Behavioural Parameters for Connected and Automated Vehicles within the LEVITATE Project

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1 Introduction

1.1 Purpose of this document

This document was created as part of the Levitate project. The purpose of this document is to define the Connected and Autonomous Vehicle (CAV) parameter sets for driving logics that are used in the Levitate project. The behaviour parameter sets are based on the microscopic traffic simulation software Aimsun Next (Aimsun, 2021). The assumptions on CAV parameters and their values were based on a comprehensive literature review, including both empirical and simulation-based studies (e.g., Cao et al., 2017; Eilbert et al., 2019; Goodall yet al., 2020; de Souza et al., 2021; Shladover et al., 2012), as well as discussions in meetings with experts, conducted as part of Levitate project.

1.2 The Levitate project

Societal **Lev**el **I**mpacts of Connec**t**ed and **A**utoma**t**ed Vehicl**e**s (LEVITATE) is a European Commission supported Horizon 2020 project with the objective to prepare a new impact assessment framework to enable policymakers to manage the introduction of Cooperative, Connected and Automated Mobility (CCAM), maximise the benefits and utilise the technologies to achieve societal objectives.

Specifically LEVITATE has four key objectives:

1. To establish **a multi-disciplinary methodology** to assess the short, medium, and long-term impacts of CCAM on mobility, safety, environment, society, and other impact areas. Several quantitative indicators will be identified for each impact type.
2. To develop a range of **forecasting and backcasting** scenarios and baseline conditions relating to the deployment of one or more mobility technologies that will be used as the basis of impact assessments and forecasts. These will cover three primary use cases – automated urban shuttle, passenger cars and freight services.
3. To apply the methods and forecast the impact of CCAM over the short, medium, and long term for a range of use cases, operational design domains and environments and an extensive range of mobility, environmental, safety, economic and societal indicators. A series of case studies will be conducted to validate the methodologies and to demonstrate the system.
4. To incorporate the established methods within a **new web-based policy support tool** to enable city and other authorities to forecast impacts of CCAM on urban areas. The methods developed within LEVITATE will be available within a toolbox allowing the impact of measures to be assessed individually. A Decision Support System will enable users to apply backcasting methods to identify the sequences of CCAM measures that will result in their desired policy objectives.

For more information see https://levitate-project.eu/.

1.3 Issues with CAV Behavioural Parameters

As there are no real-world data available, research studies have to make assumptions through available knowledge from literature and earlier level automated vehicles systems. There is a key knowledge gap concerning the manner in which CAVs will drive in traffic and interact with other road users. Simulation models specify these behaviours through a set of parameters and functions that determine the operation of the simulation models. Since there is no firm data on the behaviour of CAVs these parameters and functions must be estimated or assumed.

Within Levitate, the assumptions on CAV parameters and their values were based on a comprehensive literature review, including both empirical and simulation-based studies, as well as discussions in meetings with experts, conducted as part of the Levitate project. Some guidance on the behaviours was also obtained through studies on Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) systems. Section 2 presents the findings from the literature review.

2 Literature Review on the Expected Behaviours of CAVs

Since there is no real-world data available on fully autonomous vehicles (AVs), previous studies on autonomous vehicles have based their investigations either using microsimulation tools, driving simulators, or experimental data based on early levels of automated vehicles. Traffic microsimulation studies have attempted to predict the potential impacts of autonomous vehicles through modelling their expected behaviours (e.g., Arvin et al., 2021; Shi et al., 2020; Ye and Yamamoto, 2019; Morando et al., 2018; Tibljaš et al., 2018).

The driving behaviours of connected and automated vehicles can be simulated by changing the driving model parameters that use human drivers' data, and/or inventing new intelligent logic for vehicle communications and cooperation (Ahmed et al., 2021). In order to model the behaviours of future connected and automated vehicles and accurately represent real-world traffic conditions, a proper calibration, which consists of selection and modification of input parameters values, needs to be undertaken before running the model (FHWA, 2018; TfL, 2010). In this context, many efforts have been made earlier by various researchers to calibrate the driving model parameters. A recent study by Alhariqi et al. (2021) proposed an adaptive Intelligent Driver Model (IDM) calibration process for intelligent vehicles in mixed autonomy traffic using real-world experimental trajectory data. The experiments were carried out on a single-lane circular road with a radius of 41.4 metres (260 metres) with a fleet of 21 or 22 vehicles including one intelligent vehicle. The results revealed that the proposed adaptive IDM and calibration method accurately reproduce the traffic conditions in mixed autonomy traffic. Bhattacharyya et al. (2020) presented a methodology that adopts a genetic algorithm (GA)-based optimisation technique for calibrating traffic microsimulation models in mixed-traffic conditions. The results showed that with vehicle mode-specific optimised parameter sets, a model for non-lane based mixed-traffic conditions, can be successfully achieved. In this regard, Pourabdollah et al. (2017) calibrated three car following models that were used in SUMO, i.e., the intelligent driver model (IDM), the Krauss car following model and the Wiedemann car following model. The parameters of each model were optimised using a Genetic Algorithm from around 200 recorded trips that were collected from human drivers driving on the Drive Me route, which is an autonomous drive test route in Gothenburg, Sweden. In comparison to the other two models, the simulation results showed that the optimised IDM can best imitate driving behaviour.

Efforts made by previous research studies can be used as guidelines on the appropriate calibration of input parameters for microscopic traffic simulation models, needed to enable an accurate reflection of the traffic conditions. In order to seek the guidance on various characteristics and accordingly range of parametric values to be adopted in simulation models, various previous studies were reviewed focusing on defining the behaviours of autonomous vehicles, the findings from which are presented below.

Car Following Behaviour

To understand the car-following behaviour of future autonomous vehicles, previous studies on early level automated vehicles comprising of Adaptive cruise control (ACC) and Cooperative Adaptive Cruise Control (CACC) were reviewed. In this context, the Federal Highway Administration (FHWA) report on the meta-analysis of ACC applications (Eilbert et al., 2019) presents findings from various previous studies to characterise the behaviours of manual driving, ACC, and CACC applications. The findings of the meta-analysis showed that having a lead CACC vehicle, drivers accept the shortest adjustable time headway with CACC systems presumably due to anticipation of the driving behaviours of the lead CACC vehicle. The time headway of 0.6s has been reported most frequently in the previous studies. With respect to manual driving, the findings from previous studies, in the meta-analysis, report comparatively longer time gaps varying from 0.8 s to 1.6 s. For ACC systems, the findings from the previous studies indicate two modes of driving styles; one that keeps the time headway setting shorter up to 1.1s (to avoid any cut-in vehicles) and the other with 1.5s gap possibly because of lack of confidence in the system to stop in time. Therefore, the meta-analysis findings identify ACC vehicles to have, on average, higher time gaps than human-driven vehicles (HDVs). This finding that ACC system equipped vehicles have similar or even longer reaction times than human drivers, has been approved by other European Commission funded research (Makridis et al, 2018). The California Partners for Advanced Transportation Technology (PATH) research (Nowakowski, 2011) findings suggest an acceptable time headway from 1.1 to 2.2s for ACC systems, and from 0.6 to 1.1s for CACC systems. It is also important to note that the initial desired time gaps may be shorter than the actual operational ones due to the conservative/defensive car-following nature of ACC systems (Calvert et al., 2017). Additionally, ACC systems have been found to have desired time headway range of 1.2 - 1.8 s whereas human drivers tend to vary between 0.5 - 1.5 s. Another aspect to note is that under the congested traffic conditions, the ACC time headway distribution skews longer than those of human drivers (Calvert et al., 2017).

The Wiedemann 99 car-following model is utilised in VISSIM software (by PTV Group) to render possible the modelling of various driving behaviours. The car-following parameters concern thresholds for safety distance, speed and acceleration/deceleration rates while some of the most widely utilised are headway time, that is the time between the lead and following vehicle in crossing a given point, and is set to 0.9s (default value), oscillation acceleration that is the minimum acceleration/deceleration during the following process and is set to 0.82ft/s^2 and, standstill acceleration defined as the desired acceleration when starting from standstill and set to 11.48 ft/s^2 (default values-human driven vehicles). In the AV simulation environment, using the aforementioned model, when there is communication with the lead vehicle the time headway has been suggested to adjust to 0.3s, 0.6s or 1s, oscillation acceleration to 0.25 m/s^2 and standstill acceleration to 3.5m/s^2. In the case of no communication between the lead and the following vehicle, the acceleration parameters remain the same, but the headway time is set strictly to 1s.
Furthermore, Atkins (2016) proposed different model parameters according to SAE levels. Level 3 incorporates the degree of aggressiveness of AVs and consists of four subcategories as shown in

Table 1.

Table 1: Wiedemann model parameter variation and VISSIM user-defined attributes (adjusted from Ahmed et al., 2021)

Capability levels		Head way time (gap)	Oscillation Acceleration	Stand still acceleration	Min clearance (m)	Safety distance reduction factor	User defined min time-gap(s)	User defined min clearance (m)
Level 2		0.9	0.25	3.5	0.5	60%	3	5
Level 3	Cautious	1.8	0.1	3.2	0.8	90%	3.6	6.5
	Normal cautious	1.2	0.2	3.4	0.6	70%	3.2	5.5
	Normal assertive	0.8	0.3	3.6	0.4	50%	2.8	4.5
	Assertive	0.6	0.4	3.8	0.2	30%	2.4	3.5
Level 4	0.5	0.6	0.4	3.8	0.2	30%	2.4	3.5

In the same line, the CoEXist project (https://www.h2020-coexist.eu/), in order to simulate the expected behaviour of CAVs using VISSIM microsimulation, has developed driving behaviours depicted in model parameters and presented as cautious (conservative, safer vehicle manoeuvres, larger headways), normal (default urban motorised driving behaviour) and aggressive (traffic situation prognosis, minimum gaps). Some of these parameters are shown in Table 2.

