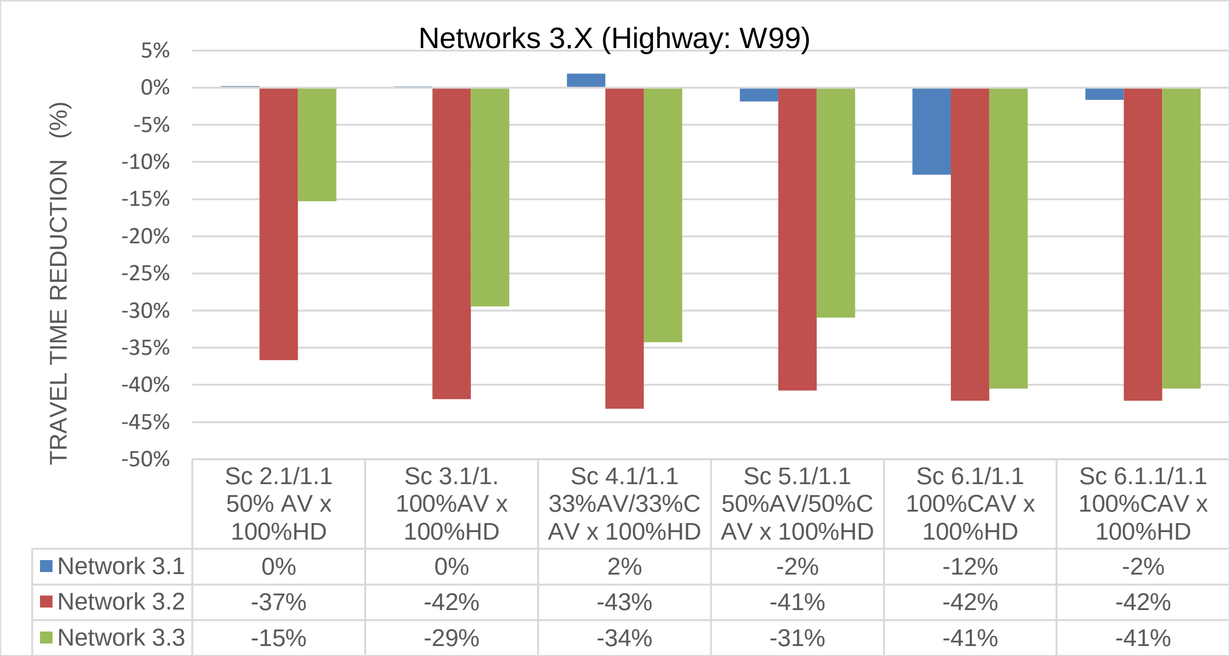
- The higher the vehicle automation level is, the lower is the travel time.
- The mix of technologies on the same road (HDVs, AVs, and CAVs) shows worse traffic performance than fully AVs.
- When a disturbance as a breakdown vehicle is added, automated vehicles' introduction brings significant travel time benefits, even when mixed up with HDVs.
- Comparing Networks 1 and 2: AVs and CAVs will place a more important role in traffic performance for roads with heavier traffic.
- The travel time variation along the scenarios is satisfactory for the W74 model
- Generally, platoons from 5 to 7 vehicles showed to be more appropriate for cities environment. A minimum volume of vehicles is required to assess the impact of this technology on travel times.
- The maximum number of vehicles in a platoon performs an essential role in minimizing travel times. For penetrations smaller than 50%, this evaluation does not bring relevant outputs to travel time.

- A high percentage of vehicles have platooning capability (higher than 50%). It can reduce the impacts of disturbances on traffic, even in urban areas.

6.3 NETWORK 3 (HIGHWAYS): COMPARISON AMONG SCENARIOS

Networks 3.X are typical highways; all the simulations were performed based on the W99 model. the baseline Network 3.1 was built to get broader results. Afterward, two variations from this baseline were created, adding exits and entrances to evaluate how autonomous vehicles would perform under more complicated traffic situations.

As detailed in section 4.2, three additional sub scenarios arising from scenario 6.1 were also explored. Other than networks 1 and 2, the sub scenarios for network three are not related to disturbances. They were built after analyzing scenario 6.1 as a necessity to get a more in-depth investigation of the platooning feature for highways. As presented for Networks 1 and 2, the results for scenarios 4,5, and 6 presented in **Fig. 40** were based on the best travel time results. It means that these results were found after evaluating a range of maximum vehicles allowed in each platoon, configured as a parameter mentioned in chapter 2.5.2. All the other parameters related to platooning were fixed to perform this evaluation.



	Sc 2.1/1.1 50% AV x 100%HD	Sc 3.1/1. 100%AV x 100%HD	Sc 4.1/1.1 33%AV/33%CAV x 100%HD	Sc 5.1/1.1 50%AV/50%CAV x 100%HD	Sc 6.1/1.1 100%CAV x 100%HD	Sc 6.1.1/1.1 100%CAV x 100%HD
🟦 Network 3.1	0%	0%	2%	-2%	-12%	-2%
🟥 Network 3.2	-37%	-42%	-43%	-41%	-42%	-42%
🟩 Network 3.3	-15%	-29%	-34%	-31%	-41%	-41%

Fig. 40. Travel Time comparison among the scenarios for networks 3.1, 3.2, and 3.3.
Source: Author.

As Network 3.1 has part of a road without exits or entrances, it reduces interaction among the vehicles, reducing lane changes, breaks, and acceleration. Furthermore, the traffic conditions enable drivers to keep the desired speed. Then, it is noticed that the benefits for scenarios 2 to 5 are almost null. For 100% CAVs (scenario 6.X) a slight reduction on travel time

(-12%) is found. It concludes that the AVs and CAVs do not bring relevant contributions to travel time in these highway segments. In any case, it is important to mention that all the simulations are considered a flat road. On the other hand, (GOÑI-ROS, et al., 2019) shows that the drivers change their longitudinal behaviors when they come from flat surfaces to slopes, reducing the free-flow capacity from 10-25%. In this study, the microscopic traffic simulation showed that CACC high penetration rates (75%) eliminated the traffic congestions in this situation.

On Networks 3.2 and 3.3, the results get a different profile. On Network 3.2, essential improvements are seen since scenario 2 (-37%) and got just five more percent to scenario 6.1.1 (-42%). As the first exit creates traffic jams, it is noticed that autonomous vehicles' capabilities of keeping lower safety distance and faster reaction on acceleration made an essential difference since 50% AVs penetration.

Network 3.3 has more interaction between vehicles than Network 2 due to exits and one more entrance leading to traffic jams. It led to more similar results to the tendency observed on Network 1 and achieved a reduction of 42% on travel time for 100% CAVs penetration. It means that the results showed for Network 3.3 on **Fig. 40** have similar tendencies to **Fig. 31** scenarios X.1. Even hybrid scenario 4 showed a better result than full AV scenario 3, showing a tendency that the 33% CAVs benefit travel time, mainly due to platoons easy forming on highways.

On the other hand, results in scenario 5 was not the one expected for Networks 3.2 and 3.3 as the reduction of travel time was lower than scenario 4. This result brought some insights about platooning configuration further explored in the next section.

In general, highway network results show the more complex and intense traffic interaction on the road. The more similar the results are with the urban environment. This traffic characteristic also shows to be more affected by the introduction of AVs or CAVs.

6.3.1 Comparison of Highways application to the literature:

Chart 11 presents a summary of the references that studied the urban environment and compared it with this one.

