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Factors Affecting the Impact of Autonomous Vehicles on Freeway Operations – An Exploratory Analysis Using PCEs

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ABSTRACT

Autonomous vehicles (AVs) and human-driven vehicles (HDVs) will share the roads for a long time, hence the need to study traffic flows mixing AVs and HDVs, especially during the AV introduction period. This paper aims to investigate the roadway and traffic characteristics that affect the impact of AVs on freeway traffic operations, using an adapted version of the HCM6 truck passenger-car equivalent (PCE) methodology. A large number of scenarios comprising different roadway characteristics, AV types and traffic flow compositions were simulated using Vissim to obtain AV PCEs. The results indicated that, for all scenarios considered, an AV has a 20% lower impact on the quality of service and operation than an HDV. A CART decision tree indicated that the most important factors affecting the AVs' impact on traffic operations are vehicle-to-vehicle connectivity level and the capability of travelling in platoons. Maximum platoon length did not matter, and the increase in the number of traffic lanes reduced the positive impact of AVs on service quality.

KEYWORDS

autonomous vehicles; passenger car equivalent; decision trees; freeways; microsimulation.

1. INTRODUCTION

Autonomous vehicles (AVs) have been under development and become the focus of a large body of research over the last two decades. Research results suggest that AVs can affect road capacity, improve safety and increase flow efficiency as their presence in the traffic composition grows over time [1]. This indicates that the advent of AVs may bring radical changes to all aspects related to mobility [2]. In general, studies indicate that in an ideal future, where AVs will comprise 100% of the vehicles on the road, they will positively affect traffic operations. However, the transition from conventional vehicles, or human-driven vehicles (HDVs), to AVs is expected to last several years or even decades. The impact that AVs of different capabilities will have on traffic flow during this transitional phase is not yet sufficiently understood [3].

The consensus among experts is that HDVs and AVs will coexist and share the roads for a long time [4]; thus, investigating the impact that AVs will have on highway operations is of great importance, especially for transportation agencies that need to assess the quality of service. One of the gaps in the literature is the lack of studies that investigate the variables that affect the impact of AVs on road traffic. To fill this gap, the main objective of this study is to investigate which and how roadway and traffic characteristics are related to the impacts of AVs on traffic operations in scenarios that represent typical conditions encountered during the initial phase of introducing AVs on highways.

The AVs that were the focus of this study are level 4 vehicles in SAE's taxonomy [5], which have size and physical characteristics compatible with conventional passenger cars, but with driving logic and behaviour that conform to the three classes of AV connectivity comprised in the CoEXist project [6]. The impact of such AVs on traffic flow was assessed using the passenger-car equivalent (PCE) method, which is similar to the method used in the Highway Capacity Manual (HCM) to estimate the impact of trucks on service quality and capacity [7, 8]. The method used to determine the road capacity and development of the AV PCE has been provided in a previous study [9]. The next sections of this paper are organised as follows: first, a concise overview of the vast literature on AVs and their impact provides the backdrop and justification for this study, as well as a description of the AV PCE approach adopted. Next, the processes used to estimate the AV PCE values are described; followed by results and statistical analyses. The paper concludes with a discussion of the results and suggestions for future development.

2. BACKGROUND

The abundant literature on the subject shows that the advent of AVs will greatly impact mobility in most of its facets, including the ethical aspects of the introduction of driverless cars on public roads [10], impacts on road safety [11], benefits to people with reduced mobility [12], reduction in travel time [13], economic impacts [14], reduced energy consumption and emissions [15], impacts on traffic flow and operations [16, 17] and increases in road capacity [18].

The predicted advantages of AVs are not just due to their autonomy but also derive from the vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) connectivity, which will result in real-time exchange of information making the transportation system more coordinated, integrated and efficient [15]. This real-time data exchange provides AVs with the capability of faster and more assertive decision-making than human drivers; thus, enabling AVs to better anticipate the actions needed to keep inter-vehicular gaps short and maintain traffic flow stability – which leads to greater capacity, provided that the number of connected AVs (CAVs) in the traffic flow is sufficiently large [19]. Conversely, AVs without V2V and V2I connectivity are only able to detect immediately adjacent vehicles and cannot anticipate speed changes in the platoon to avoid string instability [20].

Despite the extensive literature on AVs, only a handful of studies address their impact on highway operations from the quality-of-service perspective, as defined in the Highway Capacity Manual (HCM). Using the Monte Carlo simulation, parameters from the HCM 2010 were adapted to account for the presence of AVs in basic freeway segments. Two types of AVs were considered: with and without V2V and V2I connectivity. The case study results indicated that 3% of connected AVs in the traffic share would improve the service level from D to C; while 7% of unconnected AVs would be required for the same effect [21].

The HCM's capacity adjustment factor (CAF), defined as an adjustment to base capacity to reflect the impact of factors such as trucks, severe weather, incidents or work zones [7], is also a way to capture the effects of AVs on traffic flow. Adebisi et al. [22] developed CAFs for freeways carrying a mix of autonomous and conventional cars. AV penetration rates varied from 0% to 100% in 20% increments, for passenger-car only traffic flows on level, 2- or 3-lane merge, weaving and basic freeway segments. The results confirmed the positive impacts of AVs associated with increasing penetration rates. A subsequent study [23], based on the same approach, developed CAFs for signalised intersections. Another study based on CAFs [9] investigated the impacts of AVs on basic freeway segments focusing on the transition period during which AVs and HDVs share the roads and AV penetration rates are up to 60%. Based on a wide range of roadway and traffic characteristics (such as truck percentage, grade length and magnitude, number of lanes, maximum AV platoon length and AV level of connectivity), it concluded that, on average, five AVs have the same impact as four HDVs on the quality of service.