Table 2 : Model parameters for three different AV behaviours (PTV Group, 2019)

	Parameters	AV cautious	AV normal	AV Aggressive
Car -following	Headway time (s)	1.5	0.9	0.6
	Standstill Acceleration (m/s^2)	3	3.5	4
Lane change	Max deceleration for necessary lane change (m/s^2) for own vehicle	-3.5	-4	-4
	Accepted deceleration (m/s^2) for own vehicle	-1	-1	-1

Furthermore, according to Ding et al, (2021), the maximum acceleration value in CAVs is higher than in human-driven vehicles while the desired time gap is shorter showing that CAVs can maintain a smaller distance headway with the lead vehicle. After calibration process for the rear vehicle as a CAV or a HDV, for a leader-follower pair, the study showed that the optimal value for desired time gap was 2.09s, the maximum acceleration 1.83 m/s^2 and the desired deceleration 2.11 m/s^2. The bounds in optimization were 0.1 to 5 for all the parameters.

Trende et al. (2019) have presented research regarding customisable user profiles for autonomous vehicles utilising predefined driving profiles namely defensive (increased comfort and perceived safety), normal (average preferences), assertive (efficiency and trust in vehicle safety) and light rail transit (very low accelerations and decelerations, e.g., 0g to 0.14g).

Table 3 presents the ranges of accelerations for defensive assertive and low rail transit style (LRT) according to Yusof et al., (2016).

Table 3 : Acceleration ranges for different driving styles (Yusof et al., 2016)

Acceleration type	Defensive	Assertive	LRT
Longitudinal acceleration (g)	0.14 – 0.25	0.25 – 0.5	0 – 0.14
Longitudinal deceleration (g)	-0.14 – (-0.33)	-0.33 – (-0.76)	0 – (-0.14)
Lateral acceleration (g)	0.15 – 0.42	0.42 – 0.54	0 – 0.15

Acceleration and Deceleration Characteristics

In terms of acceleration and deceleration, autonomous vehicles are expected to provide a more comfortable driving experience for passengers (AASHTO, 2001). A study conducted by Le Vine et al. (2015) suggested that the autonomous vehicle is expected to accelerate and decelerate slower than a human-driven car while also being faster (or possibly the same) than light rail transit. The list of accelerations and decelerations for both the LRT and human-driven cars from previous studies are summarised in Table 4.

Table 4: Longitudinal and lateral accelerations and decelerations for light rail transit and human driven cars (Vine et al., 2015; Bogdanović and Ruškić, 2013; El-Shawarby et al., 2007; Hugemann and Nickel, 2003; Parsons Brinckerhoff Team, 2004; TCRP, 2012)

	LRT	Typical human-driven Car	Upper limit in human-driven car
Longitudinal acceleration	1.34 m/s2 or 0.14 g	2.47 m/s2 or 0.25 g	4.86 m/s2 or 0.5 g
Longitudinal deceleration	- 1.34 m/s2 or 0.14 g	- 3.27 m/s2 or -0.33 g	- 7.47 m/s2 or -0.76 g
Lateral acceleration	1.47 m/s2 or 0.15 g	4.10 m/s2 or 0.42 g	5.30 m/s2 or 0.54 g

A recent study by Chai et al. (2020) evaluated the Responsibility-Sensitive Safety (RSS) model applied to adaptive cruise control (ACC) systems. RSS is a mathematical model for assuring the safety of AVs and it defines the "safety state" of AVs based on appropriate response rules. The maximum desirable longitudinal acceleration and deceleration for ACC were set at 4m/s^2 and 5m/s^2, respectively.

Lu et al. (2020) carried out a simulation study to investigate the impact of autonomous vehicles on urban traffic networks by using SUMO software. The acceleration parameter implemented in the car-following model was 3.5 m/s^2 and 3.8 m/s^2 for no automation and full automation, respectively; the parameter of deceleration was 4.5 m/s^2 for both no automation and full automation.

Concerning a comfortable driving, Zhu et al. (2020) suggested that the acceleration range should be between -3 and 3 m/s^2 which was based on the observed following vehicle acceleration of all the car-following events. Regarding the deceleration rate, the threshold of 3.4 m/s^2 was recommended by AASHTO (American Association of State Highway and Transportation Officials, 2001) for a comfortable deceleration for most drivers, and 3m/s^2

was proposed by ITE (Institution of Transportation Engineers, 1999). The study conducted by Saptoadi (2017) also recommended the deceleration rates between 3 and 3.5m/s^2 for environment-friendly city driving, which are in line with AASHTO and ITE recommendations.

The limit of discomfort threshold of longitudinal acceleration and jerk was investigated by Bae et al. (2020) and reported to be around 2m/s^2 and 0.9m/s^3 respectively. Moon and Yi (2008) characterised the braking comfort within -2m/s^2 while maximum acceleration and deceleration values for human driving data were reported to be -5.08m/s^2 and 3.07m/s^2, respectively. Bifulco et al. (2019) proposed the frame of a novel longitudinal control strategy for AVs with vehicle to vehicle (V2V) communications and set the ego vehicle parameters as follows: maximum acceleration and deceleration at 2 m/s^2 and 3m/s^2, respectively, and minimum headway at 1.1s. Lastly, Fleming et al. (2018) suggested a set of parameters of driving behaviour for user acceptance of advanced driver assistance systems (ADAS). The driver model included minimum time headway (0.7s), maximum desired longitudinal acceleration (4m/s^2) and maximum desired longitudinal deceleration (5m/s^2).

Lane Change Behaviour

For successful lane changes, the intervehicle distance plays a crucial role especially from a safety aspect. Shorter distances tend to be a characteristic of aggressive drivers while more conservative drivers keep longer gaps. Several lane-change algorithms incorporated to warning systems or models for autonomous vehicles, have been developed, facilitating comfort and safety.

Dang et al. (2015) proposed a coordinated adaptive control system with a lane-change assistance function. As intervehicle distances vary throughout the lane change process, they have designed Time headway and TTC parameters according to three scenarios: Response to Leading Vehicle Brake (RLVB), Cutting in (Cut-in), and Catching up Slower Vehicle Ahead (CSVA). The Time headway and TTC values for safety performance in the aforementioned concepts are 1.4s and 8.2s, 1.8s and 10.5s and 1.4s and 8.2s respectively.

Cao et al. (2017) developed an optimal mandatory lane change decision model for autonomous vehicles in urban arterials and set as minimum safe headway 5.3s, a value representing the median value of an empirical distribution (Wakasugi, 2005).

Keyvan-Ekbatani et al. (2016) gathered empirical data on the mandatory lane changes for 10 drivers based on a test-drive. They have reported data of all drivers for both merging and diverging manoeuvres for different parameters that are indicatively presented in Table 5 for southbound direction.

Table 5 empirical data on test-drive mandatory lane-changes

Parameters	Merging	Diverging
	Median value	
Speed at merge (km/h)	89	81
Time on merging lane	3	52
Total time to pass merging area	23	5

Although lane-change models are either mandatory or discretionary, Toledo et al. (2003) have estimated an integrated model that takes into account both considerations. Lane-changing process includes choice of target lane and gap acceptance. Regarding the latter, the estimation results showed that critical gaps depend on the relative speeds of the lead and lag vehicle.

Sourelli et al., (2022) explored the pull-out phase of overtaking, with focus on parameters affecting the lane change decision making and performance, to inform automated manoeuvring preferences. Results showed that lane change duration manoeuvre ranged from 2.4 to 10s with a mean of 5.88s and was influenced by parameters such as longitudinal speed, standard deviation of lateral acceleration, mean longitudinal acceleration, pull-out distance and others.

Overtaking Behaviour

For modelling overtaking behaviours, previous studies have tried to build overtaking controllers based on occupant comfort, vehicle stability, and safety. Shamir (2004) based the lane changing model with the view of minimising the total kinetic energy, through limiting to using the specified maximal acceleration during the lane change manoeuvre, creating stable and comfortable trajectory. Xu et al. (2019) incorporated both safety and comfort in their proposed two-layer overtaking control model.

Overtaking manoeuvre involves passing a slower moving preceding vehicle in the same lane including pulling out of the lane followed by driving in straight line and then coming back/pulling into the same lane again. Since overtaking involves lane changing manoeuvres, the control logic can include the parametric considerations for lane changing. In this regard, Chae et al. (2021) developed an algorithm based on investigating real-world human driving data. Safety indices were used in the algorithm for defining lane changing behaviours, which were based on investigating the data on driver interaction with surrounding vehicles when changing lane (Figure 1).

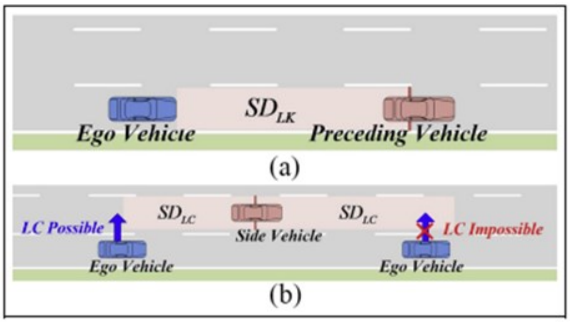

Figure 1: Concept of safety distances: (a) in the lane keeping situation and (b) in the lane change situation (Chae et al, 2021)

Safe distance in lane change situation (SD_{LC}) can be defined through the following equation:

$$SD_{LC} = \begin{cases} \max[(v_{x,\ ego} - v_{x,\ side}), 0] * \tau_{LC,\ 1} + \max[v_{x,\ ego} * \tau_{LC,\ 2}, c_{LC}], if\ \Delta p_{x,side} > 0 \\ \max[(v_{x,\ side} - v_{x,\ ego}), 0] * \tau_{LC,\ 1} + \max[v_{x,\ side} * \tau_{LC,\ 2}, c_{LC}], otherwise \end{cases} \quad (1)$$

Where:

side =the vehicle on the side lane,

Δp_x= longitudinal relative position from the ego vehicle,

$\tau_{LC,\ 1}$ =Time gap for the relative velocity of lane change,

$\tau_{LC,\ 2}$ =Time gap for the minimum clearance of lane change, and

c_{LC} =minimum clearance of lane change

Figure 2 shows velocity changes from driving data under lane change situations for ego and the side vehicles. Each lane change event is presented through a connected line where start of a lane change is marked with circle and end with cross.

