Identifying KPIs for the safety assessment of autonomous vehicles through traffic microsimulation

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Abstract

Road safety impact is critical for consideration during automation development. In combination with the fact that it is estimated that autonomous vehicles could reach up to 90% of the market share by 2050, it can be concluded that automation should be monitor in order for this transition to be as safer as possible. In this direction, this study aims to identify critical key performance indicators (KPIs) for safety assessment of autonomous vehicles through microscopic traffic simulation. For this purpose, a microscopic simulation analysis was conducted to provide multiple measurements quantifying the impacts of connected and autonomous vehicles (CAVs) in different traffic conditions. Critical safety KPIs were identified exploiting the microscopic simulation outputs in order to shed light on critical aspects that the quantification of safety needs. The obtained KPIs could guide stakeholders in optimizing the safety assessment procedures through simulation by emphasizing critical safety aspects.

Keywords: *Autonomous Vehicles, Road Safety, Safety Assessment, KPIs, Microscopic Simulation*

Περίληψη

Ο αντίκτυπος στην οδική ασφάλεια είναι σημαντικός να μελετηθεί στην ανάπτυξη του αυτοματισμού των οχημάτων. Συνδυάζοντας το γεγονός ότι εκτιμάται ότι τα αυτόνομα οχήματα θα μπορούσαν να φθάσουν έως και το 90% του μεριδίου αγοράς έως το 2050, συμπεραίνεται ότι ο αυτοματισμός πρέπει να παρακολουθεί προκειμένου αυτή η μετάβαση να είναι όσο πιο ασφαλής γίνεται. Σε αυτήν την κατεύθυνση, αυτή η μελέτη στοχεύει στον εντοπισμό κρίσιμων Βασικών Δεικτών Απόδοσης (KPIs) για την αξιολόγηση της ασφάλειας των αυτόνομων οχημάτων μέσω μικροσκοπικής προσομοίωσης της κυκλοφορίας. Για το σκοπό αυτό, πραγματοποιήθηκε μια μικροσκοπική ανάλυση προσομοίωσης ώστε να εξαχθούν πολλαπλές μετρήσεις οι οποίες αποσκοπούν στην ποσοτικοποίηση των επιπτώσεων των συνδεδεμένων αυτόνομων οχημάτων (CAV) σε διαφορετικές συνθήκες κυκλοφορίας. Βασικοί Δείκτες Απόδοσης (KPIs) ασφάλειας εντοπίστηκαν, χρησιμοποιώντας τα αποτελέσματα της μικροσκοπικής προσομοίωσης, προκειμένου να ρίξουν φως σε κρίσιμες πτυχές, οι οποίες απαιτούνται για την ποσοτικοποίηση του επίπεδου της ασφάλειας. Οι Βασικοί Δείκτες Απόδοσης (KPIs) θα μπορούσαν να καθοδηγήσουν τους ενδιαφερόμενους στη βελτιστοποίηση των διαδικασιών αξιολόγησης της ασφάλειας μέσω προσομοίωσης, δίνοντας έμφαση σε κρίσιμες πτυχές της οδικής ασφάλειας.

Λέξεις Κλειδιά: *Αυτόνομα Οχήματα, Οδική Ασφάλεια, Αξιολόγηση Ασφάλειας, Βασικοί Δείκτες Απόδοσης, Μικροσκοπική Προσομοίωση*

1. Introduction

Investigating the progress of automobile industry over the last decades, there is a significant evolution in technologies integrated into new vehicles regardless of vehicle type (Rajasekhar & Jaswal, 2016). These integrated connected technologies aim to mainly support driving tasks. Therefore, it can be mentioned that these technologies bring computerization into the vehicles, which leads to reconsider the driver's role since it changes the typical driving functions (Fagnant & Kockelman, 2015). This type of computerization pushed the automobile industry one step further by planning and developing autonomous vehicles (Rajasekhar & Jaswal, 2016). Computerization enables the vehicles to drive on their own on existing roads and navigate without direct human input (Rajasekhar & Jaswal, 2016). In short, the definite aim of the automobile industry is to create a functional and safe vehicle with the maximum level of automation. The maximum level can be considered the SAE level 5, a fully automated vehicle without any human input (SAE, 2016). Connected and Autonomous Vehicles (CAVs) are expected to dominate the market share in 2050 if the CAV prices decrease at an annual rate of 15% or 20% (Talebian & Mishra, 2018).