The estimation of AV impacts on transportation facilities is a complex task that requires accounting for the interactions among vehicles in the traffic flow, the mix of AV vehicles and other roadway and traffic characteristics. The TRB's HCM [7] is the most widely used tool to evaluate the operational performance of highway facilities and is considered the benchmark to estimate the capacity and level of service. The HCM procedures are designed to evaluate scenarios considering the environment-roadway-traffic interactions. One interesting aspect of the HCM is the use of passenger-car equivalents (PCE) to evaluate the impact that a certain vehicle class (trucks) has on the operation of a facility. PCE is the "number of passenger cars that will result in the same operational conditions as a single heavy vehicle of a particular type under identical roadway, traffic and control conditions" and provides tables with PCE values (E_T) [7]. From the fraction of trucks in the traffic mix (P_T) and E_T, one can estimate the impacts of trucks on the quality of service.

This research used the same approach to explore AV impacts on traffic flow, by means of an AV passenger car equivalent (AV PCE, denoted as E_{AV}). This study addresses a research gap concerning the impact of AVs on freeway operations, specifically from a vehicle equivalence perspective. Level of service (LOS) assessment is crucial for highway system management, as it supports roadway improvement funding decisions. Traffic monitoring stations (TMS), which provide data for LOS estimation, cannot easily distinguish AVs from HDVs. This requires using AV PCEs to represent the impact of AVs on specific highway segments. The objective of this paper is to discuss and analyse the roadway and traffic flow factors that affect AV PCEs, from the CAF viewpoint. We have specifically focused on the initial period of AV adoption when HDVs will still be the majority in the traffic mix and AV penetration rates will never be above 60% of the passenger car fleet.

2.1 Approach to evaluate AV impact on freeway segments

As AVs are still in the testing phase, the basis of the proposed method to estimate the impact of an AV on traffic flow is a passenger-car equivalent calculated using microsimulation. The procedure adopted is similar to the equivalent calculation for heavy vehicles adopted by previous studies [24, 8]. In the case of trucks, the HCM-6 adjusts demand using the following equation [7]:

$$v_p = \frac{V}{PHF \cdot N \cdot f_{HV}} \tag{1}$$

where v_p is the flow rate in the busiest 5- or 15-minute period of the hour (cp/h/ln); V is the observed hourly volume (veh/h), PHF is the peak hour factor; N is the number of traffic lanes; and f_{HV} is the adjustment factor for the effect of trucks, which is calculated by:

$$f_{HV} = \frac{1}{1 + P_T\left(E_T - 1\right)} \tag{2}$$

where P_T is the fraction of trucks in traffic and E_T is an equivalence factor, which corresponds to the number of cars that have the same impact as a truck on the quality of service.

The research reported here adapted the HCM method to include the impact due to different types of AVs in the traffic flow in the service level estimation, through an f_{AV} adjustment factor, which would result in *Equation 1* becoming

$$v_p = \frac{V}{PHF \cdot N \cdot f_{HV} \cdot f_{AV}} \tag{3}$$

where the f_{AV} adjustment factor is calculated using the following expression:

$$f_{AV} = \frac{1}{1 + P_{AV}\left(E_{AV} - 1\right)} \tag{4}$$

where P_{AV} is the decimal fraction of AVs in the traffic flow and E_{AV} is the equivalence factor of the AVs [7].

3. METHOD

In addition to the approach used to obtain the E_{AV} values, this section describes the characteristics of the simulated scenarios and the parameters adopted for the conventional vehicle and AV simulation.

3.1 Procedure to obtain AV PCE values

The calculation of the AV equivalence factor was carried out in a manner similar to that of the truck equivalence factor [25]. This involved comparing two traffic flows with the same capacity: a base flow comprising only cars and a mixed flow consisting of cars and the vehicle of interest, in this case, AVs. To calculate the E_{AV} for a given scenario (a combination of traffic and road characteristics), the base flow and mixed flow capacities were initially calculated. These correspond to the 95th percentile of flow rates observed at 5-minute intervals, expressed in veh/h/ln [7].

As described in detail in [9], CAF_i, the capacity adjustment factor due to the presence of AVs in the traffic flow for scenario i, is obtained from the relationship between the analysed scenario capacity and the base scenario:

$$CAF_i = \frac{C_{i,mix}}{C_{i,base}} \tag{5}$$

where $C_{i,mix}$ is the capacity (veh/h) for the mixed flow in scenario i; $C_{i,base}$ is the capacity (veh/h) for the base flow (only with conventional vehicles) in scenario i. The CAF_i value represents the increase (or decrease) in the capacity of the analysed scenario compared to the base scenario. In this study, base scenarios are those in which the traffic flow comprises only conventional vehicles and trucks, while in the mixed scenarios, the traffic flows also contain AVs, in addition to cars and trucks.

The passenger-car equivalent value is obtained from the following equation [8]:

$$E_{AV}(i) = \frac{1-(1-p_i)\cdot CAF_i}{p_i \cdot CAF_i} \tag{6}$$

in which $E_{AV}(i)$ is the passenger-car equivalence factor when considering scenario i; p_i is the AV percentage in scenario i; and CAF_i is the capacity adjustment coefficient due to the effects of AVs in the traffic flow, calculated for scenario i. The $E_{AV}(i)$ values for different scenarios can then be taken as an estimate of the overall impact of AVs on the highway operation, as compared to that of conventional passenger cars.