Chart 11: Results comparison with references for high application

Reference	Simulator	Application	Results	PATERLINI (2020)
ARIA et al. (2016)	VISSIM	Highway	100% CACC → ↑ 8.48%: average vehicle speed 100% CACC → ↓9.00%: travel time	Network 3.1, Sc.6.1: 100% AVs → ↓12% travel time
GOÑI-ROS et al. (2019)	Not mentioned	Highway	50% CACC → ↓15% travel time ↓55% average veh delay 100% CACC → ↓20% travel time ↓64% average veh delay	Network 3.1 Sc.3.1: ↓2% travel time Sc.6.1: 100% CAVs → ↓12% travel time -
CHEN et al. (2019)	VISSIM	Highway	90% ACC → ↓ 9% travel time 90% CACC → ↓ 11% travel time.	Network 3.1 100% CAVs → ↓42% travel time
CALVERT et al. (2019)	Not mentioned	Highway (Trucks only)	≤80% CACC → no positive effect 100% CACC → 2,9% travel time reduction	-

Source: Author.

ARIA et al. (2016) simulated CAV on highways when the network is crowded (e.g., peak hours) using PTV VISSIM. In a similar approach to Network 3.1, they found a reduction of 9% in travel time, near the 12% reduction found in this study (where the traffic was heavy but not crowded). GOÑI-ROS et al. (2019) also evaluated a highway segment without exits or additional entrances, similar o Network 3.1. As mentioned in chapter 3, their focus was on longitudinal behaviors from flat surfaces to slopes, reducing the free-flow capacity from 10 to 25%. Based on these network characteristics, a reduction of 20% in travel times for 100% CACC penetration was measured. On 50% CACC penetration, the researchers achieved a reduction of 15% in travel time, where for the simulated Network 3.1 on scenarios 2.1 or 5.1, the benefits of travel time were near zero. It means that considering a slope profile, the results on travel time reduction from Network 1 would probably be higher.

CHEN et al. (2019) simulated a highway like Network 3.2 on PTV VISSIM, applying their proposed control algorithm without platoon. On 90% of the CACC penetration rate, the reduction was 11% on travel time was. In this study, Scenario 6.1 achieved up to 42% reduction. It shows that their algorithm could get the results improved with platoons enabled. CALVERT et al. (2019) released actual results, but it is difficult to compare as they considered just the trucks with CAVs capabilities.

As in urban application, the measured impacts on traffic performance can vary significantly, depending on the network's characteristics and CAVs capability configuration. The positive impacts of AVs and CAVs were also a convergent point that shows a much higher potential for penetration rates above 50%.

Additional evaluations considering the platoon feature focus are described in the next chapters.

6.3.2 Platooning for highways application

After assessing all the highway networks when the platoon is enabled, some non-trivial results were found. It was mentioned in the evaluation of scenarios 4 and 5 from networks 3.2 and 3.3. So, a more detailed study of this feature was required. Then sub scenario X.1.1, X.1.2, and X.1.3 were created.

Sub scenarios X.1.1, X.1.2, and X.1.3 vary from the respective scenario X.1, built to study specifically platooning on highways. They differ, as on X.1, the platooning is enabling between all vehicle types. On X.1.1, just vehicles with similar dynamic behavior can perform a platoon, i.e., a passenger car cannot join a platoon with trucks and busses. Scenario X.1.2, platooning is allowed only in a part of the road, after the first segment for networks 3.2 and 3.3. In this scenario, platooning is allowed among all types of vehicles, as in 6.1. Finally, scenario X.1.3 is a combination of X.1.1 and X.1.2. They were evaluated as follow:

- Scenario X.1.1 was assessed for Scenarios and sub scenarios 4, 5, and 6;
- Sub scenarios X.1.2 and X.1.3 were assessed only 6, as 100% of vehicles can perform platoons.

Figs. 41, 42, and 43 show the results for Scenarios 4 and 5 and their sub scenarios. Figs. 44, 45, and 46 show the results for Scenarios 6 and its sub scenarios.

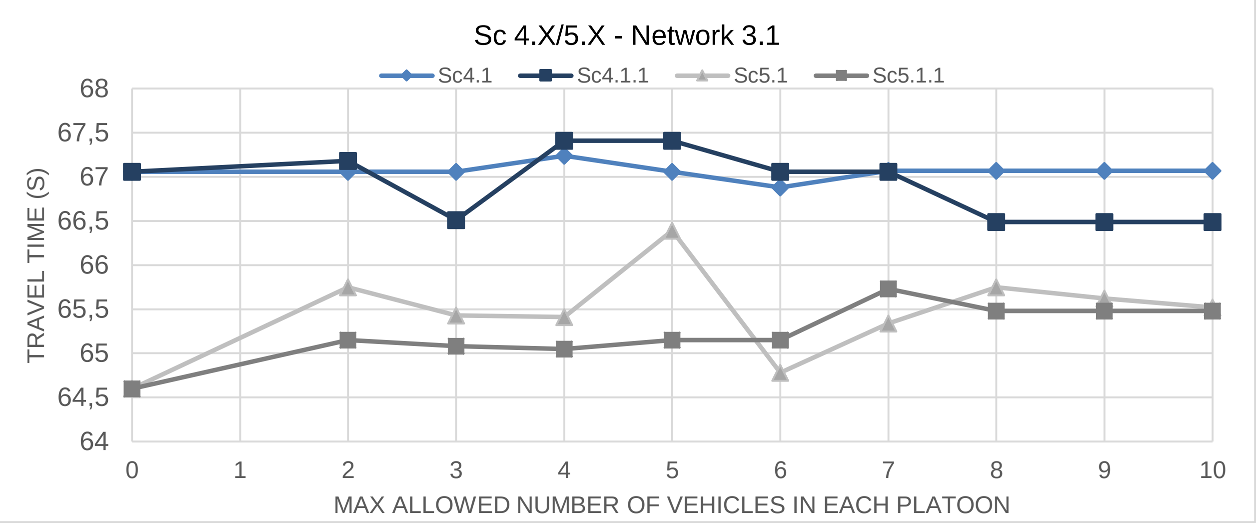


Fig. 41. Travel Time results for Network 3.1 on Scenarios 4 and 5
Source: Author.

Fig. 41 shows the results for Network 3.1. It is a segment of a highway without entrances or exits. The most relevant contribution from this experiment was the increased percentage of vehicles with platooning possibly brought benefits to the traffic performance. It is because Scenario 5 had a slight reduction in travel times by 5% on average. Furthermore, it is noticed that the maximum allowed number of vehicles in platooning for scenarios 4.X and 5.X did not bring significant differences in travel time (less than 2%). It also applies to sub scenarios.

For networks 3.2 and 3.3 on **Fig. 42** and **Fig. 43**, the tendency of better results on Scenario 5 is not confirmed.