According to Fagnant & Kockelman (2015), Autonomous Vehicles (AVs) have the potential to change the transportation systems radically. More specifically, it is estimated that road safety levels will be enhanced since road accidents will be prevented with Automated Driving (AD) evolution. A recent study revealed that traffic conflicts could be reduced depending on the penetration rate of CAVs (Papadoulis et al., 2019). Additionally, AVs are estimated to be safer than conventional vehicles by reducing human error (Teoh & Kidd, 2017). Taking into account the fact that human error is responsible for 65-95% of accidents (Conche & Tight, 2006; NHTSA, 2015), human error will be diminished when designing autonomous driving concepts. An ideal hypothesis for automated driving would be that by removing elements of human error from the task of driving, the elimination of accident risk will be accomplished (Fagnant & Kockelman, 2015; Sandin, 2016; Teoh & Kidd, 2017; FERSI, 2018). Nevertheless, a more realistic assumption is that human error will be replaced by accidents caused by imperfect automated systems (FERSI, 2018). Another study revealed that given the current traffic safety level, fully autonomous vehicles would have to be driven hundreds of millions of miles to demonstrate their reliability in terms of fatalities and injuries (Kalra & Paddock, 2016). In this direction, this study intends to support AVs monitoring through simulation in order to be less flawed, within reason, and avoid long driving distances by investigating measurements that might lead to uncertainty and risky situations.

In addition, it is expected that CAVs will increase road capacity, fuel efficiency, and lower environmental emissions (Rune Elvik, 2021; Fagnant & Kockelman, 2015; Mersky & Samaras, 2016; Ye & Yamamoto, 2018), nevertheless this outcome is highly dependent on parametrization of automation systems, as the studies imply. Regarding the advantages at a passenger level, a great proportion of the population, such as the elderly, children, and disabled will have the opportunity to commute in contrast with the prevailing conditions regarding conventional vehicles. Furthermore, shared vehicles will increase radically as commuters will not own their vehicle, but they will use an on-demand service. Additionally, the passengers or even the driver will be able to execute non-driving related tasks (NDRTs) during driving, e.g., working on an electronic device, eating, drinking, reading, watching entertainment content, and texting or calling on their phones (Kim et al., 2018).

AVs impacts and their performance have been extensively investigated through simulation approaches (Chen et al., 2017; Lam, 2016; Scheltes & de Almeida Correia, 2017; Shen et al., 2018; Talebpour et al., 2017; Zellner et al., 2016). The simulation inputs concern data from various sources such as the network geometry, traffic volume and modal split. More specifically, the data exported by the microscopic simulation can provide an initial, descriptive estimation of several impacts. Each vehicle is tracked as it interacts with surrounding traffic as well as with the environment. Moreover, microscopic simulation is used widely to evaluate new traffic control and management technologies as well as performing analysis of existing traffic operations (Owen et al., 2000). Modeling traffic flows allows researchers to simulate the driving of every vehicle inside the considered transport network and provide many traffic-related impacts, while the traffic characteristics are taking into account, leading to higher accuracy emissions estimates as well (Lopez et al., 2018; Wen-Xing Zhu & Zhang, 2017). In addition, existing literature used the microsimulation method in order to analyze traffic conflicts and present the sequence of events with the causative factors of conflicts (Young et al., 2014).

Given the aforementioned argument that CAVs will increase road safety, there is a need to identify Key Performance Indicators (KPIs) for safety assessment of CAVs through microscopic traffic simulation. This paper aims to assist in that direction by pointing out critical safety KPIs that could be evaluated through simulation. The exported KPIs list can guide further research in this direction, and it can also be exploited and expanded to other simulation tools or use cases. The present research is conducted within the EU HORIZON 2020 “SHOW” project that aims to support the migration path towards effective and persuasive sustainable urban transport through technical solutions, business models, and priority scenarios for impact assessment, by deploying shared, connected, electrified fleets of automated vehicles in coordinated Public Transport (PT), Demand Responsive Transport (DRT), Mobility as a Service (MaaS) and Logistics as a Service (LaaS) operational chains in real-life urban demonstrations.