3.2 Vehicle parameter sets for the Vissim simulations

To represent the range of AVs and levels of automation that could exist during the transition period studied, three different types of AVs were used, in terms of driving behaviour parameters, in the car following and lane change processes [6]. The first type, AV_1 (cautious), is an autonomous passenger car without V2V communication that can stop safely even if the vehicle in front of it stops instantly, which is safer, but requires greater headways. The second type, AV_2 (normal), is an autonomous car without V2V communication, whose behaviour, although deterministic, is quite similar to that of a human-driven car and which can only obtain information from the first vehicle in front of it. The third type, AV_3 (all-knowing or connected), is an autonomous car with V2V communication, which travels with headways that depend on the type of vehicle in front of it, and from which a more cooperative behaviour is expected as it can obtain information on the position and displacement of vehicles around it. These three types of AVs are level 4 vehicles in SAE's taxonomy [5], and the main reason for choosing them is that they can be simulated by Vissim 20 [25, 26].

For AV_3 speed, acceleration and headways functions were based on deterministic values, which did not vary for AVs of the same type. The settings adopted for platoon formation were the Vissim 20 default values, such as the maximum distance for vehicles to start the platoon of 250 m, headways of 0.6 s, and minimum distance of 2 m within a platoon of AVs.

To represent the conventional vehicle behaviour, the values used for the car-following, lane change and truck performance models were those obtained in recalibrations carried out in previous studies, as well as the distributions of desired speeds and mass-power ratio of the trucks [27, 28].

3.3 Simulation scenarios

All scenarios studied were simulated in the same network, which represents a tangent stretch of freeway formed by three segments, whose vertical profile is shown in *Figure 1*. The initial segment (4 km long) enables vehicles to enter the network and stabilise the traffic flow. The intermediate segment, in which data were collected through five sensors, is 8 km long and its slope varies according to the simulated scenario. The exit segment is a 4 km long downgrade with a slope of -2%, to improve the dissipation of truck-led platoons past the last detector. The number of traffic lanes on the network depends on the simulated scenario.

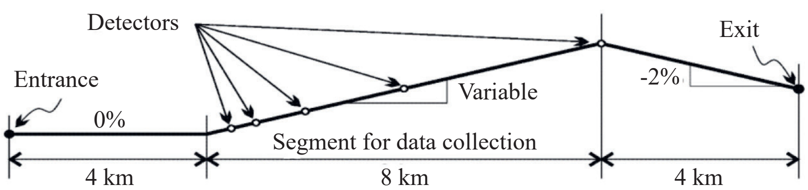

Figure 1 – Vertical profile of the simulation network

The simulations were performed at five different flow levels that correspond to 50%, 60%, 75%, 90% and 100% of the maximum possible flow, which was estimated as 2600 veh/h/ln [9].

The scenarios studied were created from variables related to traffic and highway characteristics, to analyse how these variables affect the AV equivalence factor. The variables used to create the scenarios are described in *Table 1*. The combinations of the control variables resulted in 25,515 simulated scenarios. Each simulation had a warm-up time of 30 minutes and a data acquisition time of 60 minutes.

The fleet of AVs in the traffic flow consisted of different proportions of AV_1, AV_2 and AV_3 vehicles, whose sum always totals 100%. The level of fleet connectivity described as low, medium and high connectivity are based on the proportion of vehicles AV_3 (all-knowing or connected) in the flow, as shown in *Table 2*. However, the number of AVs in the flow depends on the P_{AV} variable, the AV penetration rate in the traffic flow, which varies between 0% and 60%, as the objective of this study was to analyse scenarios with low AV penetration rates, representing the initial period of AV adoption.

Table 1 – Controlled variables in the simulation scenarios

Controlled variable		Levels	Description
P_{AV}	AV penetration rate	7	0, 10, 20, 30, 40, 50 or 60%
AV_1	Fraction of cautious AVs	4	0, 25, 50 or 75%
AV_2	Fraction of normal AVs	4	0, 25, 50 or 75%
AV_3	Fraction of all knowing AVs	4	0, 25, 50 or 75%
L	Distance travelled on grade	5	0.5, 1, 2, 4 or 8 km
N_f	Number of lanes	3	2, 3 or 4
N_p	Max length of AV platoons	4	0, 2, 4 or 8
g	Grade magnitude	3	0, 2 or 4%
P_T	Truck percentage	3	15%, 30% or 45%

Table 2 – AV fleet mixes and their level of V2V connectivity

Fleet	AV_1 (%)	AV_2 (%)	AV_3 (%)	V2V connectivity level
1	75	25	0	Low
2	50	50	0	Low
3	25	75	0	Low
4	25	50	25	Medium
5	25	25	50	Medium
6	25	0	75	Medium
7	0	75	25	High
8	0	50	50	High
9	0	25	75	High

4. RESULTS

Considering the results of 25,515 simulations, the E_{AV} values for all 22,005 scenarios with P_{AV}>0% were calculated using *Equation 6*. The mean E_{AV} value, for all simulated scenarios, resulted in 0.804, which indicates that, on average, AV impact is smaller than that of conventional vehicles and that, therefore, they can increase the roadway capacity (*Equation 4* shows that the lower the E_{AV} value, the greater the positive impact of the AVs).

The mean E_{AV} values, discretised by the V2V communication level, grade magnitude g, penetration rate of AVs (P_{AV}) and truck percentage P_T are shown in *Tables 3, 4 and 5* and suggest that the E_{AV} values are associated with the characteristics of the analysed scenarios. The following section analyses the effect of the controlled variables on AV PCE values.

