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Realization of the penetration rate for autonomous vehicles in multi-vehicle assignment models

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Abstract

Growing development in technologies that can lead to fully automated driving is at pace. This can result in an enormous change in traffic operations and network properties. However, there are uncertainties about the full deployment time of these autonomous vehicles on road networks. The transition period from vehicles with drivers to driverless will result in a mutual environment with an interaction between traditional (that is, manual) vehicles, automated vehicles and infrastructure. In this context, this research attempts to focus on the various factors of land use, user demographics and road network affecting the percentage of autonomous vehicles into the multi-vehicle assignment models and their subsequent impacts on the traffic network properties. This research aims to use a realistic approach to evaluate the percentage of autonomous vehicles to be injected into the traffic models via an indicator matrix and seven decision indices. A macroscopic traffic model is formulated for mixed traffic flow to which demand is assigned following a stochastic user equilibrium approach using the Frank Wolfe algorithm. The formulated model is applied to a real-world city network for a small part of the Italian city of Genoa. Results showed an effective improvement in traffic network properties with increment in capacities and flow speeds against the saturation grade for the given network.

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Keywords: autonomous vehicles; penetration rate; traffic model; multi-vehicle assignment; indicators

1. Introduction

In recent times, fast-developing technologies of autonomous and connected automated vehicles (AVs, CAVs) with their prototypes being tested on common roads attested to the substitution of privately owned traditional vehicles (TVs). Not only this but creating an evolutionary shift of vehicle usage trends for person and goods transportation. Albeit, the complete transition of TVs into AVs could take many years and is greatly dependent on massive investments from technological giants in developing AVs (Trivedi, 2018; Korosec, 2018). However, such a massive change makes it necessary to thoroughly evaluate their several impacts on users and society. Different papers (Sacco and Di Febbraro, 2016; Cantarella et al., 2019; Talebpour and Mahmassani, 2015) focused and to some extent forecasted

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the functionalities of AVs by evaluating the problems and opportunities in terms of traffic performances, at the same time raising a question of system equilibrium with all different classes of AVs as elaborated in J3016 Information Report (SAE, 2014).

Mobility in urban clusters requires a detailed analysis of user demographics, land usage and network characteristics for studying the interaction of mixed traffic stream on a transportation network. For the reliability of evaluation results, a system of indices and indicators have been widely used for temporal and spatial comparisons (Frei, 2006). Bergström and Magnusson (2003); Hensher et al. (2003); Ortúzar et al. (2000); Keegan and O'Mahony (2003) used indicators to evaluate the quality of services, vehicle occupation, improvement in social equity, driving behaviours and transport network assessment in terms of pedestrian mobility.

Inherently, the inclusion of AVs enhances traffic network performances in a mix of TVs and AVs. As per Liu et al. (2017), there is an increment in road capacity to 3070 veh/h with 100% penetration of AVs while Mena-Oreja et al. (2018) concludes an increase of 9.39% in traffic flow. Whereas, Olia et al. (2018) claims capacity increment for AVs penetration of 30%. Intelligently controlled AVs can induce a significant positive impact on the network even with a low penetration rate of 5% (Stern et al., 2018). Reduction in congestion and value of travel time on a compromise of increment in vehicle kilometres travel (VKT) is also noticeable impacts of AVs (Friedrich B, 2016; Correia, 2016).

However, Schmitz and von Trotha (2018) shows that the road capacity decreases by 23% if the penetration rate of AVs is up to 50%. This variability in the conclusions of studies creates uncertainty that on what core assumptions should we rely for realistic results. Narayanan et al. (2020) shows that assumptions about the factors being used in modelling studies on AVs are a real problem and are rarely used except for Martin-Gasulla et al. (2019). This generates our research question: *"How various factors govern the penetration rate of AVs into the multi-vehicle assignment models and what are their impacts on the traffic network?"*. The first objective is to evaluate the penetration rate realistically by introducing indicators from three different classes: land use, user demographics, and road network. The second objective is to analyse the effect of this penetration rate on the traffic network in a macroscopic traffic model scenario following stochastic user equilibrium assignment and compared it with system optimum assignment.

The article is structured as follows: Section II describes the main assumptions, notations and definitions for the network structure; Section III presents the transport supply model with a detailed method for penetration rate determination followed by a multi-vehicle assignment and solution algorithm. A numerical example to test the proposed model with respective results is presented in Section IV while concluding remarks are reported in Section V.