Simulation procedure conducted within a relevant European project titled LEVITATE, an ongoing project, is used in the present study to measure several essential KPIs to be perceived through on network level CAV impacts. LEVITATE is also investigating the “Societal Level Impacts of Connected and Automated Vehicles” and taxonomy of impacts and models of their interrelations were developed within the project (Elvik et al., 2019). More specifically, a list of the impact areas arising from the direct operation of CAVs, transport system-wide impacts resulting from service and operation models, and societal impacts resulting from changes in the transport system were developed.

This study is structured as follows; initially, the current section presents a brief introduction to the study aim. Then, the methodology follows, including two main subsections. The first one relates to the simulation aim, preparation, and the variables that can be exploited by the safety assessment. The second one relates to the KPIs development. After that, results are presented by including the final list of the obtained KPIs derived from the simulation along with the KPIs description and assessing details. Finally, general conclusions are included by presenting a brief description of the aim and results of this study and how stakeholders or policymakers can exploit this study, followed by study limitations and future research proposals.

2. Methodology

This section presents the study methodology and is divided in two main subsections. The first one describes the microscopic simulation analysis, that was conducted within the LEVITATE project, in which the critical KPIs for safety assessment of autonomous vehicles were examined. More specifically, the specifications regarding the study network, the use case as well as CAVs implementation are described. Moreover, all the required information related to CAV parameters, market penetration rate scenarios are also included. The second one refers to the KPIs development procedure conducted within the SHOW project and consists of an in-depth impact assessment framework.

2.1. Microscopic Simulation

In order to identify critical key performance indicators (KPIs) for safety assessment, the microscopic simulation analysis was selected to provide multiple measurements quantifying the impacts of connected autonomous vehicles (CAVs) in different traffic conditions. For the requirements of the LEVITATE project, different scenarios were formulated using the Aimsun Next mobility modelling software in the city of Athens network in Greece. The scenarios differed in terms of the market penetration rate of CAVs (0% - 100%), traffic conditions and the implementation of a city automated transport system (CATS).

The investigated network created in Aimsun Next mobility software is the city of Athens (Figure 1) and consists of 1,137 nodes and 2,580 road sections. More specifically, the total length of road sections is 348 km and the network size reaches approximately 20 km^2. The model includes data for each road section that concerned geometric as well as functional characteristics, namely length, width, number of lanes, directions, free flow speed and capacity. In addition, the respective characteristics of nodes were also included in the model network: allowed movements, number of lanes per movement, priority, traffic light control plans, free speed flow, and capacity. In addition, the OD matrices consisted of 290×292 centroids of the study network and a total number of 82,270 car trips and 3,110 truck trips for peak hour. Furthermore, the Athens model included 95 bus and 14 trolley lines and 1,030 public transport stations as well as service frequencies and waiting times at stops.

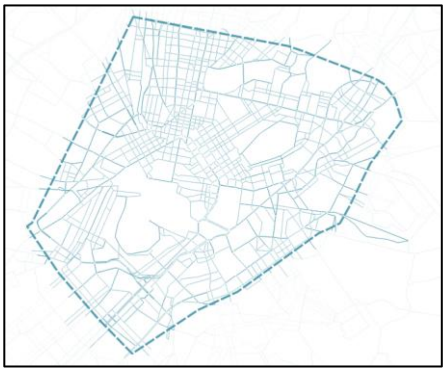

Figure 1: *The city of Athens in Aimsun software*

A point-to-point automated shuttle bus service connecting several points was implemented in the large-scale network. Four shuttle bus lines were implemented in the city of Athens in order to complement the existing public transport, as shown in Figure 2. The first shuttle bus line, Line 1, connects the metro station “Viktoria” (A) with the metro station “Panormou” (B), the second shuttle bus line, Line 2, connects the National Garden (A) and Greek Parliament with the National Archeological Museum (B), the third, Line 3, connects Omonoia Square (A) with Acropolis - Parthenon (B) and the fourth, Line 4, connects metro station “Rouf” (A) with the metro station “Neos Kosmos” (B). In addition, this service of sixteen shuttle buses was considered to have a total capacity of 10 passengers. Their dimensions were 5 meters in length and 2.5m in width. The max operating speed of the buses was 40 km/h, the mean speed 25 km/h. The frequency of the service was 15 minutes. The total length of the shuttle bus service routes was 8 km (Line 1), 6 km (Line 2), 6 km (Line 3) and 8 km (Line 4).