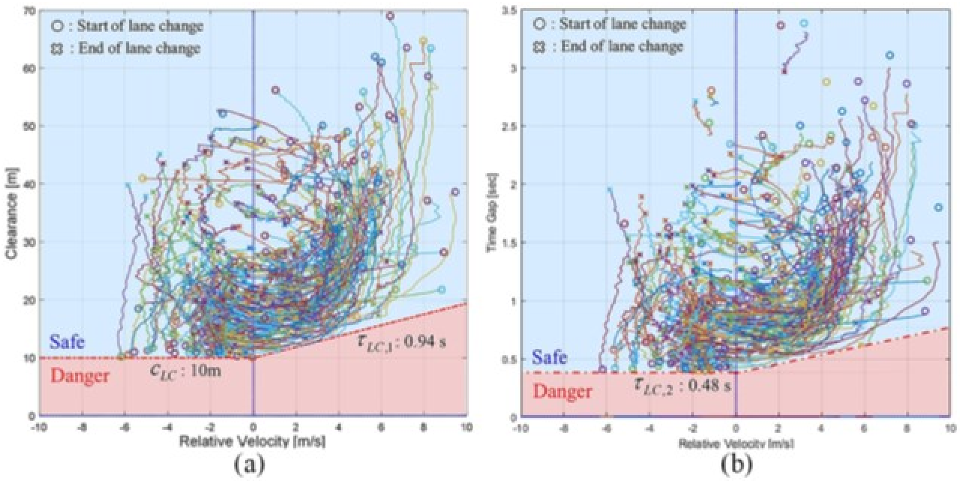

Figure 2: Driving data in lane change situation: (a) relative velocity to clearance and (b) relative velocity to TG. (Chae et al, 2021)

Table 6 presents values of the safe distance parameters determined from the driving data considering some margin on the boundary values.

Table 6: Parameters of safe distance (Chae et al, 2021)

Symbol	Value	Symbol	Value
τ_{LK}	1.36 s	$\tau_{Lc,1}$	1 s
c_{LK}	4 m	$\tau_{Lc,2}$	0.5 s
		c_{LC}	12m

Look-ahead distance

The look-ahead distance is also essential when modelling lateral vehicle behaviour. Look-ahead relates to connectivity in terms of anticipation of lane change when coming to a junction or incident. In the early 90s, the control concepts based on look-ahead systems were created to improve the efficiency and performance of longitudinal and lateral vehicle control systems (Atoui et al., 2021). The look-ahead systems measure the lateral displacement in front of the vehicle using sensors such as machine vision, radar, and LiDAR (Atoui et al., 2021). There have been extensive studies focused on using look-ahead measurement for automated steering control (Ozguner et al., 1995; Marino et al., 2011; Nguyen et al., 2017), the purpose of the Levitate project is to identify the acceptable range of look-ahead distance as well as min-max values in terms of stability, safety and comfort lane change performance for automated vehicles.

Several studies have been carried out to determine the optimal look-ahead distance adjustment with respect to vehicle speed. Pendleton et al. (2017) indicated that with lower speed and smaller look-ahead distance, the vehicle is anticipated to track the path closely, and oscillatory behaviour is also expected; while at higher speeds, when the look-ahead distance is greater, the vehicle is intended to track the path smoothly, but this will cause the cutting corner issue that the vehicle moves inside the corner instead of around it. Shan et al. (2015) also indicated that the vehicle would gradually converge on the path with less oscillation if the look-ahead distance is longer, whereas the shorter distance would converge quickly but with more oscillation. Yi et al. (2015) presented a new algorithm to improve vehicle trajectory prediction for the Adaptive Cruise Control (ACC) system via CarSim and MATLAB/Simulink. The results showed that the prediction errors rise as the look-ahead distance increases. Another study conducted by the authors proposed the kinematic vehicle lateral motion model based on a lane keeping system that considered look-ahead distance (Kang et al., 2015). In the study, the look-ahead distance was formulated as a linear function of the vehicle speed, and it was validated using CarSim and MATLAB/Simulink computational simulation results. The results showed that the look-ahead distance minimised the oscillation in control performance at torque and steering wheel angle.

A study conducted by Hasegawa and Konaka (2014) proposed a multiple look-ahead distance scheme that can estimate the lateral deviation, the heading of the vehicle, and the curvature of the reference. The simulation results indicated that the proposed control approach could meet the control objective for the references with varying radii.

Roselli et al. (2017) looked at the path tracking control with look-ahead distance for lane keeping in autonomous vehicles. The Double Lane Change (DLC) manoeuvre is used to investigate the effect of the look-ahead distance via the CarSim simulation. Figure 3 presents the results of a DLC manoeuvre carried out at 65 km/h with three look-ahead distances. The results indicated that the longer the look-ahead distance, the earlier the car would begin to steer. The look-ahead distance has significantly influenced path tracking and lateral acceleration. For example, when the look-ahead distance is too short, the car will begin to steer too late, resulting in a significant error generated on the first corner. Meanwhile, a shorter look-ahead distance generates higher acceleration because the corner is perceived later, and fast steering is required to track the path. When the look-ahead distance is too large, the manoeuvre is smoothed, and the tyres are pushed further away from the friction limit.

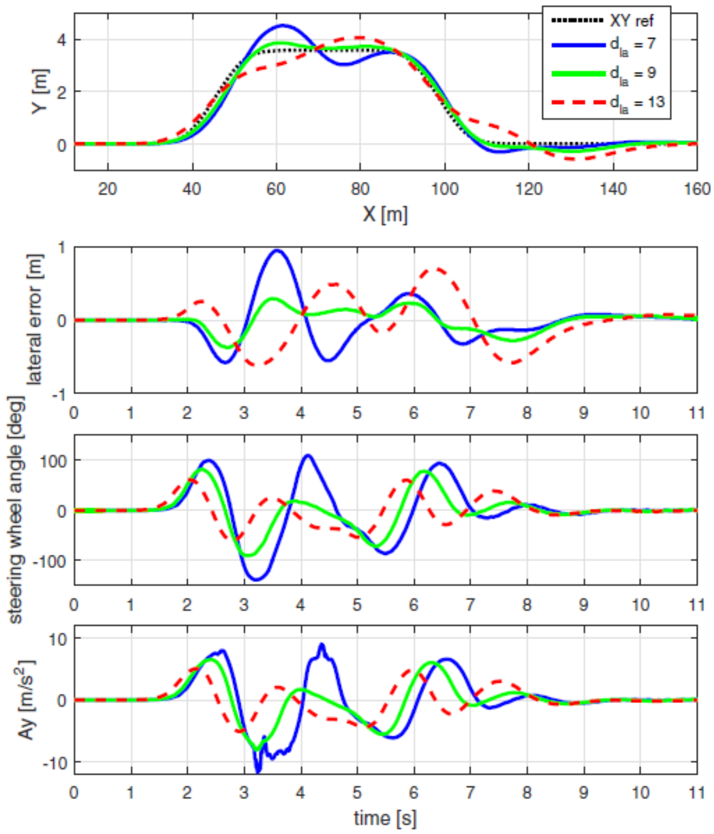

Figure 3: Look-ahead distance influence (Roselli et al., 2017)

Sever et al. (2018) have made efforts to investigate the allowable range of look-ahead distance for autonomous vehicle control. A nonlinear vehicle model with three degrees of freedom was being used in the simulation studies. A range of values from 2 to 25 meters for look-ahead distance was applied for peak values of lateral acceleration and sideslip angle and compared to the safety/comfort analysis that was performed with automated lane change manoeuvre. The study suggested that the crucial values of look-ahead distance are 8m for 80 km/h, 14 m for 100 km/h and 21 m for 120 km/h, respectively.

Behaviour at Unsignalised Intersection

Vehicles passage at unsignalised intersections is primarily defined through models based on gap acceptance which involve using some threshold value of time gap on major road (time that elapses between two successive vehicles).

With regard to defining autonomous vehicles behaviour at un-signalised junctions, Mihály et al (2020) used a multi-criteria approach in their proposed controller for collision free movement of vehicles at the intersection considering minimising travel time and consumption of energy while ensuring safe (collision free) movement of vehicles at the intersection. The controller can also be adjusted depending on the priorities and traffic characteristics at a location.

Summary

There is no real-world data available on fully automated vehicles to completely validate the findings reported by various research studies with underlying assumptions on CAVs behaviours. However, considering various presumed and expected characteristics of CAVs such as improved sensing and cognitive abilities, enhanced situational awareness, and with the integration of V2V and V2I communication, the future connected and automated vehicles can be considered to have more efficient and safer operations on road than human-driven vehicles through better/efficient decision-making, higher anticipation of upcoming lane change and any incidents ahead. Various kinds of research studies have based their investigations considering such characteristics that will promote efficient and safer traffic operations.

The key driving parameters include, but are not limited to, time headway, acceleration/deceleration characteristics, lane-change and overtaking behaviours, gap acceptance behaviours at unsignalised intersections, anticipation of lane change and incidents ahead, decision making due to V2V and V2I communication key characteristics, with the advancements in autonomous vehicle technology, giving them enhanced sensing and cognitive abilities, such vehicles can be considered to have higher anticipation of upcoming lane change and any incidents ahead.

3 Behavioural Models in Aimsun Next

To model the behaviours of different vehicle types, including human-driven vehicles and CAVs, various parameters of the behavioural models implemented in the Aimsun Next traffic simulation software are considered. The following sub-sections from 3.1-3.4 provide background information on various behavioural models in Aimsun Next, extracted from the software user's manual (Aimsun, 2021).