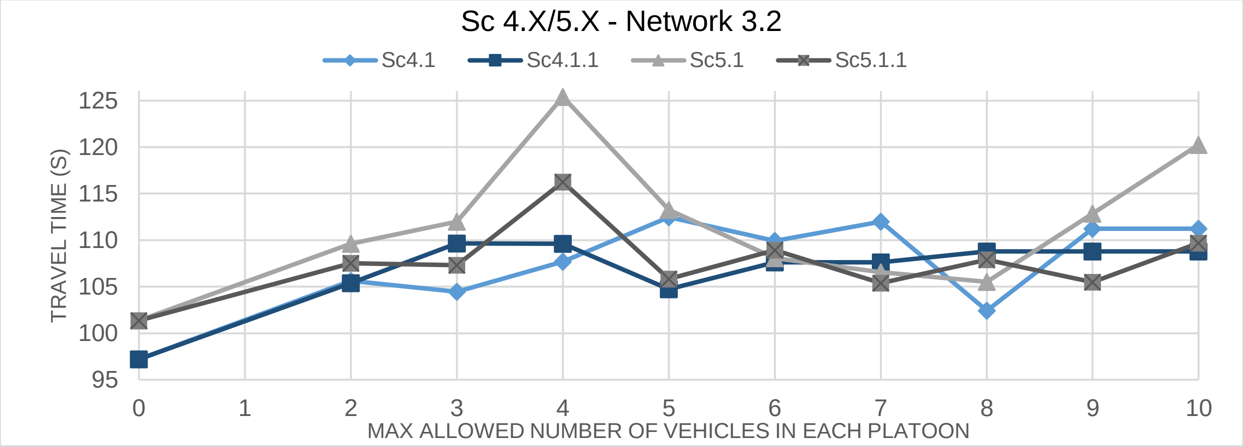


Fig. 42. Travel Time results for Network 3.2 on Scenarios 4 and 5
Source: Author.

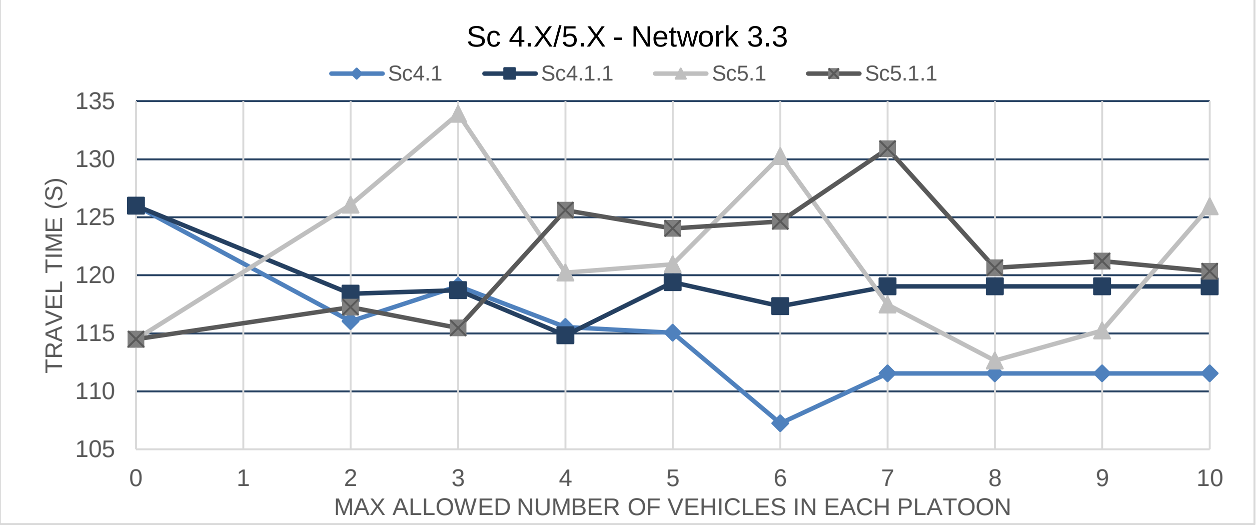


Fig. 43. Travel Time results for Network 3.3 on Scenarios 4 and 5
Source: Author.

These two experiments showed that by adding complexity to the networks, where vehicles are forced to change lanes more frequently, platooning does not bring better traffic performance on every application. On these networks, it is noticed that CAVs with platooning enabled did not improve traffic performance. Mainly on Network 3.3, where scenario 4 over-performed scenario 5.

They also bring the expected result that the higher the percentage of CAVs, the higher the variation on travel time in the platoon size function. This behavior is confirmed in Scenario 6, where 100% of vehicles are CAVs.

For Scenarios 6.X, as they have full penetration of CAVs with platooning capabilities, a more comprehensive range of platoon size was simulated, from 0 to 25, as shown in Graphics from Figs. 44, 45, and 46.

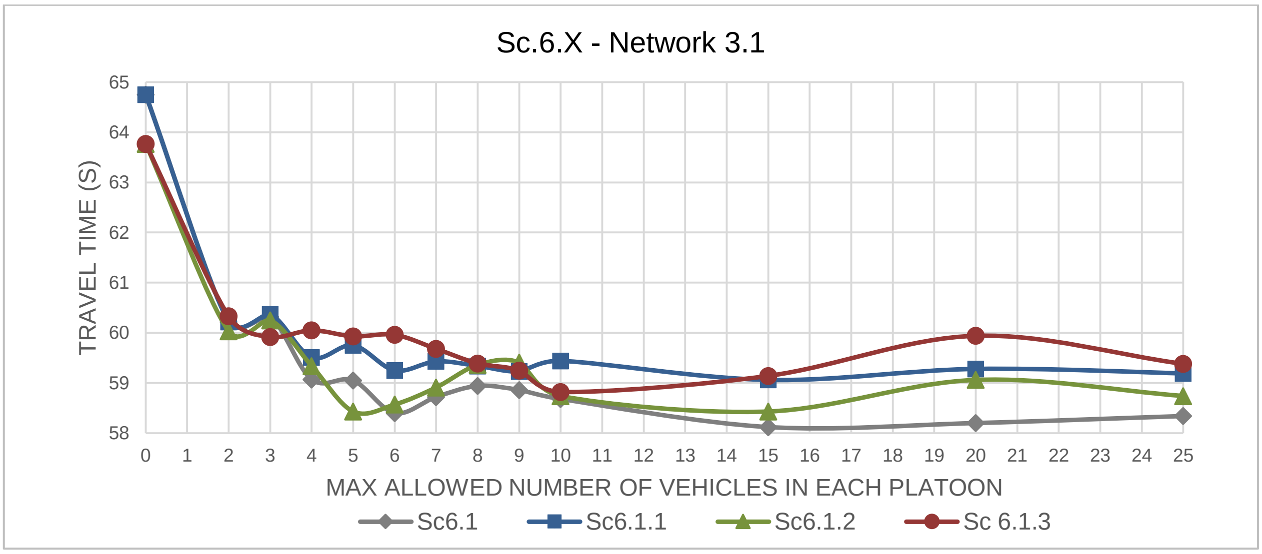


Fig. 44. Travel Time results for Network 3.1 on Scenario 6

Source: Author.

Fig. 44 shows that the best results were achieved with platooning enabled. From 2 to 25 vehicles platoon size, the variation in travel time was low. For this road, the changes of sub scenarios 6.1.1, 6.1.3, and 6.1.3 did not cause significant effects due to its characteristics of reduced interaction among the vehicles. Comparing Fig. 41 and Fig. 44 shows that the travel times can be reduced by up to 12% by increasing the CAVs penetration rate from 33% to 100%.

However, in networks 3.2 and 3.3 presented in **Fig. 45** and **Fig. 46**, these sub scenarios showed higher impacts.