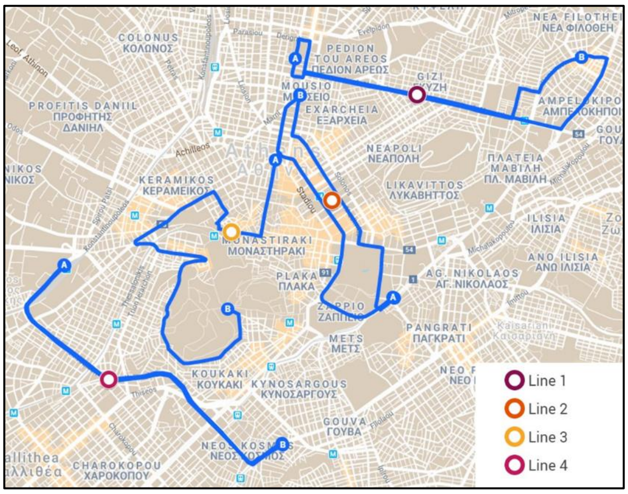

***Figure 2:** The point-to-point automated shuttle service’s bus lines*

Overall, the following scenarios were formulated:
1) Baseline (no point-to-point shuttle bus service operation)
2) Point-to-point shuttle bus service operation in mixed traffic conditions during peak hour
3) Point-to-point shuttle bus service operation using dedicated lane during peak hour
4) Point-to-point shuttle bus service operation in mixed traffic conditions during off-peak hour

Within the present research, two main driving profiles were simulated for modelling connected autonomous vehicles (CAVs), as in other studies (Mesionis et al., 2019; Sukennik, 2018) and are the following:
- 1st Generation (Cautious): limited sensing and cognitive ability, long gaps, early anticipation of lane changes than human-driven vehicles and longer time in give way situations.
- 2nd Generation (Aggressive): advanced sensing and cognitive ability, data fusion usage, confident in taking decisions, small gaps, early anticipation of lane changes than human-driven vehicles, and less time in give way situations.

The autonomous shuttle buses of the service were simulated as 1st generation CAVs since they were characterized as cautious, and it was assumed that this profile was more appropriate for a public transport mode. Similarly, the autonomous trucks were simulated as 1st generation CAVs, as well. In this study, all the autonomous vehicles that were simulated as well as the shuttle buses were assumed to be exclusively electric.

In modelling CAVs, their lane-changing behavior was considered different from human-driven vehicles behavior. Hence, the Gipps lane-changing model was applied (Gipps, 1986). This model estimates the decisions that drivers have to make before changing lane and ensures that the simulated drivers behave logically in situations that are similar in real traffic conditions. In this model, the sensitivity factor controls the clearance distance, and the overtake speed threshold is the percentage of the desired speed of a vehicle that decides to overtake. The CAV parameters, used in the microsimulation procedure, constitute findings derived from the LEVITATE project and were based on an extensive literature review as well as partners' knowledge. All vehicle parameters are shown in **Table 1**.

Table 1: *Microsimulation CAV parameters of LEVITATE*

Factors			Human Driven Vehicle	1st Generation CAV	2nd Generation CAV
Max. acceleration		*Mean*	5.0	4.5	3.5
		Min	3.0	3.5	2.5
		Dev	0.2	0.1	0.1
		Max	7.0	5.5	4.5
Normal deceleration		*Mean*	3.4	4.0	3.0
		Min	2.4	3.5	2.5
		Dev	0.25	0.13	0.13
		Max	4.4	4.5	3.5
Max. deceleration		*Mean*	5.0	7.0	9.0
		Min	4.0	6.5	8.5
		Dev	0.5	0.25	0.25
		Max	6.0	7.5	9.5
Clearance		*Mean*	1.0	1.0	1.0
		Min	0.5	0.8	0.8
		Dev	0.3	0.1	0.1
		Max	1.5	1.2	1.2
Lane Changing Model	Overtake speed threshold		90%	90%	85%
	Look ahead distance	*Min*	0.8	1.1	1.0
		Max	1.2	1.3	1.25
	Safety margin	*Min*	1.0	1.0	0.75
		Max	1.0	1.25	1.0
Reaction time in car following (sec)			0.8	0.9	0.4