2. Network structure

This section presents the major assumptions, notations to variables and network structure for the multi-vehicle assignment model. The main assumptions for the defined research objective are:

1. a macroscopic model with stable speed flow relationships is utilised for two different classes of privately owned vehicles, i.e., TVs and AVs (with AVs further divided into two groups);
2. algorithms stored in AVs for path choice in various road scenarios are already known so the choice process for this class can be assumed as deterministic; albeit, as human intervention is always allowed for real-world uncertainties the choice process is modelled as stochastic variables in a logit model with least variance parameter;
3. initial O-D demand is fixed, constant and remains stable yielding steady-state conditions for AVs and TVs;
4. the assignment of demand to the network follows the Stochastic User Equilibrium (SUE) principle.

In a considered scenario, a traffic network is represented by a synchronic graph $G = \{N, L\}$ where N is the set of nodes and L is the set of links. Each link weighs in terms of flow-dependent travel cost $c_l(q_l)$ and is assumed to be increasing with the amount of flow q_l. Moreover, the link cost functions are inseparable i.e., variation in flows on all the link is affecting the cost of a generalized link. Furthermore, a link-path incidence matrix A is set up with all possible paths for an Origin-Destination (OD) pair (ij). Indicators are defined for a set of zones Z, routes RS, activities ACT, households HH and age groups G. Keeping in view the proposed enhancement for AVs, ceteris paribus, a penetration rate equation (PRE) is defined through seven indices calculated from three different classes of indicators in the subsequent section eventually giving the penetration rate (ρ) of AVs to be used into multi-vehicle assignment model.

3. Transport supply model

In this section, a detailed formulation of the transportation supply model for the stated objectives is described. Also, the methodology for the quantification of the penetration rate of AVs based on indicators matrices is presented.

Since the traffic network is assumed to be in general congested, the travel time on each generic link depends on the total traffic flow whereas the traffic flow depends upon the headway as a function of flow. For AVs, two prominent strategies have been adopted over time for forming platoon of vehicles, i.e., constant headway policy and constant safety policy. For this research, a constant safety policy is considered to stay as realistic as possible by taking into account brake actuation time, vehicle deceleration rate and vehicle length. In the formulation of inter-vehicle safe spacing (average space headway), nose to nose time headway (bearing reaction time and deceleration rate as governing parameters) is evaluated and multiplied with space mean speed of the platoon. Time headway as a brick wall stopping scenario is given as in (1).

$$T_{\mathrm{h}} = t_{\mathrm{rec}} + \frac{v}{2\,a_{\mathrm{d}}} + \frac{l}{v} \tag{1}$$

where T_{h} is the average time headway of vehicles in a mix of traffic with t_{rec} the reaction time. a_{d} is the minimum guaranteed deceleration rate in case of emergency. Also, l is the length of the vehicle and v is the speed. t_{rec} is a combination of human reaction time to hurdle R_{h} and brake actuation time τ. This time headway will be calculated separately for TVs and AVs (the latter divided into two groups, namely, levels 1-3 and levels 4-5) based on the reaction time factor as shown in Table 1 defined in Code of Federal Regulation (2021), and vehicle to vehicle communication scenario as in Darbha et al. (2017). For the spacing of mixed traffic platoon in, we followed a weighted summation

Table 1: Reaction time calculation.

$t_{\mathrm{rec}} = \tau + R_{\mathrm{h}}$	
For TVs	For AVs
$t_{\mathrm{rec,TV}} = 0.35 + 0.65 = 1$ sec	$t_{\mathrm{rec,AV_1}} = 0.35 + 0.40 = 0.75$ sec
	$t_{\mathrm{rec,AV_2}} = 0.35 + 0 = 0.35$ sec
	$t_{\mathrm{rec,AV}} = \text{weighted average}(t_{\mathrm{rec,AV_1}}, t_{\mathrm{rec,AV_2}}) = 0.545$ sec

approach as in (2) with weights being the penetration of AVs ρ in the platoon.

$$SP_{\mathrm{mix}} = \rho \cdot SP_{\mathrm{AV}} + (1-\rho) \cdot SP_{\mathrm{TV}} \tag{2}$$

where

$$SP_{\mathrm{AV}} = v \cdot t_{\mathrm{rec,AV}} + \frac{v^2}{2\,a_{\mathrm{d,AV}}} + l \tag{3}$$

$$SP_{\mathrm{TV}} = v \cdot t_{\mathrm{rec,TV}} + \frac{v^2}{2\,a_{\mathrm{d,TV}}} + l \tag{4}$$