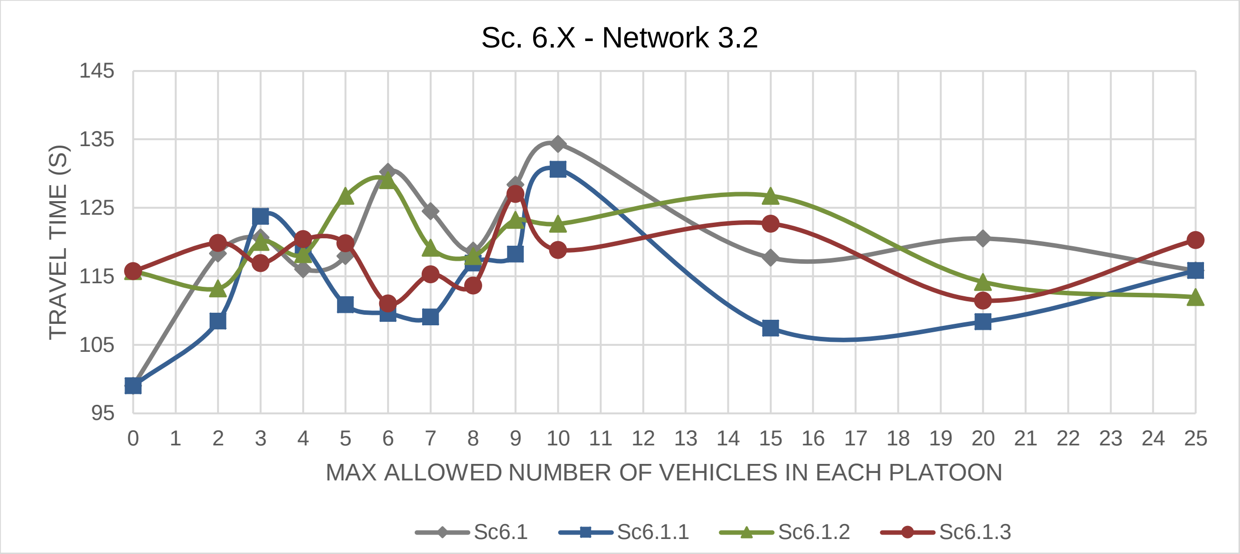


Fig. 45. Travel Time results for Network 3.2 on Scenario 6

Source: Author.

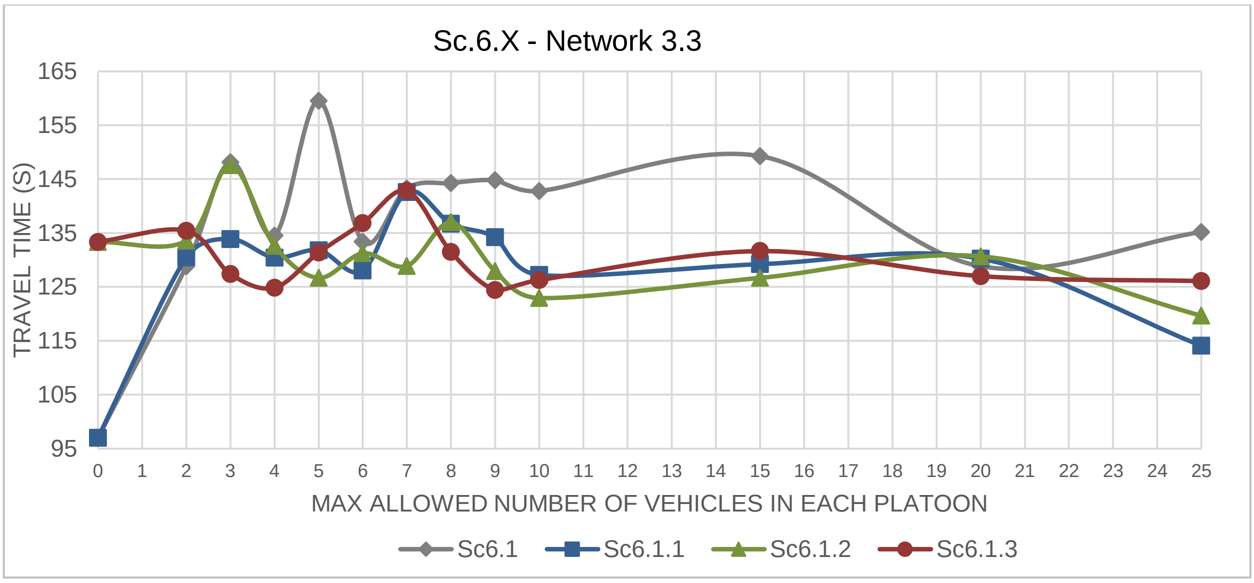


Fig. 46. Travel Time results for Network 3.3 on Scenarios 6

Source: Author.

We can see in **Fig. 46** that scenario 6.1 had worse travel times for most platoon sizes than the proposed sub scenarios. Then, sub scenarios 6.1.2 (platoon possible on the 2nd segment of networks 2.2 and 2.3) and 6.1.3 (combination from 6.1.1 and 6.1.2) showed similar results. The average travel time among all platoon sizes for both scenarios are nearly the same. Also, on sub scenarios 6.1 and 6.1.1, the platoon disabled reduced the travel time dramatically. Comparing that to results from network one leads to the point that segmenting the highways in parts where platoon is allowed or not bring benefits to total travel time. In other words, allowing or not the platoon in highways, depending on the segment characteristics, can affect traffic performance.

Besides, scenarios 6.1.2 and 6.1.3 showed that when the platoon is enabled among vehicles with different dynamic characteristics and maximum legal speed (as trucks and passenger cars), the traffic performance is reduced.

The next chapter brings a complete overview and conclusions about the platooning feature.

6.4 GENERAL PLATOONING EVALUATION ON TRAVEL TIME PERFORMANCE

The results for urban and highway applications on scenarios where platooning was enabled leads to some conclusions. To complement these conclusions, Table 3 brings a summary of the best travel time results for each network.

Table 3: List of the best maximum number of vehicles in a platoon configuration based on travel time results for each scenario on Networks 1, 2and 3.

	The best travel time results for Max Number Vehicles Platoon (Highway)					
	Network 1	Network 2	Network 3.1	Network 3.2	Network 3.3	Simulated Range
Sc 4.1	4	**4-10**	0*-**5**-10	**0***,8	**6**-10	0-10
Sc 4.2	**7-10**	**5**,9,10	-	-	**-**	0-10
Sc 4.1.1	-	-	0*-**7**-10	0*	**4**,6	0-10
Sc 5.1	0*,5,8, **9**	**4-10**	0*-**6**-10	**0*,**7,8	0*,**8**,9	0-10
Sc 5.1.1	-	**-**	**0***-10	0,5,7,9	0,2,3	0-10
Sc 5.2	**5**,10	8,**9**,10	-	-	-	0-10
Sc 6.1	4,**20**	5,6**,7,8,**9	2-**15**-25	0*	0*	0-25
Sc 6.1.1	-	-	2-**15**-25	**0,**15	0*	0-25
Sc 6.1.2	-	-	2-**5**-25	0,2,20,**25**	5,10,**25**	0-25
Sc 6.1.3	-	-	2-**10**-25	0,**6**,8,20	3,4,**9**,10,20,25	0-25
Sc 6.2	**9,**20	**10,15**	-	-	-	0-25
	*Platoon disabled, vehicles with CAVs parameters set					
	Obs: results listed for configurations until 5% difference from best travel time (the best result is **highlighted)**					

Source: Author.

6.4.1 City application:

- It is recommended platoons from 5 to 7 vehicles for cities environment. Even with good results, longer platoon should be avoided as they form a long vehicle that difficult necessary lane changes. As an example, a platoon with ten passenger cars can be up to 40 meters long. CALVERT also found this conclusion et al. (2019) justified the results because longer platoons outperformed the lane changes from vehicles around and suggested the application of platoons in non-congested traffic,
- For streets and avenues with low volumes of vehicles, this technology's impact on travel times will not be relevant. It was simulated on Network 2.
- Over intense traffic situations, the maximum number of vehicles in a platoon plays a vital role in minimizing travel times.