More specifically, the first CAV generation was considered as cautious vehicle and the second one as aggressive. However, acceleration and deceleration of CAVs were selected to be slower than human-driven vehicles based on a study conducted by Karjanto et al. (2016), in order to enable in-vehicle activities for the users, apart from driving. For this reason, the second generation was consider to have slower values than the first one, except from the normal deceleration that is higher but allows human occupants safety and considers in-vehicle activities, as well. Moreover, the “Look ahead distance” parameter, also known as “Distance Zone Factor” was also considered to be different between the conventional vehicles and the two CAV generations. This parameter emulates connectivity in the sense that autonomous vehicles will have better knowledge of junctions and turnings. Therefore, autonomous vehicles considered changing lanes earlier than human-driven vehicles. The “reaction time” parameter is the parameter that concerns the reaction time in car-following and, along with sensitivity factor, affects time headway. According to Eilbert et al. (2019), Adaptive Cruise Control (ACC) applications seem to be bimodal, which have either a gap setting 1.1 sec to eliminate cut-in vehicles or a 1.5 sec gap likely due to a lack in trust of the ACC system being able to stop in time. For these reasons, ACC driving appears to have a higher average time gap than manual driving. Therefore, the first CAV generation presented higher reaction time value compared to conventional vehicles.

Regarding the implementation of CAVs, different penetration rate scenarios were simulated and are presented in **Table 2**. The cautious CAVs, considered to be the first generation, appear first in these scenarios and are followed by the aggressive CAVs until the last scenario, where only second generation CAVs are included.

Table 2: *The CAV market penetration rate scenarios of LEVITATE*

Type of Vehicle	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**
Passenger Vehicles								
Human-driven Car	100%	80%	60%	40%	20%	0%	0%	0%
1st Generation CAV	0%	20%	40%	40%	40%	40%	20%	0%
2nd Generation CAV	0%	0%	0%	20%	40%	60%	80%	100%
Freight Vehicles								
Human-driven Truck	100%	80%	40%	0%	0%	0%	0%	0%
Freight CAV	0%	20%	60%	100%	100%	100%	100%	100%

For each one of these scenarios, the implementation of the point-to-point autonomous shuttle service was also simulated. Therefore, 32 scenarios were simulated in total (8 market penetration rate scenarios for each of the 4 point-to-point implementation scenarios). Additionally, with regards to each scenario, 10 different replications with random seeds were simulated as well. The simulation duration of each scenario was one hour, and the simulation time step was 5 minutes.

2.2. KPIs development

In an effort for a holistic impact assessment framework, the impacts of automation are assessed under different scenarios by subjective stakeholder analysis, as well as objective measurements based on simulations. For this purpose, within SHOW, through a framework that unites these different components, detailed impact assessments were performed for specific impact areas. This detailed impact assessment aggregated several KPIs from demonstration sites and simulations in order conclusions to be drawn.

The SHOW framework concerns several phases of demonstrations and simulations. Initially, stakeholders were identified, autonomous service impact criteria as well as their scenarios related on pilot demonstrations were defined. Then, based on existing literature of CAV deployment, impacts key selection criteria and their respective KPIs were acknowledged. Afterwards, demos and simulations were identified and mapped to the scenarios enabling the definition of KPIs. Lastly, an overall analysis was conducted comparing scenarios in relation to impact criteria and KPIs from simulations.