3.1 Car-Following Model

The car-following model implemented in Aimsun Next is based on the Gipps (Gipps, 1981; Gipps, 1986) model. It has been developed by including model parameters which are not global but determined by the influence of local parameters depending on the "type of driver" (speed limit acceptance of the vehicle), the geometry of the section (speed limit on the section, speed limits on turns, etc.), the influence of vehicles on adjacent lanes, etc. It consists of two components, acceleration and deceleration. The first represents the intention of a vehicle to achieve a certain desired speed, while the second reproduces the limitations imposed by the preceding vehicle when trying to drive at the desired speed. This model states that the maximum speed to which a vehicle (n) can accelerate during a time period (t, t+T) is given by:

$$V_a(n,t+T) = V(n,t) + 2.5a(n)T\left(1-\frac{V(n,t)}{V^*(n)}\right)\sqrt{0.025+\frac{V(n,t)}{V^*(n)}} \qquad (2)$$

Where:

- *Va(n,t) is the speed of vehicle n at time t;*
- *V*(n) is the desired speed of the vehicle (n) for current section;*
- *a(n) is the maximum acceleration for vehicle n;*
- *T is the reaction time*

At the same time, the maximum speed that the same vehicle (n) can reach during the same time interval (t, t+T), according to its own characteristics and the limitations imposed by the presence of the lead vehicle (vehicle n-1) is:

$$V_b(n,t+T) = d(n)T + \sqrt{d(n)^2T^2 - d(n)\left[2\{x(n-1,t) - s(n-1) - x(n,t)\} - V(n.t)T - \frac{V(n-1,t)^2}{d'(n-1)}\right]} \qquad (3)$$

where:

- *d(n) (< 0) is the maximum deceleration desired by vehicle n;*
- *x(n,t) is position of vehicle n at time t;*
- *x(n-1,t) is position of preceding vehicle (n-1) at time t;*
- *s(n-1) is the effective length of vehicle (n-1);*
- *d'(n-1) is an estimation of vehicle (n-1) desired deceleration.*

The speed for vehicle n during time interval (t, t+T) is then the minimum of these two speeds:

$$V(n,t+T) = min\{V_a(n,t+T), V_b(n,t+T)\} \qquad (4)$$

The position of vehicle n in the current lane is then updated using the integration of the speed. Acceleration and deceleration phases are integrated using different methods. The acceleration phase is integrated using the rectangle method corresponding to the following equation:

$$x(n,t+T) = x(n,t) + V(n,t+T)T \quad (5)$$

while the deceleration phase integration uses the trapezoid method following this equation:

$$x(n,t+T) = x(n,t) + 0.5(V(n,t) + V(n,t+T))T \quad (6)$$

The estimation of the leader's deceleration is a function of the "Sensitivity Factor" parameter α defined per vehicle type. The model is then:

$$d'(n-1) = d(n-1) * \propto \quad (7)$$

When α is < 1, the vehicle underestimates the deceleration of the leader and as a consequence the vehicle becomes more aggressive, decreasing the gap ahead of it. When α is greater than 1, the vehicle overestimates the deceleration of the leader and as a consequence the vehicle becomes more careful, increasing the gap ahead of it.

The model also includes the minimum headway between leader and follower as a restriction of the deceleration component. This constraint is applied before updating the position X(n,t+T).

The minimum headway constraint is defined as:

$$\underset{Then}{^{if}} \; x(n-1,t+T) - [x(n,t) + V(n,t+T) \; * T] < V(n,t+T) * MinHW(n) \quad (8)$$

and

$$V(n,t+T) = \frac{x(n-1,t+T) - x(n,t)}{MinHW(n)+T} \quad (9)$$

where:

- *x(n,t) is position of vehicle n at time t;*
- *x(n-1,t) is position of preceding vehicle (n-1) at time t;*
- *MinHW(n) is the minimum headway of vehicle (n) between it and vehicle (n+1).*

The car-following model is such that a leading vehicle, i.e. a vehicle driving freely, without any vehicle affecting its behaviour, would try to drive at its maximum desired speed. Three parameters are used to calculate the maximum desired speed of a vehicle while driving on a particular section or turn, two are related to the vehicle and one to the section or turn:

- *Maximum desired speed of the vehicle i:* V_{max} *(i)*
- *Speed acceptance of the vehicle i:* θ (i)
- *Speed limit of the section or turn s:* S_{limit} *(s)*

The speed limit for a vehicle ion a section or turn s, is calculated as:

$$S_{limit}(i,s) = S_{limit}(s) * \theta\,(i) \quad (10)$$

and

$$\mathrm{V_{max}(i,s)} = \min\{\mathrm{S_{limit}(i,s), V_{max}(i)}\} \tag{11}$$

This maximum desired speed Vmax(i,s) is the same as that referred to above, in the Gipps car-following model, as V(n).*

3.1.1 *Modified Model for Congested Highways*

The speed predicted by the Gipps car following model at high density does not match the speeds observed under congested conditions in highways. A modified model is used to adjust the dependency of the speed as a function of density. This is achieved by changing the dependency of the inter-vehicular distance (Clearance) as a function of speed which is simply linear in the Gipps model. The equation from Gipps for the clearance between vehicles is:

$$Clr(t) = \frac{V(n-1,t)^2}{2d(n-1)} - \frac{V(n,t)^2}{2d(n)} + (0.5V(n,t) + V(n,t+T) * T) \tag{12}$$

And at constant speed and maximum deceleration, this simplifies to:

$$Clr(t) = 1.5V(n,t)T \tag{13}$$

The specific model implemented to overcome the linear dependency between the inter-vehicular distance and the speed:

$$Clr(t) = \frac{V(n-1,t)^2}{2d(n-1)} - \frac{V(n,t)^2}{2d(n)} + (1-\alpha)(0.5V(n,t) + V(n,t+T) * T) + \alpha\left(0.5V(n,t) + V(n,t+T) * \left(\sqrt{\frac{V(n,t)}{V_{des}}}T\right)\right) \tag{14}$$

Implies

$$V_n(t+T) = d(n)T^* + \sqrt{(d(n)T^*)^2 - d(n)\left[2Clr(t) - V(n.t)T^* - \frac{V(n-1,t)^2}{d'(n-1)}\right]} \tag{15}$$

Where:

$$T^* = T\left(1 + \alpha\left(1 - \sqrt{\frac{V(n,t)}{V_{des}}}\right)\right) \tag{16}$$

And at constant speed and maximum deceleration, this simplifies to:

$$Clr(t) = 1.5V(n,t)T\left(1 + \alpha\left(1 - \sqrt{V(n,t)}\right)\right) \tag{17}$$

3.1.2 *Car following parameters*

The Car-following determines the clearance between leader and follower. The main behavioural parameters to control are:

- *Reaction Time*
    - *There are three different reactions times in microscopic simulation: Reaction time: This is the time it takes a driver to react to speed changes in the preceding vehicle. Reaction time at stop: This is the time it takes for a stopped vehicle to react to the acceleration of the vehicle in front. Reaction time at traffic light: This is the time it takes for the first vehicle stopped after a traffic light to react to the traffic light changing to green.*
- *Speed acceptance (see equation 9)*
    - *This parameter can be interpreted as the 'level of goodness' of the drivers or the degree of acceptance of speed limits. When is greater than 1 means that the vehicle will take as maximum speed for a section a value greater than the speed limit, while when is lower than 1 means that the vehicle will use a lower speed limit.*
- *Sensitivity Factor (see equation 6)*
    - *In the deceleration component of the car-following model, the follower makes an estimation of the deceleration of the leader using the sensitivity factor*
- *Aggressiveness*
    - *The aggressiveness parameter modifies the relationship of the inter-vehicle distance as a function of speed. This distance is simply linear in the Gipps model and does not correspond to observed behaviour under congested highway conditions.*
- *Stop and Go*
    - *This option allows a vehicle to adjust how it uses the aggressiveness value. If the option is ticked the value +a is used during deceleration and of –a during acceleration. Hence, assuming a is positive, the gap between vehicles will be larger during acceleration than deceleration for the same speed.*

3.2 Lane Changing Model

The lane-changing model can also be considered as a development of the Gipps Lane changing model. Lane change is modelled as a decision process, analysing the necessity of the lane change (such as for turn manoeuvres determined by the route), the desirability of the lane change (to reach the desired speed when the leader vehicle is slower, for example), and the feasibility of the lane change depending on the position of the vehicle in the road network with respect to the lane geometry and adjacent vehicles. The lane-changing model is a decision model that approximates the driver's behaviour as follows at each vehicle update:

- *Is it necessary to change lanes? This depends on several factors: the turning options from the current lane, the distance to the next turn and the traffic conditions in the current lane described by speed and queue lengths.*

- *Is it desirable to change lanes? This depends on whether there will be any improvement in the traffic conditions for the driver as a result of lane changing. This improvement is measured in terms of speed and distance. If the speed in the target lane is faster compared to the current lane, or if the queue is shorter by sufficient margin, then it is desirable to change lanes.*

- *Is it possible to change lanes? This requires that there is an adequate gap to make the lane change. This calculates both the braking imposed by the future* *downstream vehicle to the lane-changing vehicle and the braking imposed by the lane-changing vehicle to the future upstream vehicle. If both braking levels are acceptable, then lane changing is possible.*

To represent the driver's behaviour in the lane-changing decision process, three different zones are considered, each one corresponding to a different lane changing motivation.

- *Zone 1: The lane-changing decisions are mainly governed by the traffic conditions of the lanes involved. To measure the improvement that the driver will get from changing lanes, several parameters are considered: The desired speed of driver, the speed and distance of current preceding vehicle, speed and distance of future preceding vehicle in the destination lane. The model implemented in this zone is the overtaking manoeuvre model.*
- *Zone 2: This is the intermediate zone. Vehicles driving in the "wrong" lane (i.e. lanes where the desired turn movement cannot be made) tend to get closer to the correct side of the road from which the turn is allowed. Vehicles looking for a gap try to adapt their speed to find gaps located either downstream or adjacent to them.*
- *Zone 3: Vehicles are urgently trying to reach their valid lane, looking for gaps upstream and reducing speed, if necessary, even coming to a complete stop in order to make the lane change possible.*

  The lane changing of each vehicle at any section has five aspects:

  - *Target Lanes calculation*
  - *Vehicle behaviour considering the target lanes*
  - *Gap Acceptance model for Lane Changing*
  - *Target Gap and Cooperation*

3.2.1 *Target Lanes calculation*

The calculation of the Target Valid Lanes is based on the traffic conditions present in the section, the turn lanes specified for next junction, and the possible obstacles on the path to the junction including incidents, compulsory reserved lanes, closed lanes, turn closures and the presence of a public transport stop, in case of a public transport vehicle. All elements have a visibility distance defined as distance zone 1 and distance to zone 2.