- This study concludes that a high percentage of vehicles with platooning capability (>50%) can reduce the impacts of traffic disturbances. For lower penetration rates, the improvements are not consistent because few platoons are formed. CALVERT et al. (2019) suggested the application of platoons in non-congested traffic. CALVERT et al. (2020) released a new study from an FOT and simulation experiment of CACC city environments. The authors considered the savings in travel time enjoyable in heavy traffic, mainly if the V2I “traffic lights green extension” features are applied. YAO et al.. (2020) also found reductions of up to 27% in traffic delays for 100% CAVs in city environments.

6.4.2 Highways

- Network 3.1: segments without entrances and exits:
    - The platoon enabled is recommended.
    - It is also recommended to disable platoons between passenger car to trucks or busses as their different dynamic behavior and maximum allowed speed can lead to a lower overall traffic performance.
    - Platoon sizes: as vehicles do not change lanes frequently in these segments, longer platoons can be allowed:
        - For CAVs penetration rates, up to 50% simulation results indicate 6 to 8 vehicles as the best configuration to minimize travel times.
        - For CAVs 100% CAVs scenarios, platoon sizes by up to 25 showed promising results.
- Networks 3.2 and 3.3: segments with higher complexity, including exits and entrances:
    - Platooning should be studied in detail depending on the highway geometry and topology. The simulation performed in this study showed that it did not bring relevant improvements in travel time. It can change considerably, mainly on slopes, as a study by GOÑI-ROS et al. (2019).
    - Improvements in platooning algorithms are recommended to increase the sensitivity for cut-in and gaps, opening possibilities to others in these segments. A temporary change in driving behaviors is recommended to increase traffic performance.
    - Max recommended platoon size: up to 5 vehicles. Platoons with several vehicles should be avoided as they form a long vehicle that difficult, necessary lane changes.

In summary, depending on each network's network and traffic characteristics and the penetration of CAVs, platooning plays an essential role in minimizing travel times.

Regarding platoon sizes, on SERAJ, LI, & QIU (2018), the maximum benefits were found for 5 to 6 platoon size. Anyhow, the traffic conditions and network characteristics cause essential variations. It comes to the point that even on the same network, a dynamic platoon configuration brings benefits to traffic performance. CHANG et al. (2020) assessed platoons up to 8 vehicles and concluded that the maximum platoon size is advantageous for improving the mixed flow capacity. The platoon size can place an important role and should be assessed based on traffic characteristics from the roads. For penetrations smaller than 50%, this evaluation does not bring relevant outputs to travel time.

7 CONCLUSIONS

This research proposed a methodology to assess the impacts of Connected and Autonomous Vehicles (CAVs) on traffic flow through microscopic simulation. The methodology was validated from five different networks built to enable the experiments, including city and highway environments. The scenarios were evaluated, starting with a baseline with no vehicle automation, coming to heterogeneous scenarios considering the coexistence among HDVs, AVs, and CAVs. Finally, the full penetration of AVs and CAVs.

The first general conclusion that the experiment results brought was that AVs and CAVs to keep smaller safety distance, and their faster reaction time brings clear benefits in travel time. It was up to 71% reduction in travel time on the urban environment, and 43% for highways. It shows the more complex and intense traffic interaction on the road, the higher the impacts.

Two networks were built on cities environment considering a high intense traffic expressway and a signalized intersection with lighter traffic conditions. For both, the higher the automation level was, the lower was the travel time. The mix of technologies on heterogeneous scenarios decreases the benefits of AVs or CAVs, especially on traffic performance. As they will be necessary steps towards full automation, some actions should be further studied to increase these technologies' impacts, like dedicated lanes. One crucial output came from a simulation of disturbances along the streets, as a vehicle break-down. In these situations, the AVs and CAVs brought much higher benefits than normal traffic conditions, even in heterogeneous scenarios. Furthermore, comparing city Networks 1 and 2, it is noticed that AVs and CAVs will place a more important role in traffic performance for roads with heavier traffic.

On highways, three different networks were compared, considering an increasing complexity of vehicle interactions among them. The results reinforce that the more complex and intense traffic interaction in the road is, the more AVs and CAVs impact travel time. Without entrances, exits, or sloped profiles for highway segments, the higher impacts should come from the higher safety AVs and CAVs bring. Else, the impacts on traffic performance are evident.

This study also releases an extensive assessment of the platoon influence using a built-in software feature that enabled robust comparability among the results. These platoon characteristics showed a variation of up to 30% on travel time, mainly for high-intensity traffic situations. It should be studied in detail depending on the highway geometry and topology. In general, this study recommends maximum platoons’ size from 5 to 7 vehicles size for cities environment, and up to 5 for highways. Platoons with a higher number of vehicles should be avoided as they form a long vehicle line that difficult necessary lane changes. It was also observed that platoons allowed only for vehicles with similar dynamic characteristics improve the overall traffic performance.

In summary, depending on each network and traffic conditions and the penetration of CAVs, platooning performs a vital role in minimizing travel times. Platooning sizes can place an important role and should be assessed based on traffic characteristics from the roads. For penetrations smaller than 50%, this evaluation does not bring relevant outputs to travel time. It was also done a specific investigation comparing W74 and W99 driver models application for autonomous vehicles simulation for PTV VISSIM. Although W99 is a more complex model, it did not show meaningful results for city environments. The recommendation is to use the W74 model for city environment even on AVs scenarios, and CAVs introduction W99 model is recommended for all kinds of highway simulation.

Finally, as these other studies show, traffic performance's measured impacts can vary significantly, depending on the network's characteristics and CAVs capability configuration. The convergent point is that they show positive impacts.

7.1 FUTURE WORKS

Recommendations for future research are:

- To integrate simulators that can increase the study's capabilities on V2I and V2V features, including communication to the traffic lights on cross-sections and communication among the vehicles on merging and platoon situations.

- To assess CAVs and platooning on roads with variations on topography.

- Explore the cut-in function on platooning application. A refined algorithm can support an optimal lane change strategy.

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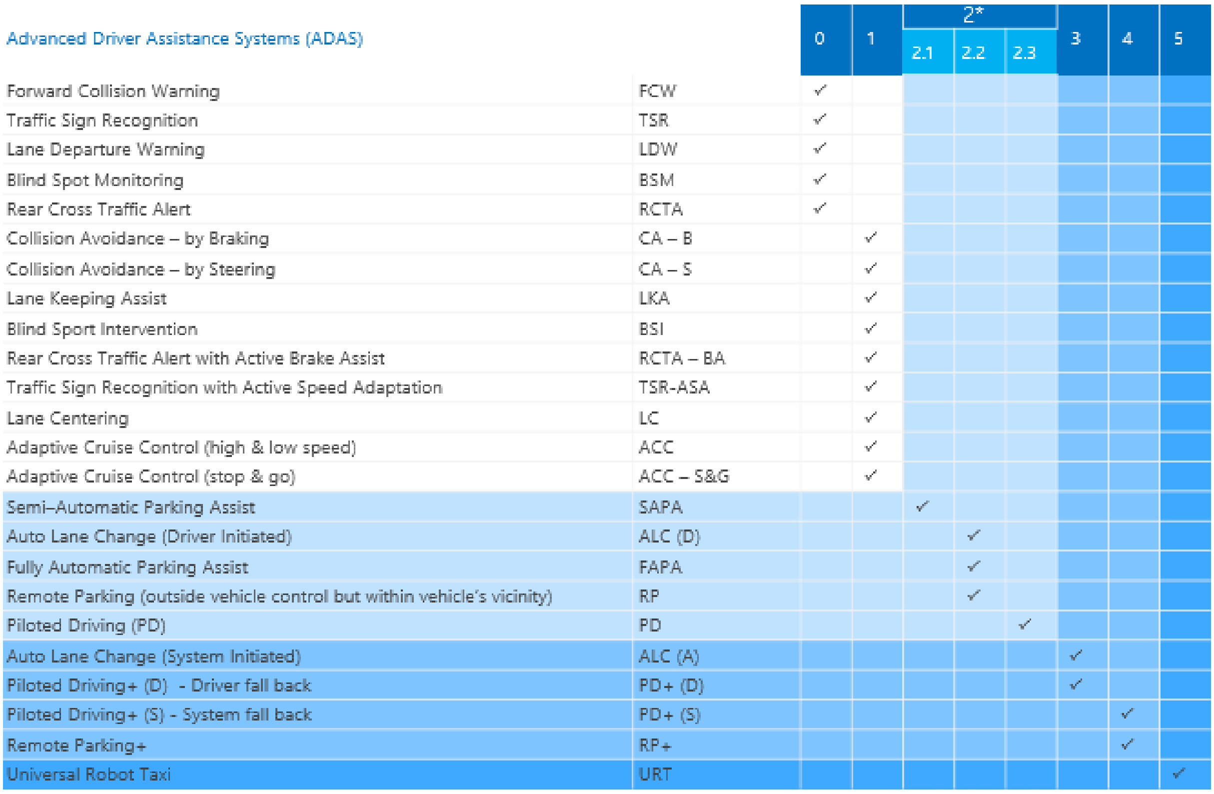
ANNEX 1 – ADAS SYSTEM CLASSIFICATION