The included KPIs in the SHOW impact assessment framework were analyzed in the following different activities, as calculated from the in-depth analyses from the different impact areas or collected from demonstration sites and simulations:

- Road safety
- Traffic efficiency, energy, and environmental impacts
- Societal, employability and equality
- Urban logistics
- User experience, awareness and acceptance

3. Results

Supported by the literature review, KPIs were defined and for the evaluation of impacts of systems and services within the area of CAV and representing holistic impact criteria (Anund et al., 2020). The metrics needed for each KPI will be collected either through measurements, observations at the demonstration site, simulations or user surveys. In addition, the KPIs were matched to research questions or target to ensure that all CAV systems and service activities are adequately covered by a holistic collection of relevant to simulation KPIs. The sources identified within the impact assessment of the SHOW project also led to the definition of relevant KPIs presented in **Table 3**. Relevant KPIs were also divided into the following categories:

- Traffic safety
- Traffic efficiency
- Environment and energy efficiency

***Table 3:** SHOW relevant KPIs for simulations*

Broader category	Impact	Research Question or target
Traffic safety	Road accidents (leading to human injury)	What is the number of accidents that caused even the slightest of injury during the operation of the AV?
	Conflicts	What is the number of conflicts with other road users and infrastructure during the operation of the AV?
	Safety enhancement	What is the safety enhancement induced by AV services when compared to the existing (public) transport services?
	Vehicle occupancy	Safety enhancement
	Illegal overtaking	Safety enhancement
	Lateral and longitudinal headways	Safety enhancement
	Harsh cornering	Safety enhancement
	Road accidents (leading to material damage)	What is the number of accidents that damage to property?
	Traffic flow	Safety enhancement
Traffic efficiency	Average speed	What is the average speed of pilot vehicles on the pilot route?
	Acceleration variance	How does the acceleration of pilot vehicle vary on the pilot route?
	Hard brake events	What is the number of hard breaking events per km?
	Non-scheduled stops	How often does a pilot vehicle have to make a non-scheduled stop?
	Service reliability	How often did the pilot vehicle arrive/depart as scheduled?
	Speed per vehicle type	How does the introduction of pilot vehicles impact the average speed for all vehicle types?
	Vehicle delay	How does the introduction of pilot vehicles impact the average vehicle delay for all vehicle types?
	Vehicle stops	How does the introduction of pilot vehicles impact the number of stop?
	Hard braking events in traffic	How does the introduction of pilot vehicles impact the number of hard braking event?
	Total intersection delay	How does the introduction of pilot vehicles impact the vehicle delay on intersection?
	Total network travel time per vehicle type	How does the introduction of the new mobility system affect the total network travel time?
	Total mileage	How does the introduction of the new mobility system affect the vehicle kilometres travelled per mode?
	Total network delay	How does the introduction of the new mobility system affect the total network delay?
	Average network speed	How does the introduction of the new mobility system affect the average network speed?
Environment and energy efficiency	Energy use	How does the introduction of the new mobility system change energy consumption of vehicles?
	CO_2, PM, NOx emissions	How does the introduction of the new mobility system change the amount of vehicle emissions related to transport in the area of interest?
	Air quality	How does the introduction of the new mobility system affect the air quality in the area of interest?
	Noise levels	How does the introduction of the new mobility system affect the traffic noise in the area of interest?
	Reduction in CO_2	90% for CO_2 at city level
	Reduction in noise level	30% reduction
	Reduction in energy consumption	20% for passenger transport, 40% for freight
	Reduction in energy consumption	10% reduction

Moreover, through microscopic simulation, multiple measurements quantifying the impacts of CAVs in different traffic conditions were extracted. **Table 4** presents some of the traffic, environmental and safety on network level impacts based on the KPIs of **Table 3** that were available to be exported through simulation. These impacts were influenced by the market penetration rate as well as the automated shuttle service operation scenario and are the following:

- Number of conflicts: total number of conflicts
- Traffic flow: mean flow (veh/h)
- Average speed: mean speed (km/h)
- Delay Time: mean delay time (sec/km)
- Number of stops: total number of stops of all vehicles in the simulation period in the whole network
- Travel Time: mean travel time (sec/km)
- Distance Travelled: total distance travelled of the vehicles that exited the network (km)
- CO2 Emissions: total CO2 emissions (kg)
- NOx Emissions: total NOx emissions (kg)
- PM10 Emissions: total PM10 emissions (kg)

The environmental impacts obtained by the simulation using the Aimsun software, were calculated applying the formula developed by Panis et al. (2006). This model computes carbon dioxide (CO_2), nitrogen oxides (NO_X) and particulate matter (PM_{10}). In addition, through simulation, the trajectories files of all scenarios were extracted and analyzed in the SSAM tool. This analysis provided the number of conflicts that occurred in the simulation scenarios and are shown in **Table 4**, as well.