Table 3 – Mean AV PCEs for an AV fleet with low V2V connectivity (75% AV_1 + 25% AV_2)

g (%)	**P_T (%)**	**AV penetration rate P_{AV}**					
		10%	**20%**	**30%**	**40%**	**50%**	**60%**
0	15	1.00	0.96	0.94	0.96	0.95	0.96
	30	0.89	0.89	0.86	0.89	0.89	0.90
	45	0.88	0.93	0.91	0.90	0.90	0.90
2	15	0.94	0.96	0.93	0.95	0.95	0.95
	30	1.00	0.93	0.92	0.93	0.92	0.93
	45	0.91	0.92	0.91	0.91	0.91	0.91
4	15	0.98	0.94	0.91	0.93	0.93	0.94
	30	0.95	0.94	0.94	0.95	0.95	0.95
	45	0.97	0.93	0.94	0.95	0.93	0.94

Table 4 – Mean AV PCEs for an AV fleet with medium V2V connectivity level (25% AV_1 + 50% AV_2 + 25% AV_3)

g (%)	**P_T (%)**	**AV penetration rate P_{AV}**					
		10%	**20%**	**30%**	**40%**	**50%**	**60%**
0	15	0.87	0.84	0.82	0.81	0.83	0.83
	30	0.81	0.80	0.83	0.82	0.80	0.82
	45	0.85	0.82	0.85	0.84	0.82	0.83
2	15	0.78	0.82	0.81	0.80	0.81	0.82
	30	0.85	0.83	0.84	0.84	0.83	0.83
	45	0.82	0.82	0.82	0.83	0.82	0.83
4	15	0.76	0.82	0.80	0.82	0.82	0.82
	30	0.90	0.89	0.87	0.87	0.86	0.87
	45	0.84	0.85	0.87	0.87	0.87	0.87

Table 5 – Mean AV PCEs for an AV fleet with high V2V connectivity level (25% AV_2 + 75% AV_3)

g (%)	**P_T (%)**	**AV penetration rate P_{AV}**					
		10%	**20%**	**30%**	**40%**	**50%**	**60%**
0	15	0.78	0.75	0.72	0.72	0.71	0.70
	30	0.71	0.75	0.75	0.73	0.73	0.73
	45	0.74	0.77	0.79	0.76	0.76	0.76
2	15	0.75	0.74	0.71	0.70	0.70	0.69
	30	0.82	0.78	0.77	0.75	0.75	0.74
	45	0.78	0.77	0.77	0.75	0.77	0.77
4	15	0.71	0.72	0.72	0.72	0.72	0.73
	30	0.84	0.82	0.80	0.80	0.78	0.78
	45	0.81	0.81	0.81	0.81	0.81	0.81

5. FACTORS AFFECTING AV PCE

CART (Classification and Regression Trees) is a method for exploratory data analysis frequently used in data mining to find relationships, patterns or trends within large data sets [29]. Starting from a root node, the algorithm repeatedly splits the data into binary nodes, based on the best attribute and a threshold value. This recursive partitioning progressively splits data into smaller groups (nodes) whose components are increasingly similar, while increasing the differences between newly created groups. The process is repeated until a stopping rule is met or there are no more splits that would improve the model [30].

CART has advantages over other traditional statistical techniques due to its non-parametric nature, ability to handle various data types, robustness to outliers, ability to capture interactions and non-linear relationships and handling of missing data [30]. CART is particularly good for identifying patterns and relationships in complex datasets because it generates mutually exclusive groups that are easy to interpret and understand [29]. The main limitation is that the model does not result in a parametric equation and can experience overfitting, especially when the tree is very complex. Exploratory data analyses with CART have been used in many areas of transport engineering, including the assessment of service quality in public transport systems [31], to establish the relationship between variables as injury severity and driver/vehicle characteristics, highway/environmental variables and accident variables [32, 33], to analyse relationships between socioeconomic attributes, land use and destination choices [34], and to analyse the importance of variables connected to urban destination choices [35, 36].

CART decision trees can be a useful tool to explore and understand relationships within large data sets [30, 31, 34, 36, 37] when, as in this research, one is not particularly interested in predicting accurate values for the dependent variable. In this study, a CART model was used to identify the relative importance of the effects of each controlled variable on the AV PCE values. Features that are higher up in the tree and contribute to meaningful splits will generally have higher importance scores [29]. Therefore, the accuracy rate was not calculated as the decision tree was used to investigate the effects of the independent variables. *Tables 3–5* provide mean values for selected AV fleet mixes.

To analyse how the controlled variables affect the AV PCE values, a decision tree model was trained with a CART algorithm, in which E_{AV} is the dependent variable as the distribution of E_{AV} values is significantly non-normal, according to the Kolmogorov-Smirnov test (p<0.05).

The SPSS software package for statistical analyses was used to fit the CART model. To avoid model overfitting, the following parameters were used for the model: maximum tree depth = 5; minimum number of cases in child nodes = 10; minimum number of cases in parent nodes = 50; minimum improvement in the variance reduction = 0.00005; and average minimum error = 0.05.

The final tree consists of five hierarchical levels. *Figure 2* schematically represents the decision tree map obtained with the independent variables used for the partition, complemented by *Table 6*. In *Figure 2,* node 0 represents the initial node (the complete data set), and the subsequent nodes are child nodes, of which those shaded are terminal nodes, that is, the leaves. The sample used for the model (node 0, N=21870) excludes not only scenarios with P_{AV}=0%, but also those identified as outliers after calculating the Mahalanobis distance. *Figure 2* also presents the node segregation criteria.

From the hierarchical structure of the decision tree (*Figure 2*), one can observe the effect of each factor on the AV PCE value (E_{AV}). The most important factor is V2V connectivity, as the first variable selected for segregation was AV_3.