3.1. Penetration rate of AVs

The PRE is defined depending upon three major classes of indicators namely land use, user demographics and road network. The structure of the indicator classes explains the diversity of the impacts and dependence of the usage of AVs in the coming decades. The primary reason for developing the matrix of 24 indicators as shown in Table 2 is to identify the systematic and more quantitative approach of including the new type of mobility into the transportation models. The classification of indicators helps to identify and differentiate the impact of various sub-systems of the urban infrastructure on this new form of mobility and vice versa. In addition, the matrix has the advantage of possible expansion for every class and type of transport model.

Table 2: Indicators matrix

Level of inclusion	Indicator	Notation	Dimension
Land Use	Land profit	$LP_{k,t}$	euros
	Maintenance cost	$M_{k,t}$	euros
	Parking land	PL	km^2
	Land unit rent	$R_{k,t}$	euros
	Number of residents	$r_{k,t}$	persons
	Population size	PS	persons
	Point of interests	$a_{z,act}$	—
User	Houshold income	I_t	euros
	Vehicle ownership	ω_{prt}	—
	Household size	hh_s	persons
	Age group	ω_g	years
	Tranportation expenditure	e_{tr}	euros
	Number of trips	ADT_g	trips/day
	Value of travel time	VOT	%
	Vehicle maintenance cost	M_{veh}	euros
	Average travel time	$ATT_{\text{prt},r}$	hours
	Vehicle kilometer travel	VKT	km
	Generalized user cost	$c_{ij,h}$	euros
Road network	Length of roads	λ_z	km
	Percentage of NMT	ω_{NMS}	%
	Volume of traffic	q	veh/hour
	Capacity of roads	Q	veh/hour
	Free flow travel time	t_0	hours
	Transportation infrastructure	TCA	%

3.1.1. Decision indices

From the above matrix, seven decision indices are formulated below, reflecting the objective of a realistic approach to input the penetration ρ of AVs into the analytical traffic model.

1. **Landowner profit index (LOPI)** is a variance of landowner profit as in (5) for a land unit k over a period t given the inflation i_t for that period, revealing the extent of inequity in the vicinity type. The slow relationship between transportation and land use activities for equity balance according to Wegener (1995) suggests that by choosing AVs, a time during transit can be utilised as a working hour by renting at a farther place. The assumption is the fixed maintenance cost and one city centre with services accumulated in selected zones.

$$LOPI_{k,t} = \sum_{k} \frac{LP_t}{(1+i_t)^{t-1}} \tag{5}$$

$$LP_{k,t} = R_{k,t} \cdot \frac{r_{k,t}}{hh_s} - M_{k,t} \tag{6}$$

2. **Transportation land usage index (TLI)** evaluates the density of transport links to examine the infrastructural provision in a certain spatial unit. Higher population density does not guarantee a higher number of services, but higher services do guarantee a higher population (Janasz, 2018). A ratio of the density of transportation links (weighted by ω_{NMS} or precisely soft mobility provision as cities turning more streets car-free in overcoming COVID-19 aftereffects) to the population density (weighted by the number of services ω_{SF} such as work,

education, leisure etc.) depicts the index value as in (7)

$$TLI = \frac{1}{|Z|} \sum_{z \in Z} \frac{\lambda_z \cdot \omega_{\text{NMS}}}{PS \cdot \frac{1}{\omega_{\text{SF}}}} \tag{7}$$

3. **User mobility index (UMI)** formulated by Kaparias and Bell (2011), it represents the user mobility status within the specified network. The index is upgraded by introducing a relationship between average travel time on a route using a private vehicle, length of the route, reliability factor ω_{R} for the route and value of travel time as in (8)

$$UMI = \omega_{\text{prt}} \cdot \frac{1}{|RS|} \cdot \sum_{r \in RS} \frac{ATT_{\text{prt},r} \cdot VOT}{L_{\text{prt},r} \cdot \omega_{\text{R}}} \tag{8}$$

where ω_R the percentage of travel time not more than 10% higher than average travel time on a certain route.