3.2.2 Vehicle behaviour considering the target lanes

The strategy is for every vehicle try to reach the set of target lanes defined by zone 2 and 3 and the vehicle behaviour is as follows:

- *If the vehicle´s current lane is not within the subset of valid lanes determined by Zone 3 (TL3), the vehicle´s behaviour is determined by Zone 3.*
- *If the vehicle´s current lane is within the subset of valid lanes determined by Zone 3(TL3) but outside of the subset of valid lanes determined by Zone 2, the vehicle´s behaviour is determined by Zone 2(TL2).*
- *If the vehicle´s current lane is within the subsets of valid lanes of both Zone 3 and 2, the vehicle´s behaviour is determined by Zone 1(TL1).*

When the current lane of a vehicle is in a valid lane determined by zone 2 and 3, in general the behaviour is modelled as if it was in zone 1, i.e. overtaking manoeuvres may be initiated. There is an exception when a vehicle's leader is affected by an obstacle (turn *movement, incident, lane closure, etc) that is closer than the vehicle's own obstacle, then the evaluation to overtake the leader includes using a lane that can be outside of the subset of lanes given by Zone 2.*

3.2.3 Gap Acceptance model for Lane Changing

The gap acceptance model is consistent with the car following model, in order to avoid artificial breakdown situations:

$$V_n(t+\tau_n) = b_n\tau_n + \sqrt{(b_n\tau_n)^2 - b_n\left[2(x_l(t) - x_n(t) - l_l - s_n) - V(t)\tau_n - \frac{V_l^2(t)}{b_l}\right]} \qquad (18)$$

and

$$Clr(t) = (x_l(t) - x_n(t) - l_l - s_n) = \frac{v_l^2(t)}{2b_l} - \frac{v_n^2(t+\tau_n)}{2b_n} + \big(0.5V_n(t) + V_n(t+\tau_n)\big)\tau_n \qquad (19)$$

The Gipps car following model is stable i.e. it does not require decelerations above the maximum desired deceleration αb_n, where b_n is an estimation of the vehicle leader desired deceleration and α is Aggressiveness level parameter.

$$V_n(t+\tau_n) \geq Max(v_n(t) + \alpha b_n\tau_n;\ 0) \qquad (20)$$

This is achieved when:

$$Clr(t) \geq \frac{V_l^2(t)}{2b_l} + 0.5V_n(t)\tau_n + Max\left[0, -\frac{V_n^2(t)}{2b_n} + (1-0.5\alpha)\alpha b_n{\tau_n}^2 + (1-\alpha)V_n(t)\tau_n\right] \qquad (21)$$

The Gipps car following model avoids crashes when the Gap remains positive all over the deceleration process. This gives an additional constraint:

$$Clr(t) \geq Max\left[0, \frac{V_l^2(t)}{2b_l} + 0.5V_n(t)\tau_n + Max\left[0, -\frac{V_n^2(t)}{2b_n} + (1-0.5\alpha)\alpha b_n{\tau_n}^2 + (1-\alpha)V_n(t)\tau_n\right]\right] \qquad (22)$$

This condition must be fulfilled to apply the Gipps car following model with a new leader when a vehicle changes lane (i.e. selection of possible leader and gap acceptance).

Furthermore, applying this constrain at the end of the deceleration process i.e. when $V_n(t+\tau_n) \cong V_n(t) \cong V_l(t)$ yields:

$$Clr(t) = \frac{V_l^2(t)}{2b_l} - \frac{V_l^2(t)}{2b_l} + 1.5V_l(t)\tau_n \geq 0 \qquad (23)$$

And

$$b_l \leq \frac{b_n}{1 - \frac{3b_n\tau_n}{V_l(t)}} \qquad (24)$$

- *if the vehicle changes lane, the speed and position of the vehicles at time t+dt is evaluated:*

- *For the vehicles that are already updated, current speed and position is used.*
- *For the others, the speed and position assuming that the vehicle changes lane at time*
- *t+dt is evaluated.*
- *The gap is acceptable if the physical quantities at time t+dt fulfils the three following*
- *requirements:*
- *the gaps are positive*
- *the computed speeds are positive,*
- *the decelerations imposed are smaller than α MaxDesiredDecel*
- *Using the previous equations this can be achieved with one condition at time t that need to be fulfilled for both the upstream and downstream clearance distance:*

$$Clr_{Up}(t) \geq Max\left[0, \frac{V_{lc}^2(t)}{2b_{lc}} + 0.5V_{Up}(t)\tau_{Up} + Max\left[0, -\frac{V_{Up}^2(t)}{2b_{Up}} + \alpha_{Up}\left(1-0.5\alpha_{Up}\right)\alpha b_{Up}{\tau_{Up}}^2 + \left(1-\alpha_{Up}\right)V_{Up}(t)\tau_{Up}\right]\right] \quad (25)$$

and

$$Clr_{Dw}(t) \geq Max\left[0, \frac{V_{Dw}^2(t)}{2b_{Dw}} + 0.5V_{lc}(t)\tau_{lc} + Max\left[0, -\frac{V_{lc}^2(t)}{2b_{lc}} + \alpha_{Dw}(1-0.5\alpha_{Dw})b_{lc}{\tau_{lc}}^2 + (1-\alpha_{Dw})V_{lc}(t)\tau_{lc}\right]\right] \quad (25)$$

3.2.4 *Target Gap and Cooperation*

To change lane, the target lane is searched for an adequate gap. The upstream vehicle of the gap must and be able to follow the vehicle that is looking for a gap using the crash free car following model or be willing to cooperate. The subject vehicle intending to change lane will then progressively adapt to the speed of the downstream vehicle using the two-leaders car following model with a negative gap if needed. When choosing an adjacent or backward gap, the vehicle intending to change lane will always have a speed that is lower than the one imposed by its current leader. To avoid this penalty, the lane changing vehicle can instead choose a forward gap if it is able to overtake the downstream vehicle before the forthcoming obstacle. Selecting a forward gap will however not cause it to exceed the Gipps car following speed imposed by its current leader. The percentage of upstream vehicles that cooperate in the lane changing model is defined for each section or vehicle type using the Lane Changing Cooperation parameter in the Road Type Editor or the Vehicle Type Editor. Note that upstream vehicles will only cooperate with requesting vehicles being in Zones 2 and 3; that is, vehicles for which the lane change is compulsory.

The order of evaluation of gaps in each zone is:

- *Zone 1*
  - *1st Adjacent gap*
- *Zone 2*
  - *1st Forward gap o 2nd Adjacent gap*
- *Zone 3*

- 1st Adjacent gap o 2nd Backward gap

3.2.5 Overtaking Manoeuvre

An overtaking manoeuvre takes place in Zone 1 when the vehicle is in its set of valid lanes and changes lane to pass another vehicle. In order to promote or discourage overtaking, there are two parameters:

- *Overtake Speed Threshold is the percentage of the desired speed of a vehicle below which the vehicle may decide to overtake. This means that whenever a vehicle is constrained to drive slower than Overtake Speed Threshold % of its desired speed, it will try to overtake. The default value is 90%.*
- *Lane Recovery Speed Threshold is the percentage of the desired speed of a vehicle above which a vehicle will decide to get back into the adjacent slower lane. The default value is 95%.*

Therefore, if a vehicle with a desired speed of 100kph was to follow a vehicle at a speed < 90kph, it would try to overtake. Subsequently, when it achieved a speed > 95 kph, it would return to its original lane It is recommended that the Lane Recovery Speed Threshold value is greater than Overtake Speed Threshold, otherwise some overtaking manoeuvres may be aborted as they start. Similarly, if these values are set too small, vehicles will not initiate an overtaking manoeuvre unless the speed gap is very large and would return to the slower lane too soon. Note that the sensitivity to these parameters is low. These two parameters may be edited from the Tables Window for a Dynamic Experiment, from the attributes of an experiment or may be set by vehicle type to override the default experiment parameters.

3.2.6 Return to Lane after Overtake

The tendency to move back to the slower lane after overtaking is determined by the road type, the specific road section, and by the Staying in Overtaking Lane parameter for a vehicle type. If the road section allows for Return to Inside lane After Overtaking, either set by the road type or modified for the specific road section. Then, after every lane change manoeuvre, a new value for the Keep Fast Lane boolean attribute for the vehicle is generated based on the Staying in Overtaking Lane percentage for the vehicle type. If this value is false, then the Lane Recovery Speed Threshold is ignored, and the vehicle will remain in the lane it used to overtake.

3.2.7 Determine the side of the manoeuvre

The roadside determines the overtaking manoeuvre according:

- *When a vehicle attempts to overtake another vehicle, it will try to do so using the adjacent left lane when driving on the right side, or the adjacent right lane when driving on the left.*
- *When a vehicle is driving fast enough and wants to move back to the slower lane, it will try to go to the rightmost lane when driving on the right and to the leftmost lane when driving on the left.*

3.3 Lane Changing parameters

- *Distance Zone Factor: The Distance Zone Factor is used to modify the distance zones used in the Lane Changing Model to determine where vehicles consider their lane choice for a forthcoming turn. The default distances are set in the Road Type and may be modified for each turn to reflect local conditions in the Turn Editor. The zone distances may then be modified by vehicle type to adjust where lane changes start to be considered and, if a range is given, to randomise behaviour for each vehicle of that type.*
- *Cooperation: The cooperation value fines whether a vehicle creates a safe gap for another vehicle that changes lane to enter.*
- *Overtake Speed*
  - *Overtake Speed Threshold is the percentage of the desired speed of a vehicle below which the vehicle may decide to overtake. This means that whenever a vehicle is constrained to drive slower than Overtake Speed Threshold % of its desired speed, it will try to overtake. The default value is 90%.*
  - *Lane Recovery Speed Threshold is the percentage of the desired speed of a vehicle above which a vehicle will decide to get back into the adjacent slower lane. The default value is 95%.*
- *Aggressiveness: This parameter allows vehicles to enter shorter gaps without forcing the rear vehicle to brake, followed by a relaxation process to gradually recover the stability of the car following models. The aggressiveness % controls the sensitivity of a vehicle to the deceleration of the leader, determining how short can these gaps be. That is, if aggressiveness is set to 100% (which should not be used, it's the most extreme case) this means zero sensitivity, and the new allowed gap (at all speed situations) would be that needed at a stop situation (as if the vehicle was parking). An aggressiveness 0%, the full gap is used as described above, with no change in sensitivity. All intermediate values will make the gap shorter according to the aggressiveness % and also to the current speed of the leader. Aggressiveness applies to all lane changing manoeuvres that are not cooperative. This parameter may be set for a Road Type or may be adjusted by Vehicle Type.*
- *Imprudent Lane Changing: This option determines whether vehicles can enter gaps that do not ensure car following stability. The vehicle changing lane, or its follower, might need to brake up to twice their maximum deceleration. Only vehicles where the vehicle type also has the 'Imprudent lane changing' activated will accept those gaps.*