Node 1 represents scenarios containing only AVs without V2V communication capability (AV_3=0%), in which the most important factor is the proportion of AVs travelling with headways similar to conventional vehicles (AV_2). Traffic flows with AV_2≤50% result in E_{AV}=0.912 (at node 3); otherwise, the positive effect of AVs on the quality of service is greater, as E_{AV}=0.855 (at node 4). The scenarios in which the traffic flow contained AVs capable of V2V communication (AV_3>0%) were clustered in node 2 and presented a lower E_{AV}, which indicates that AVs in these scenarios have a greater positive impact on the traffic flow. For the clustering of nodes 5 and 6, the proportion of trucks P_T was selected as the decision variable, which makes it the second most important factor. This separation indicates that the scenarios with a high proportion of trucks (P_T>15%), clustered in node 6, have E_{AV} greater than those of node 5. That is, the higher proportion of trucks in the traffic flow reduces the beneficial effects of AVs, as compared to scenarios with a lower proportion of trucks (P_T≤15%, grouped in node 5). This suggests that the greater the proportion of trucks in the traffic flow, the smaller the positive impact of AVs on the service quality.

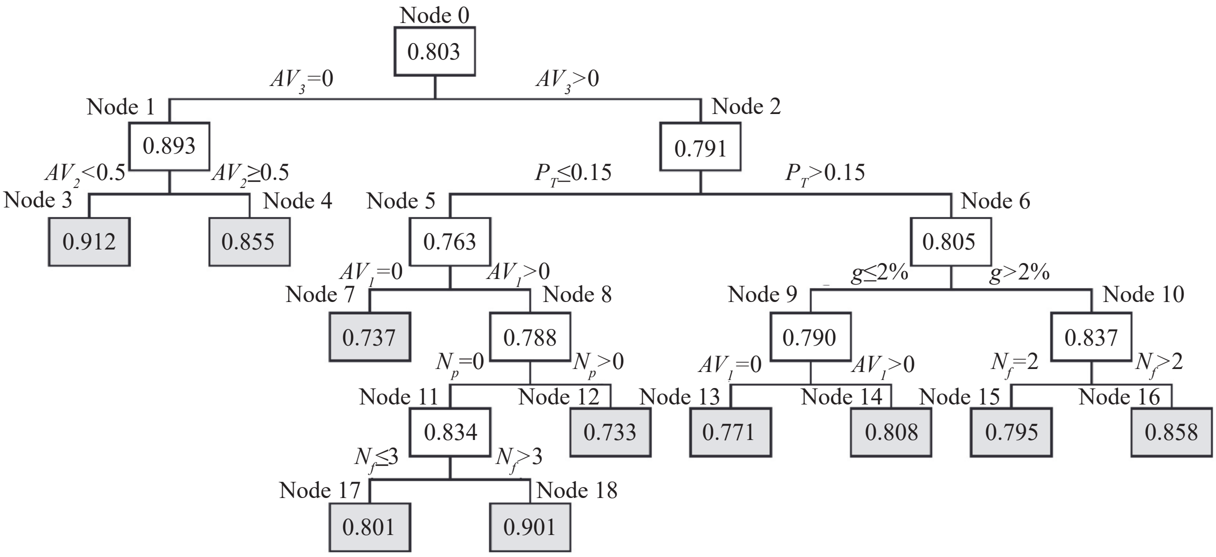

Figure 2 – CART decision tree for AV PCEs

Table 6 – Node definitions from CART decision tree for AV PCEs

Node	Rule to define E_{AV}	E_{AV}		Sample size	
		Mean	Std. dev.	N	%
0	Initial node	0.803	0.108	21870	100.0
1	AV_3=0.00	0.893	0.096	2430	11.1
2	AV_3>0.00	0.791	0.104	19440	88.9
3	AV_3=0.00; AV_2≤0.50	0.912	0.093	1620	7.4
4	AV_3=0.00; AV_2>0.50	0.855	0.091	810	3.7
5	AV_3>0.00; P_T≤0.150	0.763	0.102	6480	29.6
6	AV_3>0.00; P_T>0.150	0.805	0.102	12960	59.3
7	AV_3>0.00; P_T≤0.150; AV_1=0.00	0.737	0.094	3240	14.8
8	AV_3>0.00; P_T≤0.150; AV_1>0.00	0.788	0.103	3240	14.8
9	AV_3>0.00; P_T>0.150; g≤0.02	0.790	0.101	8640	39.5
10	AV_3>0.00; P_T>0.150; g>0.02	0.837	0.097	4320	19.8
11	AV_3>0.00; P_T≤0.150; AV_1>0.00; N_p=0	0.834	0.114	810	3.7
12	AV_3>0.00; P_T≤0.150; AV_1>0.00; N_p>0	0.773	0.094	2430	11.1
13	AV_3>0.00; P_T>0.150; g≤0.02; AV_1=0.00	0.771	0.100	4320	19.8
14	AV_3>0.00; P_T>0.150; g≤0.02; AV_1=0.00	0.808	0.098	4320	19.8
15	AV_3>0.00; P_T>0.150; g>0.02; N_f≤2	0.795	0.095	1440	6.6
16	AV_3>0.00; P_T>0.150; g>0.02; N_f>2	0.858	0.091	2880	13.2
17	AV_3>0.00; P_T≤0.150; AV_1>0.00; N_p=0; N_f≤3	0.801	0.095	540	2.5
18	AV_3>0.00; P_T≤0.150; AV_1>0.00; N_p=0; N_f>3	0.901	0.121	270	1.2

Node 5 represents scenarios with V2V connectivity (AV_3>0%) and a low volume of trucks. In these scenarios, cautious AVs (AV_1>0%) were decisive for the partitioning at nodes 7 (E_{AV}=0.737) and 8 (E_{AV}=0.788), as the presence of AV_1 in the flow significantly reduces the positive impact of AVs, due to its characteristics and limitations.