The microsimulation results showed that the number of conflicts was reduced when more autonomous vehicles existing the network during peak hour conditions and remained constant during off peak hour. Also, it was revealed that the number of conflicts was approximately the same for the different automated shuttle bus service scenarios. Regarding traffic-related impacts, if the shuttle bus drives on a dedicated lane, then delay and travel time, traffic flow, number of stops and total distance travelled remain the same for all mobility scenarios. In addition, the existence of the shuttle bus service did not significantly affect traffic measurements for all market penetration scenarios.

Table 4: *Network level Impacts for different simulation scenarios*

	Impacts	A	B	C	D	E	F	G	H
No policy intervention	Number of conflicts	142,212	120,636	94,324	98,203	71,640	52,373	76,424	76,066
	Traffic flow (veh/h)	44,385	52,805	52,885	45,338	37,885	31,665	61,947	64,102
	Average speed (km/h)	21	21	21	21	21	20	23	23
	Delay Time (sec/km)	243	215	214	215	219	234	141	133
	Number of stops	251,630	281,888	279,662	253,567	223,436	203,093	345,147	368,191
	Travel Time (sec/km)	317	293	295	297	304	322	230	223
	Distance Travelled (km)	90,542	113,469	113,750	97,758	80,939	68,180	138,733	144,848
	CO_2 Emissions (kg)	72,367	60,312	43,301	25,855	13,574	2,025	3,250	3,396
	NOx Emissions (kg)	258	211	139	68	47	27	32	32
	PM_{10} Emissions (kg)	12	11	8	5	2	1	1	1
Mixed traffic – Peak hour	Number of conflicts	142,756	118,797	110,906	97,758	72,147	52,633	76,027	75,304
	Traffic flow (veh/h)	44,309	52,634	52,521	45,086	38,059	31,639	61,602	63,972
	Average speed (km/h)	21	21	21	21	21	20	23	23
	Delay Time (sec/km)	245	216	213	211	220	235	141	133
	Number of stops	250,333	281,745	277,019	250,437	226,743	202,368	341,576	366,750
	Travel Time (sec/km)	319	293	293	294	305	323	230	222
	Distance Travelled (km)	90,141	113,297	112,955	96,914	81,461	68,085	137,776	144,550
	CO_2 Emissions (kg)	72,448,076	60,249,674	43,144,951	25,776,612	13,592,004	2,025,099	3,224,744	3,381,025
	NOx Emissions (kg)	258,831	210,899	138,723	67,716	47,459	27,436	31,398	32,108
	PM_{10} Emissions (kg)	12,178	10,932	7,976	4,581	2,387	590	981	1,032
Dedicated lane – Peak hour	Number of conflicts	142,125	121,369	112,595	98,816	70,901	53,207	76,881	76,532
	Traffic flow (veh/h)	44,309	52,634	52,521	45,086	38,059	31,639	61,602	63,972
	Average speed (km/h)	21	21	21	21	21	20	23	23
	Delay Time (sec/km)	247	216	214	215	222	234	140	134
	Number of stops	44,309	52,634	52,521	45,086	38,059	31,639	61,602	63,972
	Travel Time (sec/km)	21	21	21	21	21	20	23	23
	Distance Travelled (km)	89,319	113,272	114,589	96,901	80,687	67,811	138,650	145,091
	CO_2 Emissions (kg)	72,124,828	60,207,343	43,316,539	25,839,178	13,591,489	2,037,809	3,252,943	3,390,728
	NOx Emissions (kg)	258,495	210,803	139,068	67,677	47,437	27,558	31,608	32,140
	PM_{10} Emissions (kg)	12,064	10,930	8,060	4,593	2,367	594	990	1,036
Mixed traffic – Off hour	Number of conflicts	56,454	52,987	48,229	44,602	40,530	30,128	35,596	32,421
	Traffic flow (veh/h)	39,195	45,722	46,342	46,033	42,657	37,961	49,243	49,485
	Average speed (km/h)	25	25	25	25	24	23	26	26
	Delay Time (sec/km)	137	114	107	107	115	125	74	70
	Number of stops	197,205	222,725	224,270	237,819	234,426	220,827	243,423	247,518
	Travel Time (sec/km)	212	193	189	191	202	214	165	160
	Distance Travelled (km)	88,346	106,617	108,672	110,054	101,725	89,795	117,085	117,839
	CO_2 Emissions (kg)	46,289,044	38,236,408	27,486,297	17,414,275	10,186,184	3,016,915	3,886,832	3,896,277
	NOx Emissions (kg)	164,533	134,199	92,105	53,923	42,773	31,911	33,828	33,905
	PM_{10} Emissions (kg)	9,063	8,143	6,133	4,172	2,474	899	1,176	1,180