Based on the SAE automation level definition, several ADAS being made available qualify to be classified as a Level 2 system. However, the functionality and system delivery level varies between the different systems and their implementation by different OEMs. Therefore to make a more apparent distinction, SBD classifies the system into 2.1, 2.2, and 2.3. See table below for distinction:

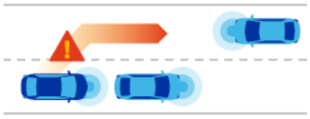


Advanced Driver Assistance Systems (ADAS)		0	1	2*			3	4	5
				2.1	2.2	2.3			
Forward Collision Warning	FCW	✓							
Traffic Sign Recognition	TSR	✓							
Lane Departure Warning	LDW	✓							
Blind Spot Monitoring	BSM	✓							
Rear Cross Traffic Alert	RCTA	✓							
Collision Avoidance – by Braking	CA – B		✓						
Collision Avoidance – by Steering	CA – S		✓						
Lane Keeping Assist	LKA		✓						
Blind Sport Intervention	BSI		✓						
Rear Cross Traffic Alert with Active Brake Assist	RCTA – BA		✓						
Traffic Sign Recognition with Active Speed Adaptation	TSR-ASA		✓						
Lane Centering	LC		✓						
Adaptive Cruise Control (high & low speed)	ACC		✓						
Adaptive Cruise Control (stop & go)	ACC – S&G		✓						
Semi–Automatic Parking Assist	SAPA			✓					
Auto Lane Change (Driver Initiated)	ALC (D)				✓				
Fully Automatic Parking Assist	FAPA				✓				
Remote Parking (outside vehicle control but within vehicle's vicinity)	RP				✓				
Piloted Driving (PD)	PD					✓			
Auto Lane Change (System Initiated)	ALC (A)						✓		
Piloted Driving+ (D) - Driver fall back	PD+ (D)						✓		
Piloted Driving+ (S) - System fall back	PD+ (S)							✓	
Remote Parking+	RP+							✓	
Universal Robot Taxi	URT								✓

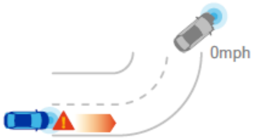
Source: (SBD, 2018).

ANNEX 2 – LIST OF C-ITS PRIORITY SERVICES

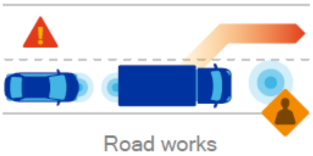
Vehicle-to-vehicle services		
Traffic jam	Dangerous end of queue	Already deployed using LTE-V2X long-range mode when considered as "hazard information" (otherwise similar service as "electronic emergency brake light")
	Traffic jam ahead	Already deployed using LTE-V2X long-range mode
Stationary vehicle warning	Stopped vehicle	
	Broken-down vehicle	
	Post-crash	
Special vehicle warning	Emergency vehicle in operation	Already deployed using LTE-V2X long-range mode
	Stationary safeguarding emergency vehicle	
	Stationary recovery service warning	
Exchange of IRCs	Request IRC	
	Response IRC	
Dangerous situation	Electronic emergency brake light	
	Automatic brake intervention	
	Reversible occupant restraint system intervention	
	Fog	Already deployed using LTE-V2X long-range mode
	Precipitation	
	Traction loss	



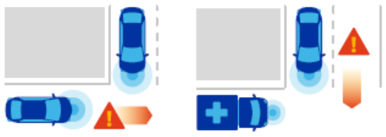
Do not pass warning (DNPW)



Blind curve/ Local hazard warning



Road works warning



Intersection movement assist (IMA) at a blind intersection

Vulnerable road user (VRU) alerts at a blind intersection

Left turn assist (LTA)

Source: (5G Automotive Association, 2019)