Node 8 was subdivided according to the effect of AVs travelling in platoons (N_p>0). This indicates that platoon formation leads to a significant difference between the equivalence factor of scenarios with AVs travelling in platoons (node 12, E_{AV}=0.773) and scenarios without platoon formation (node 11, E_{AV}=0.834). These results suggest that the AVs that can travel in platoons positively affect the quality of service.

From node 11 onwards, it can be seen that increasing N_f, the number of traffic lanes, reduces the positive impact of AVs as E_{AV}=0.901 for node 18 (end node), which includes scenarios with 4 lanes of traffic, and E_{AV}=0.801 for node 17 (end node) scenarios, where there are 2 or 3 traffic lanes.

Node 6 shows that, for scenarios with AVs with V2V communication (AV_3>0%) and a greater volume of trucks (P_t>15%), grade magnitude becomes the factor that determines the impact of AVs on the traffic operation. For scenarios with steeper slopes (g>2%, node 10), the number of lanes is the most important variable to define the impact of the AVs: for 3 or 4 lanes, the positive impact of the AVs is smaller (E_{AV}=0.858, node 16) than in scenarios where there are only two lanes of traffic (E_{AV}=0.795, node 15). Furthermore, node 6 shows that, for scenarios where there is no significant slope (g≤2%, node 9), the factor that determines the impact of AVs is the presence of "cautious" AVs: if AV_1>0% (node 13), the positive impact of AVs is greater (E_{AV}=0.771), compared to scenarios where AV_1>0% (node 14, E_{AV}=0.808).

5.1 Main factors affecting the AV PCE

The correlation analysis using Spearman's ρ coefficient, shown in *Table 7,* indicates that AV_1 is directly correlated with E_{AV} – that is, a greater proportion of AV_1 reduces the positive effect of AVs on the highway operation, as AV_1 requires greater inter-vehicle gaps because they lack V2V communication.

Table 7 – Correlations between AV PCEs (E_{AV}) and controlled variables, as measured by Spearman's ρ

	Controlled variable								
	AV_1	AV_2	AV_3	P_{AV}	P_T	L	N_f	N_p	g
ρ	0.352	0.044	−0.339	−0.072	0.211	−0.0004	0.096	−0.256	0.131
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	0.580	<0.001	<0.001	<0.001

The correlation factor obtained for AV_2 was low (ρ=0.044, indicating that this type of AV does not have a great impact when compared to HDVs, because their driving behaviour parameters are similar to those of human drivers. Truck percentage (P_T) is positively correlated with E_{AV}, which suggests that an increase in the proportion of trucks in traffic diminishes the positive effect of AVs.

On the other hand, AV_3 and P_{AV} correlation coefficients are negative, meaning that their increase leads to a reduction in E_{AV}, which is explained by the fact that all-knowing AVs have V2V connectivity, perform manoeuvres that are more assertive and are able to travel with smaller headways. The correlation coefficient of N_p is also negative, suggesting that AV platoons are correlated with a reduction in E_{AV}.

Regarding the road characteristics, the correlation coefficients indicate that, in general, grade magnitude (g) and number of lanes (N_f) are associated with an increase in E_{AV}. This can be explained by the fact that steep up grades impact the speed of trucks, which can create moving bottlenecks impeding AVs, and the literature suggests that the positive impact of AVs is lower in segments with a greater number of traffic lanes. As expected, the distance travelled on the slope by the AVs (L) does not have a significant correlation with E_{AV} as the AVs studied are automobiles and, therefore, little affected by the slope length.

When comparing the absolute values of the correlation coefficients, it can be observed that the variables that most affect E_{AV} are those related to the AV fleet mix, the ability of AVs to travel in platoons and the proportion of trucks in the traffic flow.

5.2 The impact of V2V connectivity level on the AV PCE

To assess how scenario characteristics affect the AV PCE average values for fleets with low, medium and high levels of V2V connectivity, linear regression models were calibrated in which the dependent variable is E_{AV} and the controlled variables are the independent variables. From the standardised coefficients of the regressions, shown in *Table 8*, the impacts of each variable on the E_{AV} value can be compared.

Table 8 – Standardised linear regression coefficients

AV fleet	Level of V2V connectivity	Standardised regression coefficients (β)*					
		P_{AV}	N_f	N_p	P_T	g	r**
1	Low				0.12	0.11	0.17
4	Medium		0.15	−0.15	0.09	0.81	0.24
9	High	−0.08	0.15	−0.15	0.23	0.14	0.35

*All β coefficients are statistically significant ($p<0.05$); **Model's correlation coefficient*

Table 8 indicates that, for AV fleets without V2V connectivity (fleet 1, AV_3=0%), the factors that most affect E_{AV} are not directly related to AVs: truck percentage (P_T) and grade magnitude (g). For fleets with an average level of V2V connectivity (fleet 4, with AV_3=25%), the number of lanes (N_f) and maximum size of AV platoons (N_p) are also significant factors. Only for fleets with a high level of V2V connectivity (fleet 9, with AV_3=75%) was the penetration rate of AVs also significant to define the E_{AV} value, albeit to a much lower degree than the other factors.