3.4 Gap acceptance in give way behaviour

3.4.1 *Description*

*A Gap-Acceptance model is used to model give way behaviour. This model determines whether a vehicle approaching an intersection can or cannot cross depending on the nearby vehicles with higher priority at the junction. This model takes into account the distance of vehicles to the hypothetical collision point, their speeds and their acceleration rates. It then determines the time needed by the vehicles to clear the intersection and produces a decision that also includes the level of risk of each driver. The gap required to make the manoeuvre is determined by the time spent waiting for a gap to appear in the opposing flows. The initial value is MaximumGap; the final value is MinimumGap. After waiting for GapReductionStartTime * MaximumGap seconds, the gap is progressively reduced, reaching the minimum gap value after GapReductionEndTime * MaximumGap seconds. This is illustrated in* Figure 4*.*

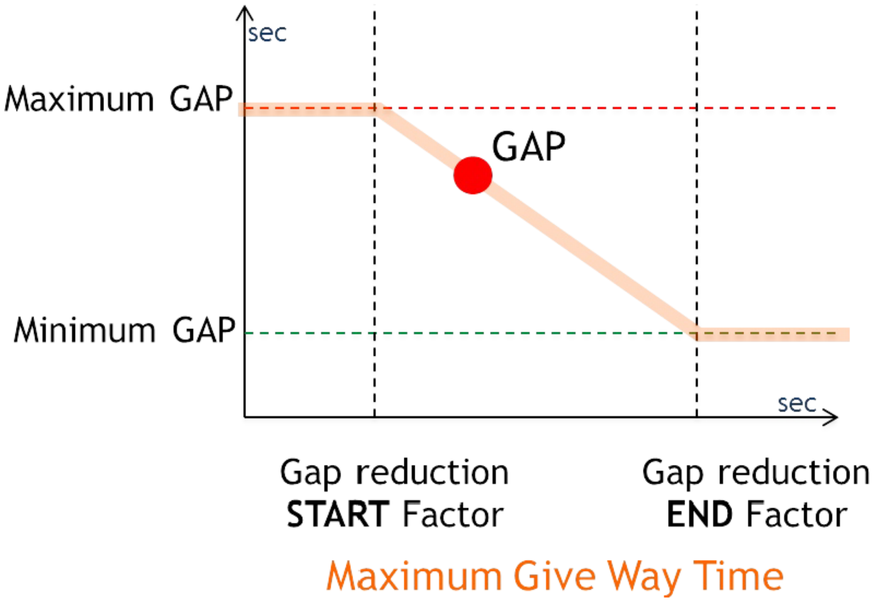

Figure 4: *Maximum Give Way Time (Aimsun, 2021)*

The following algorithm, illustrated in Figure 5 is applied in order to determine whether a vehicle approaching a Give Way sign can cross or not: Given a vehicle (VEHY) approaching a Give Way junction,

1. *Obtain the closest higher priority vehicle (VEHP)*
2. *Determine the Theoretical Collision Point (TCP)*
3. *Calculate time (TP1) needed by VEHY to reach TCP*
4. *Calculate estimated time (ETP1) needed by VEHP to reach TCP*
5. *Calculate time (TP2) needed by VEHY to cross TCP*
6. *Calculate estimated time (ETP2) needed by VEHP to clear the junction*
7. *If TP2 (plus a safety margin) is less than ETP1, vehicle VEHY has enough time to cross; therefore, it will accelerate and cross*
8. *Else, if ETP2 (plus a safety margin) is less than TP1, vehicle VEHP will have already crossed TCP when VEHY reaches it, then search for the next closest vehicle with a higher priority, it becomes VEHP and go to step 2*
9. *Else, vehicle VEHY must give way, decelerating and stopping if necessary.*

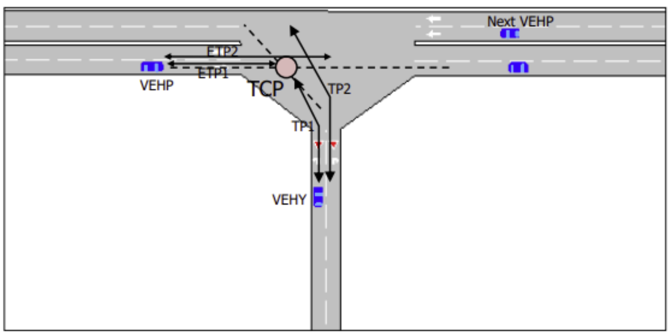

Figure 5: Gap acceptance in give way behaviour (Aimsun, 2021)

Safety Margin Factor: In the gap acceptance calculations to determine when a vehicle can move at a priority junction, the safety margin is set for the Road Type, may be modified for a specific turn to reflect the road geometry and may further be adjusted by vehicle type. This parameter provides a multiplier, with a truncated normal range.

3.5 Parameters to model in Aimsun Next

Based on the above presented behavioural models and findings from literature as well as discussions with experts, the following parameters in Table 7 were used to model behaviours of human-driven vehicles and CAVs in Aimsun Next.

Table 7: Human-driven and CAVs parameters in Aimsun Next

Driving Model	Parameter	Description
Car-following model	Time gap (In Aimsun Next, reaction time along with sensitivity factor, affects time gap)	Time that elapses between rear end of the lead vehicle and front bumper of following vehicle.
	Max. acceleration	Maximum acceleration that a vehicle can achieve under any circumstances
	Normal deceleration	Maximum deceleration a vehicle can use under normal conditions
	Max. deceleration	Maximum deceleration a vehicle can use under special circumstances, such as emergency braking.
	Clearance	The distance a vehicle keeps between itself and the leading vehicle when stopped.
	Safety margin factor	It generates give-way behaviour at unsignalized junctions. The higher the value indicates more conservative behaviour.
Lane-changing model	Look ahead distance factor (anticipation of lane change)	It determines where the vehicles consider their lane change
	Overtaking	It controls overtaking manoeuvres when a vehicle changes lane to pass another.

4 Modelling CAV Behaviours

4.1 Driving Characteristics

With incremental development towards perfection in automation, the concept of first- and second-generation systems was introduced. Both types are assumed to be fully automated vehicles with level 5 automation. The main idea behind modelling these two types is based on the assumption that technology will advance with time. Therefore, 2nd Gen CAVs will have improved sensing and data handling capabilities, decision making, driver characteristics, and anticipation of incidents etc. In general, the main assumptions on CAVs characteristics are as follows:

- 1st Generation: Sensing and computational capability is limited. These vehicles are considered to be conservative in their driving characteristics whereby they leave larger gap, have higher anticipation of lane change and incidents etc. (relating to connectivity) than human driven vehicles and takes more time during give way situations.
- 2nd Generation: Sensing and computational capability is advanced, can use data fusion and is more confident in taking decisions. These vehicles are considered to appear more aggressive in their driving characteristics whereby they leave smaller (compared to human driven vehicles) headway to preceding vehicle, have higher anticipation of lane change or incidents etc. (relating to connectivity) than human driven vehicles and 1st Generation CAVs, and takes less time during give way situations.

It is considered that all AVs will be connected. Decision-making by using information received using connectivity in 1st generation would be limited so some behaviours will be limited due to this. 2nd generation vehicles are considered to be advanced in decision-making by using information using connectivity and so, this will be reflected in their driving behaviours. The CAV driving behaviours developed in the Levitate project is presented in Table 8 below.

Table 8: CAV driving behaviour in Levitate project

Description	1st Generation	2nd Generation
Sensing and cognitive ability	Limited to on-board sensing instruments and analytics capability is limited by on-board computing power	Improved on-board capabilities and enhanced by comprehensive traffic management system
Decision-making	Limited to situational awareness given by on-board instruments.	Advanced capability due to enhanced situational awareness aided by comprehensive traffic management system
Driving characteristics	Executes manoeuvres leaving greater time and space compared to human-driven vehicles allowing for system errors	Executes manoeuvres leaving less time and space compared to human-driven vehicles since system errors are reduced
Anticipation (lane change, incidents, etc.) relating to connectivity	Earlier than human-driven	Later than human-driven

The default driving logic in Aimsun Next is based on Gipps model (Gipps, 1981; Gipps, 1986). Various parameters of the driving logic were adjusted to implement human-driven vehicle (HDV) and CAV behaviours. The assumptions on CAV parameters and their values were based on a comprehensive literature review in Section 2. Some guidance on the behaviours was also obtained through studies on ACC and CACC systems. The key parameters which were changed to model the driving behaviours of CAVs along with the associated assumptions are as presented in Table 9.

Table 9: HDV and CAV Parameters

Parameter	Description	Human-Driven Vehicle	1st Generation CAV	2nd Generation CAV
Time gap In Aimsun Next, reaction time along with sensitivity factor, affects time gap	Time that elapses between rear end of the lead vehicle and front bumper of following vehicle.	Lesser than 1st Gen CAV	More than HDVs	Shorter than HDVs and 1st Gen CAVs
Max. acceleration	maximum acceleration that a vehicle can achieve under any circumstances	Larger average acceleration and range	Lesser average acceleration and range than HDVs (comfortable ride experience)	Lesser than HDVs and 1st Gen CAVs (comfortable ride experience)
Normal deceleration	maximum deceleration a vehicle can use under normal conditions	Larger variation in deceleration	Lesser variation in deceleration than HDVs (comfortable ride experience)	Lesser variation in range than HDVs (comfortable ride experience)
Max. deceleration	Maximum deceleration a vehicle can use under special circumstances, such as emergency braking.	Less than CAVs	More than HDVs	More than HDVs and 1st Gen CAVs
Clearance	The distance a vehicle keeps between itself and the leading vehicle when stopped.	More variability in clearance	Lesser variation in clearance than HDVs	Lesser variation in clearance than HDVs
Safety margin factor	It generates give-way behaviour at unsignalized junctions. The higher the value indicated more cautious behaviour.	Lesser than 1st Gen CAV	Higher than HDVs, (cautious behaviour)	Shorter than HDVs (assertive behaviour)
Look ahead distance factor (anticipation of lane change)	It determines where the vehicles consider their lane change	More variation	1st generation CAVs will consider changing lane earlier than human-driven vehicles would, due to limited situational awareness	2nd generation CAVs will consider changing lane later than human-driven vehicles would, due to advanced situational awareness
Overtaking	It controls overtaking manoeuvres when a vehicle changes lane to pass another.	Defaults in Aimsun Next	conservative driving behaviour. Same logic as of HDVs	Aggressive lane change logic compared to human-driven vehicles,

Based on the literature findings and discussions in traffic micro-simulation meetings, the following are suggested values for some of the behaviours of passenger cars.