As can be observed, automation decreased delay and travel time during both peak hour and off peak hour conditions for the last two market penetration rate scenarios while for the rest these factors remained constant. In addition, traffic flows, the number of stops and total distance travelled values seemed to be increased when the number of autonomous vehicles was increased for most of the market penetration rate scenarios. The total distance travelled varied among the scenarios since the traffic conditions were different due to the introduction of automation and the different number of vehicles exiting the network. Furthermore, the introduction of CAVs, as well as the shuttle bus service different implementations led to approximately similar average speed, due to the fact that the study network was a highly congested area and therefore large differences in mean speed were not expected. Concerning emissions, the CO_2, NO_x and PM_{10} levels were significantly lower when the number of CAVs was increased. Despite of the number of stops, the emissions were reduced due to the increase of the CAVs that were considered to be electric. In addition, the different implementation types of the automated shuttle bus service did not seem to have any significant differences. In general, the introduction of CAVs seem to lead at first to more congested traffic conditions and finally shift to significantly improved conditions. That is caused by the shift from high percentages of human-driven vehicles to mixed traffic conditions and finally to high percentages of CAVs.

4. Conclusions

The present study aims to identify critical key performance indicators (KPIs) for safety assessment of autonomous vehicles through traffic microscopic simulation which is a solid tool for testing policies, new mobility technologies and alternatives before intervening in reality. For this purpose, a microscopic simulation analysis was conducted to provide multiple measurements quantifying the impacts of CAVs in different traffic conditions. Different scenarios were formulated using the Aimsun Next mobility modelling software in the city of Athens network.

From the knowledge gained from the microsimulation, insights are provided for factors that should be taken into account for the development of sustainable urban mobility. These insights take the form of a new group of KPIs matching the research questions of the SHOW research project. Traffic safety, traffic efficiency, and energy - environmental efficiency were found to be the most critical groups of indicators for the safety and impact assessment. Many of the proposed KPIs showed significant and essential impacts of CAVs in the examined urban environment, as the results from the microsimulation showed. More specifically, the number of conflicts was significantly reduced when more CAVs were present in the network during peak hour conditions and remained constant during off peak hour. Regarding traffic-related impacts, automation decreased delay and travel time during both peak hour and off peak hour conditions for high CAV market penetration rates. In addition, traffic flows, number of stops and total distance travelled values seemed to be increased when the number of autonomous vehicles was increased. Finally, CO_2, NO_x and PM_{10} levels were significantly lower when the number of CAVs was increased. The obtained KPIs could guide stakeholders in optimizing the safety assessment procedures through simulation by emphasizing critical safety aspects.

The present study does have certain limitations. An overall analysis comparing these different scenarios in relation to impact criteria and KPIs from simulations is not conducted in this study. Since traffic microsimulation was employed, assumptions regarding CAVs modelling were unavoidable. As a consequence, several pending issues remain open for future research. Various impacts in relation to other services need to be further investigated, taking into account different networks, vehicle types and automation levels. A further analysis could also be conducted in order to score the KPIs evaluation. The scoring method could allow stakeholders and decisions-makers to consider the perceptions and concerns while simultaneously considering the performance of scenarios from KPI data obtained from demonstrations and simulations.

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