4. **Household transportation budget index (HBTI)** is formulated by Nicolas et al. (2003) upgraded here as in (10). It shows a relation between the total household expenditure for transport, total income, and the total generalized discounted cost for all OD pairs. The user generalized cost as in Szeto et al. (2015) is used as an inclination towards adaptation of AVs in case if a household owns a private vehicle.

$$ETS_h = \frac{e_{\text{tr},h}}{I_{\text{t},h}} \tag{9}$$

Where ETS is the economic transportation state of a household and B_{prt} is a binary operator which is 1 if the household owns a vehicle or vice versa.

$$HBTI_t = \frac{1}{|HH|} \sum_{h \in HH} ETS_h \cdot B_{\text{prt}} \left[\frac{c_{t,h}}{(1 + i_t)^{t-1}} \right] \tag{10}$$

5. **Social inclusion index (ACC)** is developed by Kaparias and Bell (2011) indicates the accessibility to activities on a spatial level via different zones. Trip propensity function $PF_{i,j}$ from Putman (2015) as skewed peak form with a gamma distribution as in (11) is superimposed with given index to yield (12). The difference of minimum and maximum values reveals vacant developable space which in terms of Wegener (1995) equitable development scenario gives a direct proposition for adaptation of AVs.

$$PF_{i,j} = \frac{d_{i,j}^{-1.330}}{\sum_j d_{i,j}^{-1.330}} \tag{11}$$

where $d_{i,j}$ is the distance between any OD pair (i, j).

$$ACC_i = \frac{1}{|ACT|} \sum_{a \in ACT} \left(\sum_{j \in Z} \beta_j \cdot a_{j,a} \cdot PF_{i,j} \right) \tag{12}$$

6. **Opportunity index (OI)** is defined by Kaparias and Bell (2011) for a special group of population quantifying their ease of mobility concerning the general population for the same set of activities. It consists of people who cannot drive themselves (disable, underage etc.) so AVs serving the purpose and allowing them to move on their own. This index is reformed by a weighted average with the population in each age group as in (14).

$$SMOB_g = \sum_{a \in ACT} \frac{ADT_{g,a}}{ADT_{\mathrm{tot},a}} \cdot \omega_a \tag{13}$$

where $SMOB_g$ is the mobility of a special group for all activities in ACT.

$$OI = \frac{1}{|G|} \sum_{g \in G} SMOB_g \cdot \omega_g \tag{14}$$

7. **Land coverage index (LC)** indexed as in Kaparias and Bell (2011), is a ratio of vehicles kilometres travelled over time to the relative growth of transport infrastructure. The long-term adaptivity property of land use goes in line with that of AVs which are not at large now and requires another decade or so for a reasonable percentage to be present on a network. The index presented in (15) can have values in the interval of [-100,100].

$$LC = \frac{\Delta VMT_5}{\Delta TCA_5} \tag{15}$$

Following our objective, the PRE index is obtained by using the computed averaged indicators and integrating them. Integrating all the defined indices under all assumptions defined in Section II by performing linear regression over a choice of upgrading or buying a new vehicle gives us a single value of penetration rate of AVs by analysing PRE from (16) against Table 3 following quantile approach of Frei (2006). The regression results are not reported here due to space restrictions whereas, coefficients are kept positive and negative given the nature of indicator as explained.

$$PRE_{AV} = LOPI_t + TLI - UMI + HBTI_t + ACC_i + OI + LC \tag{16}$$

Table 3: Quantiles approach

PRE	ρ (%)
0 - 140	20
141 - 280	40
281 - 420	60
421 - 560	80
561 - 700	100

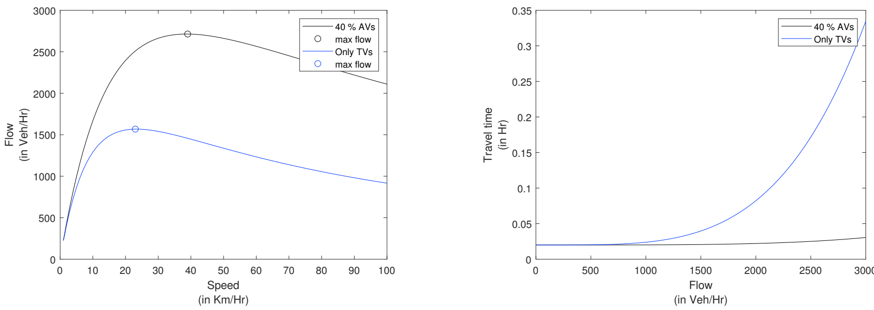
This ρ is used to obtain the inter-vehicle spacing of a mixed traffic stream from (2). Once we have the inter-vehicle spacing of the mix platoon, we can proceed with the platoon density and consequently final flow relationship. The density of a road link as a function of velocity is computed by (17).