4.2 Car-following

Human driven vehicles need to keep time gap of 1.2 (± 0.4) s in car-following situation.
1st generation vehicles need to keep time gap of 1.3 (± 0.2) s in car-following situation.
2nd generation vehicles need to keep time gap of 0.6 (± 0.1) s in car-following situation.

The time gap is translated into reaction time (RT) in the car-following model in Aimsun Next as follows: time gap = 1.5 x RT + constant (where constant is in standstill = clearance). The derived reaction times to be introduced in Aimsun Next are the following:

- Human driven vehicles: 0.80 (± 0.26) s in car-following situation.
- 1st generation vehicles: 0.90 (± 0.13) s in car-following situation.
- 2nd generation vehicles: 0.40 (± 0.06) s in car-following situation.

The deviation for the reaction times can be introduced by defining for each vehicle type in the experiment settings (i.e., Human-driven, 1st and 2nd generation vehicles) a different distribution of reaction time, associating a probability between 0 - 1.0. The reaction times for the deviation need to be a multiple of the simulation step.

The values are rounded off and adjusted to be consistent for a simulation step of 0.1s. Since a range of reaction times will be provided, it is recommended to use a small simulation step common for all reaction times, e.g., 0.1, to be consistent with the deviations. The smaller the simulation step, the longer the simulation time.

Regarding the **sensitivity factor**, this parameter is applied in the calculation of the deceleration of the leader and is used to indicate whether the vehicle underestimates or overestimates the deceleration of the leader. The recommendation is to keep this factor to its default value (i.e., same as for human-driven vehicles) as it will add bias on top of the effect due to the adjustment of the reaction time parameter values. Adjustment of this parameter could be considered at a later stage if additional effects in the car-following and gap acceptance model are to be investigated.

General recommendation: In order to observe an impact on the time gap and achieve the desired ranges, the reaction time is the main parameter to be adjusted and is independent of the speed. Other parameters that affect the gap, such as the maximum acceleration and sensitivity factor depend on the speeds, therefore the evaluation of the impact on the gap would require further investigation and a sensitivity analysis.

4.3 Max. acceleration

In general, autonomous vehicles are expected to have a more comfortable driving experience for passengers.

The max. acceleration for human driven vehicles is set to be + 5 m/s^2 (± 2).
The max. acceleration for 1st generation vehicles is set to be + 4.5 m/s^2 (± 1).
The max. acceleration for 2nd generation vehicles is set to be + 3.5 m/s^2 (± 1).

The maximum acceleration values can be given as input in the vehicle type parameters. This parameter is expected to affect the time gap. It involves mechanical characteristics of the vehicle together with the driving mode. The smaller the max. acceleration, the larger the time gap the vehicle will accept.

4.4 Max. deceleration

The max. deceleration for human driven vehicles is set to be - 5 m/s^2 (± 1)
The max. deceleration for 1st generation vehicles is set to be - 7 m/s^2 (± 0.5)
The max. deceleration for 2nd generation vehicles is set to be - 9 m/s^2 (± 0.5).

4.5 Normal acceleration

The normal acceleration for human driven vehicles is set to be + 5 m/s^2 (± 2 m/s^2)
The normal acceleration for 1st generation vehicles is set to be + 3 (± 1) m/s^2.
The normal acceleration for 2nd generation vehicles is set to be + 3 (± 1) m/s^2.

1st generation and 2nd generation vehicles are considered to follow driving profile that generates comfortable ride experience to the user. Therefore, typical acceleration is considered to be 3 m/s^2. Furthermore, the range in acceleration is considered to be shorter than human-driven vehicles.

The normal acceleration cannot be set as an input value. It is an output from the Gibbs model as a function of the maximum acceleration and current speed.

4.6 Normal deceleration

- The normal deceleration for human driven vehicles is set to be - 3.4 m/s^2 (± 1 m/s^2)
- The normal deceleration for 1st generation vehicles is set to be - 4 m/s^2 (± 0.5 m/s^2.
- The normal deceleration for 2nd generation vehicles is set to be - 3 m/s^2 (± 0.5 m/s^2)

1st generation and 2nd generation vehicles are considered to follow driving profile that generates comfortable ride experience to the user. Therefore, typical deceleration is considered to be -4 for 1st generation and -3 m/s^2 for 2nd generation. Furthermore, the range in acceleration is considered to be shorter than human-driven vehicles.

4.7 Minimum gap at standstill (Clearance)

The minimum gap at standstill for human driven vehicles is set to be 1 m (± 0.5 m).
The minimum gap at standstill for 1st generation vehicles is set to be 1 m (± 0.2 m).
The minimum gap at standstill for 2nd generation vehicles is set to be 1 m (± 0.2 m).

4.8 Look ahead distance – lane change

Look ahead relates to connectivity in terms of anticipation of lane change when coming to a junction or incident.

1st generation CAVs will consider changing lane earlier than human-driven vehicle would, under the assumption that they will leave more time and space because of limited situational awareness compared to human-driven vehicles and to allow for system errors.

2nd generation CAVs will consider changing lane later than human-driven vehicles would, under the assumption that they will leave less time and space because of advanced situational awareness compared to human-driven vehicles.

This parameter refers to the Look-Ahead Distance Factor. The following values are used:

- The look ahead distance factor for human driven vehicles is set to be between [0.8;1.2].
- The look ahead distance factor for 1st generation vehicles is set to be between [1.1;1.3].
- The look ahead distance factor for 2nd generation vehicles is set to be between [1;1.25].

It is recommended to keep the default value as this parameter will only have an effect in case of congested motorways.

4.9 Overtaking

Human-driven vehicles default lane change threshold is 90% and lane recovery threshold is 95%.

1st generation vehicles are considered to have conservative driving behaviour but in the interest of traffic flow, they will follow same lane change logic as human-driven vehicles, i.e., 90% and 95% for lane change and lane recovery, respectively.

2nd generation vehicles are considered to be well connected to traffic management system and they are considered to have greater level of information regarding other vehicles kinematics. Therefore, they will follow aggressive lane change logic compared to human-driven vehicles, i.e., 85% and 95% for lane change and lane recovery, respectively.

4.10 Behaviour at signalised junction

It is true that human-driven vehicles anticipate signal change visually and also by prior knowledge of the intersection. Therefore, they start accelerating as soon as the traffic signal turns green.

It relates to the **reaction time at stops** and **reaction time at traffic lights**. Different values are recommended for AVs compared to human-driven vehicles. For instance, 0.4s could be given for 2nd generation and 0.9s for 1st generation vehicles. The ranges for these parameters can be introduced with a distribution in the same way as the reaction times in the car-following described above.

4.11 Behaviour at unsignalised junction (Safety margin factor)

Safety margin factor allows human-driven vehicles to wait at give way junctions if the vehicles consider to meet at theoretical collision point. Table 10 shows that 1st generation vehicles can be considered to be conservative and leave longer gap compared to human-driven vehicles, i.e., 25% higher. In case of 2nd generation, because they are considered to be confident in driving manoeuvres and therefore, they will leave smaller gap compared to human-driven vehicles, i.e., 25% lower.

Table 10: Human-driven and CAVs gap acceptance at unsignalised junction

	Human-driven	**1st generation**	**2nd generation**
Gap acceptance at unsignalised junctions	Safety margin factor = 1	Safety margin factor = higher than human-driven ([1,1.25])	Safety margin factor = lower than human-driven ([0.75,1])

4.12 Key Parametric Assumptions for Automated Passenger Cars

The values range of the key driving behaviour indicators used within Levitate project is presented in Table 11

Table 11: CAV parameters to use in traffic microsimulation within LEVITATE

Parameter	Human-Driven Vehicle	1st Generation CAV	2nd Generation CAV	Comment
Reaction time in car following (Reaction Time)	0.8 sec	0.9 sec	0.4 sec	This parameter, along with sensitivity factor, affects time headway. This can be set under Experiment >> Reaction Time tab >> Reaction Time Settings. Be sure to choose option 'Variable (Different for Each Vehicle Type).
Max. acceleration	5 (3, 0.2, 7) Mean (min, dev, max)	4.5 (3.5, 0.1, 5.5) Mean (min, dev, max)	3.5 (2.5, 0.1, 4.5) Mean (min, dev, max)	This can be set for Vehicle type under Microscopic Model >> Main tab.
Normal deceleration	3.4 (2.4, 0.25, 4.4) Mean (min, dev, max)	4 (3.5, 0.13, 4.5) Mean (min, dev, max)	3 (2.5, 0.13, 3.5) Mean (min, dev, max)	Same as above.
Max. deceleration	5 (4.0, 0.5, 6.0) Mean (min, dev, max)	7 (6.5, 0.25, 7.5) Mean (min, dev, max)	9 (8.5, 0.25, 9.5) Mean (min, dev, max)	Same as above.
Clearance	1 (0.5, 0.3, 1.5) Mean (min, dev, max)	1 (0.8, 0.1, 1.2) Mean (min, dev, max)	1 (0.8, 0.1, 1.2) Mean (min, dev, max)	Minimum gap at standstill. This can be set for vehicle type under Dynamic Models >> Main tab.
Safety margin factor	1	[1;1.25]	[0.75;1]	This is generating give-way behaviour at unsignalised junctions.
Look ahead distance factor	[0.8;1.2]	[1.1;1.3]	[1;1.25]	Also known as Distance Zone Factor. This is changed to emulate connectivity in the sense that AVs will have better knowledge of junctions and turnings so they will consider changing lanes earlier than human-driven vehicles.
Overtaking	Begin at 90%, Fall back at 95%	Begin at 90%, Fall back at 95%	Begin at 85%, Fall back at 95%	

4.13 Key Parametric Assumptions for Automated Freight Vehicles

For modelling the freight vehicles, primarily the following assumptions were made.