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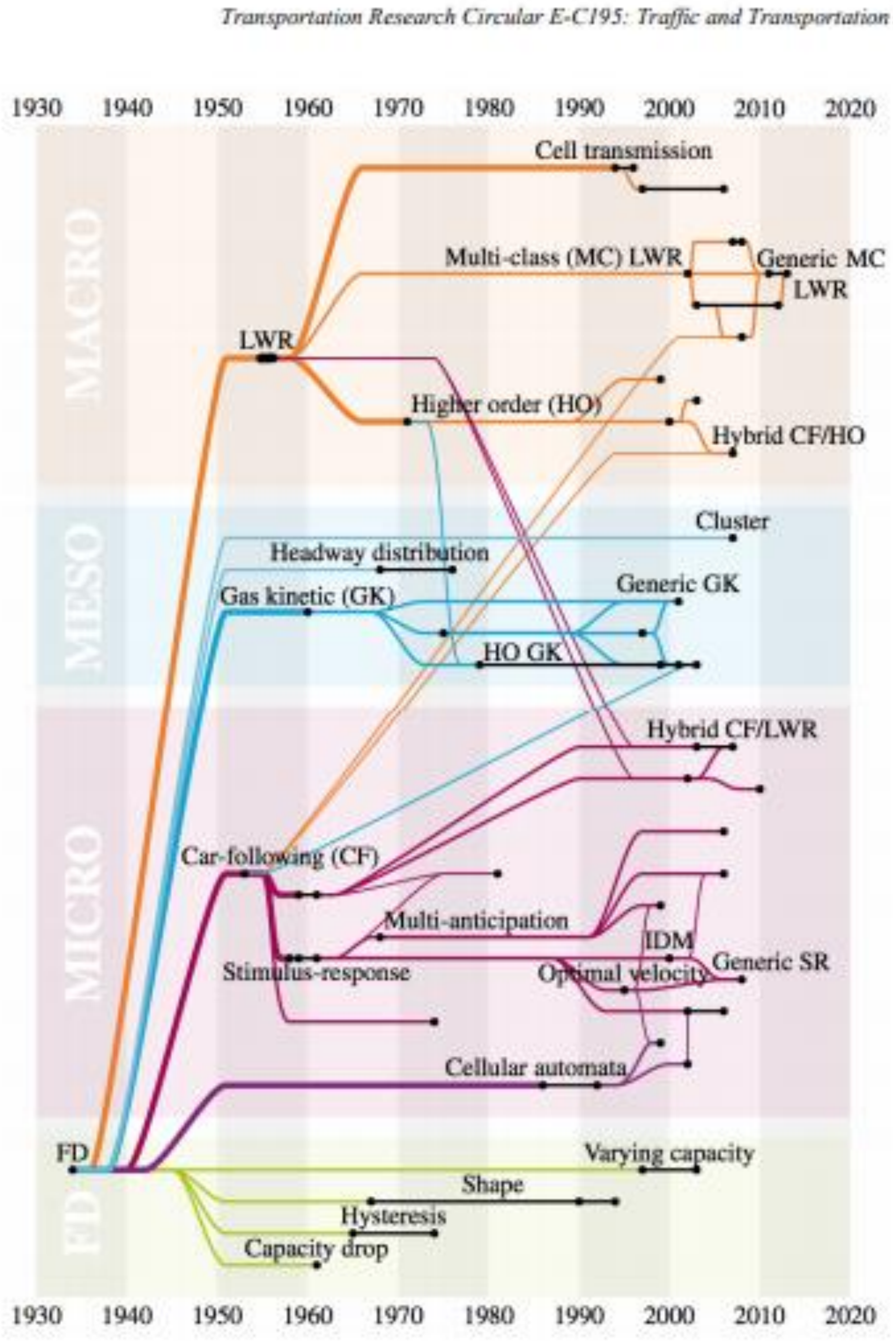
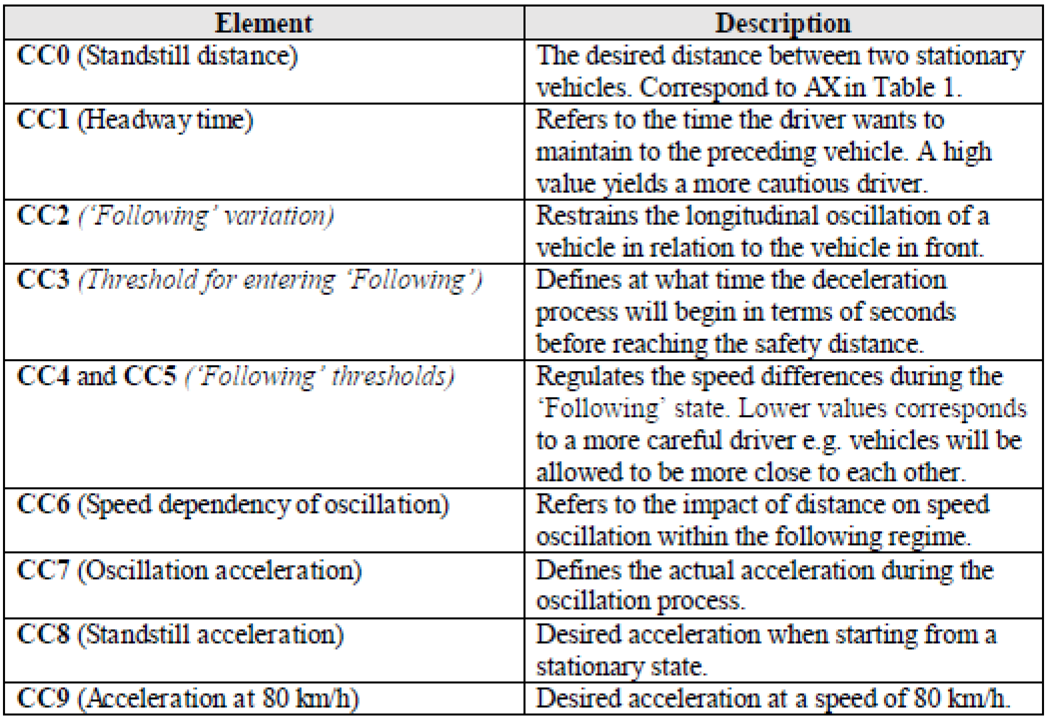
ANNEX 3 – TRAFFIC SIMULATION GENEALOGY



Source: Transportation Research Circular E-C195: Traffic and Transportation Simulation (2015)

ANNEX 4– WIEDEMANN 99 ADJUSTABLE PARAMETERS



Element	Description
CC0 (Standstill distance)	The desired distance between two stationary vehicles. Correspond to AX in Table 1.
CC1 (Headway time)	Refers to the time the driver wants to maintain to the preceding vehicle. A high value yields a more cautious driver.
CC2 *('Following' variation)*	Restrains the longitudinal oscillation of a vehicle in relation to the vehicle in front.
CC3 *(Threshold for entering 'Following')*	Defines at what time the deceleration process will begin in terms of seconds before reaching the safety distance.
CC4 and **CC5** *('Following' thresholds)*	Regulates the speed differences during the 'Following' state. Lower values corresponds to a more careful driver e.g. vehicles will be allowed to be more close to each other.
CC6 (Speed dependency of oscillation)	Refers to the impact of distance on speed oscillation within the following regime.
CC7 (Oscillation acceleration)	Defines the actual acceleration during the oscillation process.
CC8 (Standstill acceleration)	Desired acceleration when starting from a stationary state.
CC9 (Acceleration at 80 km/h)	Desired acceleration at a speed of 80 km/h.

Source: (Vissim User Manual, 2019)

ANNEX 5– DATA INPUT FOR SIMULATED NETWORKS

NETWORK 1:

	Sc1.1 / 1.2 100% Human		Sc2.1 / 2.2 50% Human		Sc3.1 / 3.2 100% AV		Sc4.1 / 4.2 33%HD 33% AV 33% CAV		Sc5.1 / 5.2 50% AV 50% CAV		Sc6.1 / 6.2 100% CAV		Des Veh Speed
I. Nações Unidas Ave.	Rel Flow (%)	Volume CET	Rel Flow (%)	Volume	Rel Flow (%)	Volume	Rel Flow (%)	Volume	Rel Flow (%)	Volume	Rel Flow (%)	Volume	km/h
100: Car	73	1801,64	37	913,16	0	0	25	525	0	0	0	0	7
200: HGV	1	24,68	0,5	0,02	0	0	0,5	10,5	0	0	0	0	7
300: Bus	12	296,16	6,5	160,42	0	0	4	84	0	0	0	0	7
610: Motorcylce	14	345,52	12	296,16	0	0	12	252	0	0	0	0	7
630: Car_AV	0	0	37	913,16	81	1999,08	25	525	40	987,2	0	0	7
650: HGV_AV	0	0	0,5	12,34	1	24,68	0,5	10,5	1	24,68	0	0	7
660: BUS_AV	0	0	6,5	160,42	18	444,24	4	84	10	246,8	0	0	7
670: Car_CAV	0	0	0	0	0	0	25	525	40	987,2	80	1974,4	7
680: Bus_CAV	0	0	0	0	0	0	4	84	9	222,12	20	493,6	7
Total	100	2468	100	2468	100	2468	100	2100	100	2468	100	2468	
II. Bandeirantes Ave.	Same split as Nacões Unidas Ave.	1000	Same split as Nacões Unidas Ave.	1000	Same split as Nacões Unidas Ave.	1000	Same split as Nacões Unidas Ave.	1000	Same split as Nacões Unidas Ave.	1000	Same split as Nacões Unidas Ave.	1000	
III. Dr. Cardoso de Melo Ave.	Same split as Nacões Unidas Ave.	400	Same split as Nacões Unidas Ave.	400	Same split as Nacões Unidas Ave.	400	Same split as Nacões Unidas Ave.	400	Same split as Nacões Unidas Ave.	400	Same split as Nacões Unidas Ave.	400	