$$k_{\mathrm{mix}}(\rho, v_{\mathrm{mix}}) = \frac{1}{\rho \cdot \left(v_{\mathrm{mix}} \cdot t_{\mathrm{rec,AV}} + \frac{v_{\mathrm{mix}}^2}{2\,a_{\mathrm{d,AV}}} + l\right) + (1-\rho) \cdot \left(v_{\mathrm{mix}} \cdot t_{\mathrm{rec,TV}} + \frac{v_{\mathrm{mix}}^2}{2\,a_{\mathrm{d,TV}}} + l\right)} \tag{17}$$

Consequently, the flow as a function of the average mix speed and percentage of AVs is given by (18). Whereas, travel time with respect to mixed stream flow, penetration rate of AVs and physical and functional charcteristics of network links, namely vector ψ, is given by (19). The realtionships (18) and (19) are represented for a generic link of 1km in Fig. 1(a) and Fig. 1(b), respectively.

$$q_{\mathrm{mix}}(\rho, v_{\mathrm{mix}}) = v_{\mathrm{mix}} \cdot k_{\mathrm{mix}}(\rho, v_{\mathrm{mix}}) \tag{18}$$

$$tt(\rho, q_{\mathrm{mix}}) = \frac{\text{link length}}{v_{\mathrm{mix}}(q_{\mathrm{mix}}(\rho, \psi))} \tag{19}$$



(a) (b)

Fig. 1: (a) Speed-flow relationship for generic link (b) Travel time -flow relationship for generic link

3.2. Multi-vehicle assignment model

To set up a multi-vehicle assignment model, two assignment procedures (for TVs and AVs) are merged following the stochastic user equilibrium (SUE) approach. Path choice process for AVs is considered deterministic whereas for TVs a general logit model is followed with doubly constrained distribution having logit parameter $\theta = -0.03$. For each path from the link-path incidence matrix A connecting an OD pair (i, j) the link cost vector is calculated at each iteration based on link flows at the previous iteration and feedback to the systematic utilities of each path consequently upgrading the path choice probability matrices for both classes of vehicles. Thus, generating two probability matrices based on systematic utilities (ST) for any link n and path m between any OD pair (i, j) as in (20) and (21).

$$ST_{n,m,i,j}(q^{k-1}_{\mathrm{TV}}) = -A^{\mathrm{T}}_{m,ij} \cdot c(q^{k-1}_{\mathrm{TV}}) + ST^{\mathrm{o}}_{n,m,i,j} \tag{20}$$

$$ST_{n,m,i,j}(q^{k-1}_{\mathrm{AV}}) = -A^{\mathrm{T}}_{m,ij} \cdot c(q^{k-1}_{\mathrm{AV}}) + ST^{\mathrm{o}}_{n,m,i,j} \tag{21}$$

Since the considered network is congested where link flows and costs are mutually dependent, the equilibrium assignment is used to determine mutually consistent link flows and costs. In this case, generalized link costs are dependent on total flows through the link cost function as in (22).

$$c = c(q(Q, \psi)) \tag{22}$$

Where Q is the vector of link capacities in the network and ψ is the vector of link physical and functional parameters. Thus, equilibrium assignment can be defined by fixed point models as in (23) based on link flows and cost functions in accordance with demand D (Cantarella et al., 2019).

$$c^* = c[q(c^*, D)] \in c(S_q) \subset \mathbb{R}^n \tag{23}$$

For consistency check of the proposed model, results are compared with those of system optimum (SO) assignment having an ideal state of the considered network with a minimized total cost in absence of AVs.

3.2.1. Solution algorithm

To compute the proposed fixed-point model for SUE assignment an upgraded version of a convex combinations algorithm, that is, the Method of Successive Averages – Frank Wolfe (MSA-FA) algorithm, is used. Steps followed in a basic iteration of the algorithm are:

STEP 1 Compute an initial feasible solution

1.1 Calculate all link costs based on free-flow travel times i.e link flows=0.
1.2 Search for the shortest paths for all OD pairs.
1.3 Determine the link flows based on the piecewise optimal step size.