- The "physical parameters" such as size, weight, acceleration, deceleration, etc. were taken from the default values of Aimsum Next. For "AV truck" we took it from "truck", and for the "AV delivery van" we took it from "car" with slightly increased length.
- The "behavioral parameters" such as car-following, headway, etc. were taken from the cautious AV / 1st gen AV cars with reduced values on max acceleration and deceleration.

The details on each parametric value for human-driven and automated LGVs and HGVs are presented in Table 12 below.

Table 12: LGV and HGV parameters to use in traffic microsimulation within LEVITATE

Vehicle Type	Parameter	WP6				WP7				WP5 (Truck)			Mainroads modelling Guidelines (2021) (Truck)			
		Mean	Deviation	Minimum	Maximum	Mean	Deviation	Minimum	Maximum	Mean	Minimum	Maximum	Mean	Deviation	Minimum	Maximum
LGV (Reaction time 0.8s)	Length (m)	7	2	5	9	6	0	6	8.50	--	--	--	8.65 - 12.00	1.0 - 1.9	5.5 - 10.0	11.65 - 14.5
	Width (m)	2.25	0.2	2	2.8	2.00	0	2.00	2.00	--	--	--	2.4 - 2.5	0.0	2.4 - 2.5	2.4 - 2.5
	Max. desired speed (km/h)	85	10	70	100	30	0	30	80	--	--	--	100 - 110	5.0 - 5.5	80 - 99	110 - 121
	Clearance (m)	1.5	0.5	1	2.5	1.50	0.5	1.00	2.50	--	--	--	2.0 - 3.0	0.15 - 1.30	0.50 - 2.70	3.30 - 3.80
	Max. acceleration (m/s2)	2.00	0.5	1.5	2.5	1.00	0.5	0.6	1.80	1	0.6	1.8	1.50 - 1.60	0.15 - 0.80	0.80 - 1.20	1.80 - 2.40
	Normal deceleration (m/s2)	3.50	1.00	2.50	4.8	3.50	1.00	2.5	4.8	--	--	--	2.2 - 3.0	0.22 - 0.30	1.76 - 2.00	2.64 - 3.50
	Max. deceleration (m/s2)	5.00	0.5	4.00	6.00	5.00	0.5	4.00	6.00	5	4	6	3.00 - 5.00	0.06 - 0.50	2.88 - 4.00	3.12 - 6.00
	Sensitivity factor	1.00	0	1.00	1.00	--	--	--	--	--	--	--	1.00	0	1.00	1.00
	Safety Margin Factor	1	0	1	1	1	0	1	1	--	--	--	--	--	--	--
	Look-Ahead Distance Factor			0.8	1.2	--	--	0.8	1.2	--	--	--	--	--	--	--
	Length (m)	13	3	10	16	17	0	7.99	20.0	--	--	--	8.65 - 12.00	1.0 - 1.9	5.5 - 10.0	11.65 - 14.5

HGV **(Reaction time 0.8s)**	**Width (m)**	2.25	0.2	2	2.8	2.50	0	2.50	2.50	--	--	--	2.4 - 2.5	0.0	2.4 - 2.5	2.4 - 2.5
	Max. desired speed (km/h)	85	10	70	100	30	0	30	80	--	--	--	100 - 110	5.0 - 5.5	80 - 99	110 - 121
	Clearance (m)	1.5	0.5	1	2.5	1.5	0.5	1	2.5	--	--	--	2.0 - 3.0	0.15 - 1.30	0.50 - 2.70	3.30 - 3.80
	Max. acceleration (m/s2)	1.5	0.5	1	2	3.5	0.2	2.0	5.0	--	--	--	1.50 - 1.60	0.15 - 0.80	0.80 - 1.20	1.80 - 2.40
	Normal deceleration (m/s2)	3.5	1	2.5	4.8	2.40	0.25	1.40	3.40	--	--	--	2.2 - 3.0	0.22 - 0.30	1.76 - 2.00	2.64 - 3.50
	Max. deceleration (m/s2)	5.00	0.5	4.00	6.00	4.00	0.5	3.00	5.00	--	--	--	3.00 - 5.00	0.06 - 0.50	2.88 - 4.00	3.12 - 6.00
	Sensitivity factor	1.00	0	1.00	1.00	1.00	0	1.00	1.00	--	--	--	1.00	0	1.00	1.00
	Safety Margin Factor	1	0	1	1	1	0	1	1	--	--	--	--	--	--	--
	Look-Ahead Distance Factor	--	--	0.8	1.2	--	--	0.8	1.2	--	--	--	--	--	--	--
LGV-AV **(Reaction time 0.9s)**	**Length (m)**	7	2	5	9	6	0	6	8.5	--	--	--	8.65 - 12.00	1.0 - 1.9	5.5 - 10.0	11.65 - 14.5
	Width (m)	2.25	0.2	2	2.8	2.00	0	2.00	2.00	--	--	--	2.4 - 2.5	0.0	2.4 - 2.5	2.4 - 2.5
	Max. desired speed (km/h)	85	10	70	100	30	0	30	80	--	--	--	100 - 110	5.0 - 5.5	80 - 99	110 - 121
	Clearance (m)	1.5	0.1	1.3	1.7	1	0	1	1	--	--	--	2.0 - 3.0	0.15 - 1.30	0.50 - 2.70	3.30 - 3.80
	Max. acceleration (m/s2)	2	0.5	1.5	2.5	3.50	0.1	2.50	4.50	1	0.6	1.8	1.50 - 1.60	0.15 - 0.80	0.80 - 1.20	1.80 - 2.40
	Normal deceleration (m/s2)	3.5	1.00	2.50	4.8	3	0.13	2.5	3.5	--	--	--	2.2 - 3.0	0.22 - 0.30	1.76 - 2.00	2.64 - 3.50

	Max. deceleration (m/s2)	5.00	0.5	4.00	6.00	6	0.25	5.50	6.50	5	4	6	3.00 - 5.00	0.06 - 0.50	2.88 - 4.00	3.12 - 6.00
	Sensitivity factor	1.00	0	1.00	1.00	0.70	0	0.30	0.90	--	--	--	1.00	0	1.00	1.00
	Safety Margin Factor	1.13	0	1	1.25	1.13	0	1	1.25	--	--	--	--	--	--	--
	Look-Ahead Distance Factor	--	--	1.1	1.3	--	--	1.1	1.3	--	--	--	--	--	--	--
HGV-AV (Reaction time 0.9s)	**Length (m)**	13	3	10	16	17	0	7.99	20	--	--	--	--	--	--	--
	Width (m)	2.25	0.2	2	2.8	2.5	0	2.5	2.5	--	--	--	--	--	--	--
	Max. desired speed (km/h)	85	10	70	100	30	0	30	80	--	--	--	--	--	--	--
	Clearance (m)	1.5	0.1	1.3	1.7	1	0.3	0.5	1.5	--	--	--	--	--	--	--
	Max. acceleration (m/s2)	1.5	0.5	1	2	3.5	0.1	2.50	4.50	--	--	--	--	--	--	--
	Normal deceleration (m/s2)	3.5	1	2.5	4.8	3	0.13	2.50	3.50	--	--	--	--	--	--	--
	Max. deceleration (m/s2)	5.00	0.5	4.00	6.00	6	0.25	5.50	6.50	--	--	--	--	--	--	--
	Sensitivity factor	1.00	0	1.00	1.00	1	0	1	1	--	--	--	--	--	--	--
	Safety Margin Factor	1.13	0	1	1.25	1.13	0	1	1.25	--	--	--	--	--	--	--
	Loo-Ahead Distance Factor	--	--	1.1	1.3	--	--	1.1	1.3	--	--	--	--	--	--	--

5 CAV deployment scenarios

With technology advancing and maturing, CAVs will be expected to evolve. This is captured and implemented by two different generations of CAVs, i.e., 1st generation and 2nd generation. This assumption agrees with (Bansal and Kockelman, 2016). The characteristics and parametric assumptions of these two CAV types are presented earlier in Table 8, 10 and 11, and their deployment scenarios in Levitate are shown in Table 13.

Table 13: CAV Deployment scenarios in Levitate

Type of Vehicle	A	B	C	D	E	F	G	H
Human-Driven Vehicle - passenger vehicle	100%	80%	60%	40%	20%	0%	0%	0%
1st Generation (Cautious) CAV - passenger vehicle	0%	20%	40%	40%	40%	40%	20%	0%
2nd Generation (Aggressive) CAV - - passenger vehicle	0%	0%	0%	20%	40%	60%	80%	100%
Human-driven - Freight vehicle	100%	80%	40%	0%	0%	0%	0%	0%
Freight CAV	0%	20%	60%	100%	100%	100%	100%	100%

There is little widespread agreement about the market penetration of CAVs according to chronological years so Levitate has estimated impacts on the basis of the proportion of the total fleet accounted by each vehicle type (Table 13). The step increase/decrease in fleet proportion is kept at 20 to keep the number of scenarios manageable for the simulation runs. For each scenario (A, B, …), 10 simulation replications (commonly chosen number) are performed in the Aimsun Next software to account for the stochasticity in microscopic simulation.

The scenarios for each sub-use case should be developed that relate to different variations in the implementation of sub-use cases. It should be noted that the selected parameter values are based on assumptions for the scope of the project, and the differing values can lead to different identified impacts. The suggested values may change in the future as automated driving is developing rapidly and it is hard to anticipate which way it should go.

Final Remarks

The modelling of CAVs behaviours in Levitate project is based on the idea of incremental development towards perfection in automation, leading to the concept of first- and second-generation vehicles. Based on this assumption, the early generation of connected and automated vehicles have been considered to have cautious driving characteristics, limited sensing and cognitive abilities, data handling and decision making as compared to the second generation of CAVs.

The results in Levitate are reflective of the manner in which CAVs with such characteristics and behaviours would operate/perform and consequently impact the transport system. Together with the Levitate modelling on CAVs behavioural parameters and impact assessment results, there are useful insights for planners, policy makers, and also vehicle manufacturers.

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