Figure 3 shows how E_{AV} varies as a function of AV fleet and AV penetration rate. One can notice that there is a small reduction in E_{AV} with an increasing penetration rate, but the effect of the V2V communication level (AV fleet type) is more significant.

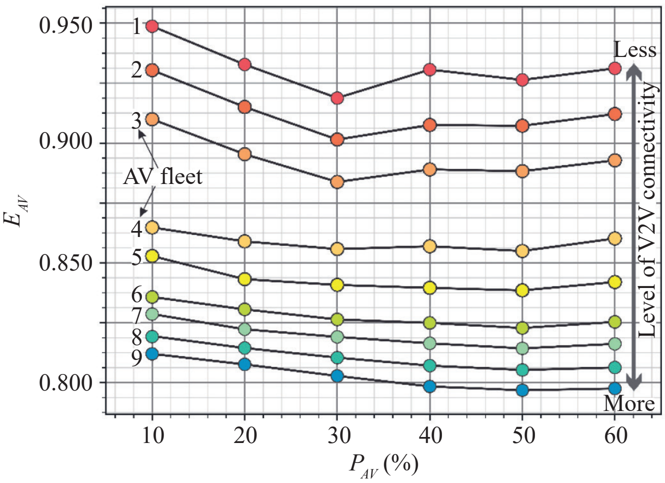

Figure 3 – Effects of AV penetration rate (P_{AV}) and V2V connectivity level on average AV PCEs (E_{AV})

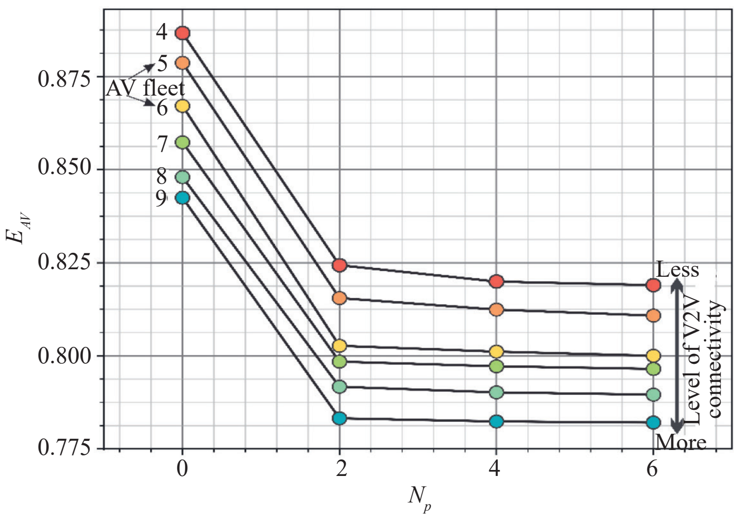

Figure 4 – Effect of maximum AV platoon length (N_p) and V2V connectivity on average AV PCEs (E_{AV})

Figure 4 shows another important aspect related to V2V communication: the ability to form AV platoons (when N_p>0) has a large positive impact (smaller E_{AV} values), but maximum platoon length (N_p) does not influence the AV PCE – at least for the scenarios studied, in which the penetration rate of AVs is relatively small to reflect the transition period.

When analysed by the AV fleet, it can be observed that traffic flows with compositions of a low level of V2V communication resulted in higher E_{AV} values, which means a lower positive impact of AVs on highway operation. On the other hand, fleets with a higher level of V2V communication and fewer cautious AVs (fleets 5, 6, 7, 8 and 9) have a higher positive effect on the traffic flow (lower E_{AV} values), as can be seen in *Figure 3.*

Figure 5 shows the combined effect of the AV penetration rate, truck percentage and level of V2V communication of the AV fleet. The E_{AV} values decrease as the V2V connection level increases, indicating the importance of AV platoons. Even in compositions with a low level of V2V communication, the values of the AV PCEs were less than one, indicating that the AVs have less impact than a conventional vehicle.

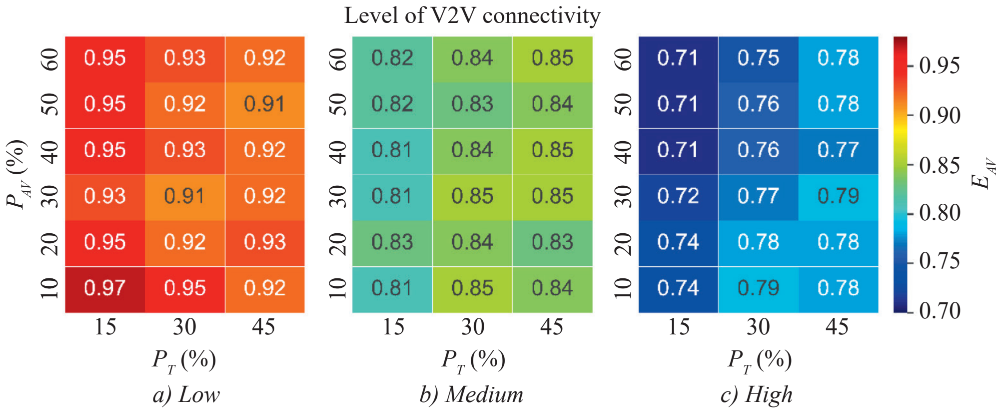

Figure 5 – Effect of AV penetration rate (P_{AV}), truck percentage (P_T) and V2V connectivity level on average AV PCEs (low: fleet 1, medium: fleet 4, and high: fleet 9)

When grouped by the truck percentage and AVs in the fleet (*Figure 5*), the E_{AV} values show that the AV PCE is higher in flows with higher proportions of trucks. It can also be observed that in scenarios with 45% of trucks, E_{AV} is less sensitive to the increase in the AV penetration rate. This can be explained by the fact that the increase in the truck percentage reduces the total number of cars in the flow – including AVs that, in smaller quantities, no longer provide significant gains in capacity.