1.4 If total flows on all paths are less than the original demand between an OD pair return to step 1.1, otherwise go to the next step.

STEP 2 Linearize the generalized link cost function following Taylor polynomial first-order giving recurssive equation as (24).

$$c^k = c^{k-1} + \frac{1}{k}\left\{c[q(c^{k-1})] - c^{k-1}\right\} \tag{24}$$

STEP 3 Find the new solution based on linearized function using feasible flows.

STEP 4 Check the convergence of the solution based on the duality gap equation to be compared with the given gap threshold of 0.001.

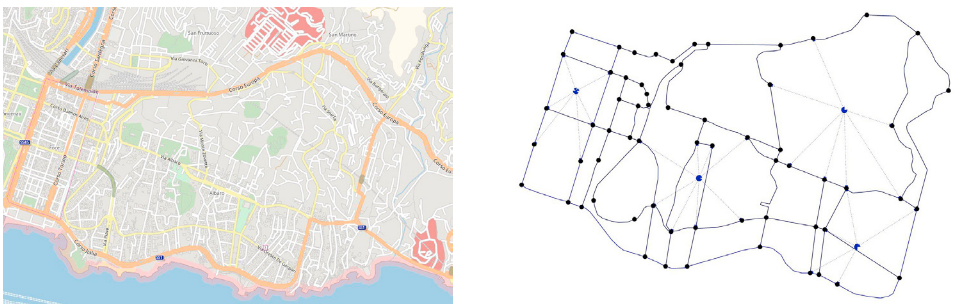
$$\sum_n c_n^k(q_n^k) - \sum_{i \in O} \sum_{j \in D} c_{i,j}(q_{i,j}^k) \tag{25}$$

STEP 5 If no convergence achieved return to step 3, otherwise end.

4. Network application

In this section, an application of the proposed methodology is explained together with the skimmed results.

The formulated model for the quantification of the penetration rate of AVs and subsequent multi-vehicle assignment is applied on a small network of an Italian city of Genoa as shown in Fig. 2(a) and (b). The considered network covers an area of 3 km^2 divided into four zones. The relevant transportation network is represented by a graph having 64 nodes and 182 links. The motivation of using relatively small network with actual trip demand is to keep the implementation and the result analysis simple enough. The socio-economic and demographical data for the city is retrieved from the Italian National Institute of Statistics (ISTAT) whereas, trips information is extracted from *Statista* and *Odyssee-Mure*. The OD matrices represent a typical evening rush hour with trips being attracted majorly towards



(a) (b)

Fig. 2: (a) Area considered for application (b) Network of the considered area

the eastern residential area and Nervi (eastern side of the city). The assignment over a considered network gives us total equilibrium costs $c_{T,eq}$ and total network optimum costs c_{opt} in a mixed traffic scenario with 40% AVs following the quantification methodology described earlier. The illustration of total costs in both assignments is presented in Fig. 3(a). It is evident that in both SUE and SO assignment the total cost is decreased for the same demand with the inclusion of AVs as the capacity changes. It is interesting to note that the total cost at equilibrium is even smaller (i.e. $c_{T,eq} = 352$) than the total optimum cost (i.e. $c_{opt} = 372$) in only the TVs scenario with an implication on model convergence as it satisfies the duality gap threshold earlier. This depicts the potential improvement of road network capacity with the inclusion of AVs following the quantified penetration rates.

Furthermore, by looking into Fig. 3(b), (c), and (d), it can be observed that between all OD pairs over the same paths in the network the flow is increased at some paths by 37% in a mixed traffic scenario as compared to the only TVs scenario. A similar trend is observed for speeds over the same paths for both of the scenarios however the gains