Source: Author

Continue to the next page

NETWORK 2:

	Sc1.1 / 1.2 100% HDV		Sc2.1 / 2.2 50% HDV		Sc3.1 / 3.2 100% AV		Sc4.1 / 4.2 33%HD/33% AV/ 33% CAV		Sc5.1 / 5.2 50% AV 50% CAV		Sc6.1 / 6.2 100% CAV		Des Veh Speed
I. Cardeal Arco Verde t	Rel Flow (%)	Volume CET	Rel Flow (%)	Volume	Rel Flow (%)	Volume	Rel Flow (%)	Volume	Rel Flow (%)	Volume	Rel Flow (%)	Volume	km/h
100: Car	75	1125	37,5	562,5	0	0	25	375	0	0	0	0	30
300: Bus	10	150	5	75	0	0	4	60	0	0	0	0	30
610: Motorcylce	15	225	15	225	0	0	13	195	0	0	0	0	40
630: Car_AV	0	0	37,5	562,5	80	1200	25	375	40	600	0	0	30
660: BUS_AV	0	0	5	75	20	300	4	60	10	150	0	0	30
670: Car_CAV	0	0	0	0	0	0	25	375	40	600	80	1200	30
680: Bus_CAV	0	0	0	0	0	0	4	60	10	150	20	300	30
Total	100	1500	100	1500	100	1500	100	1500	100	1500	100	1500	
II. Horácio Lane St													
100: Car	85	85	42,5	42,5	0	0	29	29	0	0	0	0	25
300: Bus	0	0	0	0	0	0	0	0	0	0	0	0	-
610: Motorcylce	15	15	15	15	0	0	13	13	0	0	0	0	30
630: Car_AV	0	0	42,5	42,5	100	100	29	29	50	50	0	0	25
660: BUS_AV	0	0	0	0	0	0	0	0	0	0	0	0	-
670: Car_CAV	0	0	0	0	0	0	29	29	50	50	100	100	25
680: Bus_CAV	0	0	0	0	0	0	0	0	0	0	0	0	-
Total	100	100	100	100	100	100	100	100	100	100	100	100	
III. Francisco Leitão St													
100: Car	85	85	42,5	85	0	0	29	58	0	0	0	0	25
300: Bus	0	0	0	0	0	0	0	0	0	0	0	0	-

NETWORK 2 (page 2):

	Sc1.1 / 1.2 100% HDV		Sc2.1 / 2.2 50% HDV		Sc3.1 / 3.2 100% AV		Sc4.1 / 4.2 33%HDV /33% AV/33% CAV		Sc5.1 / 5.2 50% AV/ 50% CAV		Sc6.1 / 6.2 100% CAV		Des Veh Speed
I. Cardeal Arco Verde t	Rel Flow (%)	Volume CET	Rel Flow (%)	Volume	Rel Flow (%)	Volume	Rel Flow (%)	Volume	Rel Flow (%)	Volume	Rel Flow (%)	Volume	km/h
610: Motorcylce	15	15	15	30	0	0	13	26	0	0	0	0	30
630: Car_AV	0	0	42,5	85	100	200	29	58	50	100	0	0	25
660: BUS_AV	0	0	0	0	0	0	0	0	0	0	0	0	-
670: Car_CAV	0	0	0	0	0	0	29	58	50	100	100	200	25
680: Bus_CAV	0	0	0	0	0	0	0	0	0	0	0	0	-
Total	100	200	100	200	100	200	100	200	100	200	100	200	
IV. Joaquim Antunes St													
100: Car	85	85	42,5	35,7	0	0	29	24,36	0	0	0	0	25
300: Bus	0	0	0	0	0	0	0	0	0	0	0	0	-
610: Motorcycle	15	15	15	12,6	0	0	13	10,92	0	0	0	0	30
630: Car_AV	0	0	42,5	35,7	100	84	29	24,36	50	42	0	0	25
660: BUS_AV	0	0	0	0	0	0	0	0	0	0	0	0	-
670: Car_CAV	0	0	0	0	0	0	29	24,36	50	42	100	84	25
680: Bus_CAV	0	0	0	0	0	0	0	0	0	0	0	0	-
Total	100	84	100	84	100	84	100	84	100	84	100	84	
V. Virgílio Carvalho St													
100: Car	85	85	42,5	51	0	0	29	34,8	0	0	0	0	25
300: Bus	0	0	0	0	0	0	0	0	0	0	0	0	-
610: motorcycle	15	15	15	18	0	0	13	15,6	0	0	0	0	30
630: Car_AV	0	0	42,5	51	100	120	29	34,8	50	60	0	0	25
660: BUS_AV	0	0	0	0	0	0	0	0	0	0	0	0	-
670: Car_CAV	0	0	0	0	0	0	29	34,8	50	60	100	120	25
680: Bus_CAV	0	0	0	0	0	0	0	0	0	0	0	0	-
Total	100	120	100	120	100	120	100	120	100	120	100	120	

Source: Author

NETWORK2 3.X:

	Sc1.1 / 1.2 100% Human		Sc2.1 / 2.2 50% Human		Sc3.1 / 3.2 100% AV		Sc4.1 / 4.2 33%HD 33% AV 33% CAV		Sc5.1 / 5.2 50% AV 50% CAV		Sc6.1 / 6.2 100% CAV		Des Veh Speed
I. Networks 3.X (primary input)	Rel Flow (%)	Volume CET	Rel Flow (%)	Volume	Rel Flow (%)	Volume	Rel Flow (%)	Volume	Rel Flow (%)	Volume	Rel Flow (%)	Volume	km/h
100: Car	70	3500	35	1750	0	0	23,3	375	0	0	0	0	90
200: HGV	20	1000	10	500	0	0	7	60	0	0	0	0	70
300: Bus	10	500	5	0	0	0	3,3	60	0	0	0	0	70
630: Car_AV	0	0	35	1750	70	3500	23,3	375	35	600	0	0	90
660: HGV_AV	0	0	10	500	20	1000	7	60	10	150	0	0	70
660: BUS_AV	0	0	5	0	10	0	3,3	60	5	150	0	0	70
640: Car_CAV	0	0	0	0	0	0	23,3	375	35	600	70	1200	90
660: HGV_CAV	0	0	0	0	0	0	7	60	10	150	20	300	70
680: Bus_CAV	0	0	0	0	0	0	3,3	60	5	150	10	300	70
Total	100	5000	100	5000	100	5000	100,8	5000	100	5000	100	5000	
II. Network 3.3 (add input)													
100: Car	70	350	35	175	0	0	23,3	375	0	0	0	0	90
200: HGV	20	100	10	50	0	0	7	60	0	0	0	0	70
300: Bus	10	50	5	0	0	0	3,3	60	0	0	0	0	70
630: Car_AV	0	0	35	175	70	350	23,3	375	35	600	0	0	90
660: HGV_AV	0	0	10	50	20	100	7	60	10	150	0	0	70
660: BUS_AV	0	0	5	0	10	0	3,3	60	5	150	0	0	70
640: Car_CAV	0	0	0	0	0	0	23,3	375	35	600	70	1200	90
660: HGV_CAV	0	0	0	0	0	0	7	60	10	150	20	300	70
680: Bus_CAV	0	0	0	0	0	0	3,3	60	5	150	10	300	70
Total	100	500	100	500	100	500	100,8	500	100	500	100	500	

Source: Author