The results indicate that increasing the number of traffic lanes also causes an increase in E_{AV} (*Figure 6*), which corresponds to a reduction in the positive impact of AVs. This phenomenon can be explained by the disturbances caused in the traffic flow due to the increase in lane changing manoeuvres by AVs that can be observed in a segment with more traffic lanes [38].

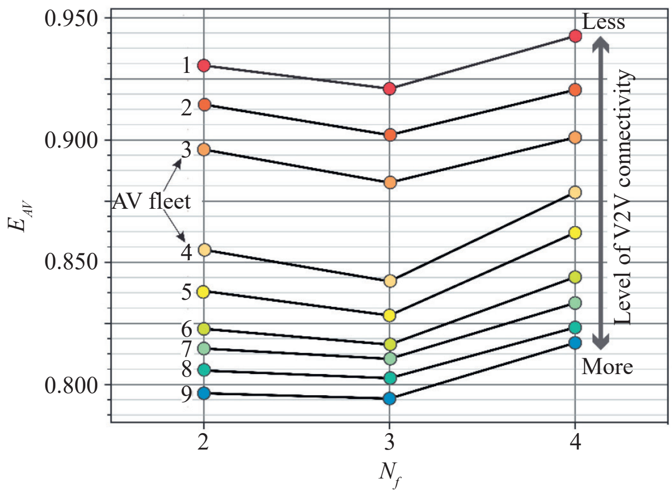

Figure 6 – Effect of number of lanes (N_f) and V2V connectivity on average AV PCEs (E_{AV})

6. CONCLUDING REMARKS

It is highly likely that AVs will share highways with conventional vehicles for the first few decades after being introduced. Therefore, understanding how AVs will affect the operational performance of highways is of great importance to maintain highway operations at acceptable service levels. In this context, the objective was to obtain the passenger-car equivalent values for the AVs and to investigate the main factors that influence their value. To meet this aim, this study used an adaptation of the procedure to obtain truck PCEs used in the HCM, based on traffic flows of equal capacity.

The mean E_{AV} value, obtained from 22,005 simulated scenarios, was 0.804, which means that, on average, five AVs would have the same impact as four conventional automobiles on the quality of service. Therefore, the presence of AVs can increase capacity and improve the quality of service on highways such as the type studied. The magnitude of this impact depends on several variables. The following conclusions can be drawn from the analyses:

The level of V2V connectivity of the AV fleets was the factor that most contributed to the reduction in E_{AV} values. AVs capable of forming platoons, sharing information and having a more cooperative car-following behaviour have a significantly greater positive impact than AVs that cannot travel in platoons.

AV platoons have a positive impact, but the maximum number of AVs in platoons does not seem to have much influence on the E_{AV} value, at least for scenarios representing the introductory phase of AVs, where their penetration rate is relatively low.

The penetration rate of AVs is an important factor in determining the E_{AV} value, but to a much smaller extent than the level of V2V connectivity, the proportion of trucks, number of lanes, magnitude of slopes and the presence of AV platoons.

The positive impact of AVs is greater in sections with 3 lanes of traffic, when compared to scenarios with 2 or 4 lanes of traffic.

The CART method proved very useful to investigate the effect of the controlled variables on AV PCE values, as the importance of the controlled variables was identified by the variables used by the model to cluster the data into groups that are more homogeneous.

It is suggested, for future work, to extend AV PCE analysis to autonomous trucks and consider scenarios with urban highways, traffic lights and different types of intersections to understand the possible impacts of AVs on urban traffic. Furthermore, it could be interesting to study the effects of other factors, such as the posted speed limit, the inclusion of an exclusive traffic lane for trucks or AVs and adverse weather conditions. This study used the Wiedemann 99 model modified to represent the AV behaviour [6]; it would be interesting to compare its results with those from studies based on other car-following models for AVs.

DATA AVAILABILITY

Some or all data, models or code that support the findings of this study are available from the corresponding author upon reasonable request.

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Renan Favero, José Reynaldo Setti

Fatores que afetam o impacto dos veículos autônomos nas operações em rodovias – uma análise exploratória usando PCEs

Resumo

A necessidade de estudar correntes de tráfego que misturam veículos autônomos (AVs) e automóveis convencionais conduzidos por humanos (HDVs) deve-se ao fato que esses dois tipos de veículo deverão compartilhar as vias por um longo tempo, especialmente durante a fase inicial advento dos AVs. O objetivo deste artigo é investigar como as características do tráfego e da via afetam o impacto dos AVs na operação de autoestradas, usando uma abordagem inspirada no fator de equivalência veicular (PCE) do HCM6. Os valores do PCE foram obtidos usando-se o software Vissim para simular um grande número de cenários combinando características da via, tipos de AV, e composições da corrente de tráfego. Os resultados obtidos indicam que, de um modo geral, o impacto de um AV no tráfego é 20% menor que o impacto de um HDV. Uma árvore de decisão CART mostrou que os fatores que mais afetam o impacto dos AVs no tráfego são a conectividade veículo-a-veículo e a capacidade de viajar em pelotões. O comprimento máximo dos pelotões de AVs parece não ter um efeito significativo, mas o aumento do número de faixas de tráfego está associado a um decréscimo do impacto positivo dos AVs na qualidade de serviço.

Palavras chaves

veículos autônomos; fator de equivalência veicular; árvores de decisão; autoestradas; microssimulação.