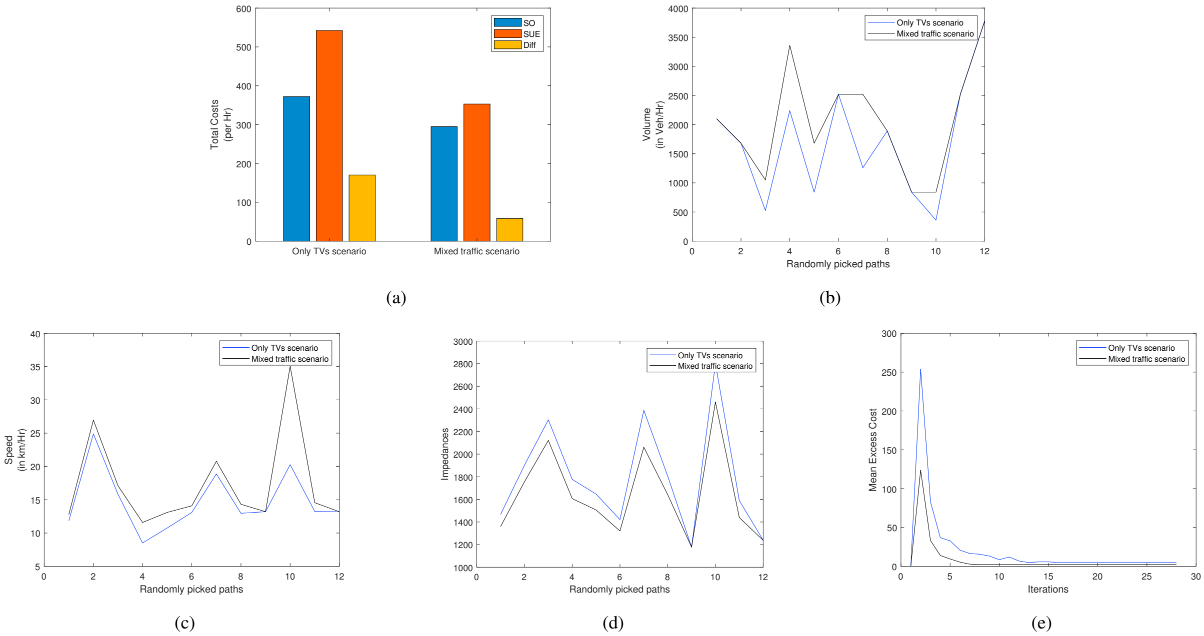


Fig. 3: (a) Total costs for SUE and SO assignment; (b) Flow difference between the two scenarios over selected paths (c) Speed difference between the two scenarios over selected paths (d) Impedance for two scenarios (e) Mean excess cost at equilibrium

in speed is lesser around 10% for most of the paths. Subsequently, the impedances over all the paths also decreases more efficiently in a mixed traffic scenario with AVs as compared to all manual vehicle scenario.

Following Fig. 3(e), we can witness the decrement in mean excess cost in the case of only manual vehicles but in the case of mixed traffic, this decrement is more prominent with the number of iterations required to reach equilibrium in SUE assignment. It can be seen that for mixed traffic stream equlibrium reached after 8th iteration whereas, for manual vehicles it starts to reach equlibrium after 15th iteration. Finally, these results fulfil the objective of this research to quantify the penetration rate and its consequences on the transportation network performance characteristics. Results show the potential benefits not only for the network but AVs benefits both types of vehicles by improved link capacities and speeds. This also reflects the ability of present road networks to cater significant increase in demand without any performance loss and further investment in the public infrastructure bearing in mind the capabilities of AVs.

5. Conclusions

In this section conclusions to the proposed methodology and its consequent results are detailed together with the possible way forward to the theme.

In this research, an effective methodology is provided to fill the gaps in the existing literature related to the impacts of AVs on transportation networks in presence of realistic penetration rates. Pertaining to the stated objectives in Section 1, the quantification methodology based on land use, user demographics and road network indicators is proposed to evaluate the realistic penetration rate. Later, using this penetration rate in the formulated general congested macroscopic flow model, effects on network performance in presence of mixed traffic are determined to seek the answer for the defined research question. To validate the objective an application to the real-world network of the Italian city of Genoa is performed through a multi-vehicle assignment model. The consistency of the SUE assignment model is checked by comparing the results with that of the SO assignment.

Results from the realistic application show that the proposed approach directs to an appropriate and effective method for more practical applications. It is also evident that considered methodology is capable of producing the link-wise level of services to identify that which of them needs more detailed analysis. There are limitations related to the types of links being used by the AVs, there can be links with AVs ready infrastructure to allow this new form of mobility to perform at its best. However, this is out of the scope of this research and can be considered for further studies. To conclude, it is worth saying that for effective and sustainable planning we should be clear about the numbers based on realistic quantifications to solve the already present puzzles instead of creating more for which the presented research can serve as a foundation.

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