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Evaluation of macroscopic fundamental diagram characteristics for a quantified penetration rate of autonomous vehicles

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Abstract

Background The availability of private vehicles with autonomous features is widespread nowadays. Various car manufacturers are providing attributes like collision warning, city automatic emergency braking, adaptive cruise control, pedestrian detection, lane-keeping assistance and lane departure warning, rear cross-traffic and blind-spot warning in their high-end models.

Purpose Such features can automatically manage the macroscopic fundamental traffic parameters such as speed, headway, etc adaptively. Consequently leading to a heterogeneous traffic stream with diverse car-following behaviour comprising completely manual/traditional (TVs) and autonomous vehicles (AVs). This questions the applicability of classic traffic flow theory relationships on such heterogeneous traffic streams.

Methodology This paper focuses on developing the macroscopic fundamental diagram for such heterogeneous traffic streams based on the quantified penetration rate (QPR) for autonomous vehicles. The penetration rate is devised by taking into account user demographics, land usage and road network properties. QPR is used as an input for heterogeneous urban traffic stream scenarios to calculate the aggregated urban traffic network dynamics of flow and density for the same network. Travel time versus flow characteristics is evaluated based on calibrated hyperbolic urban link travel time function for both interrupted and uninterrupted flows following the aggregated speed and density output from MFDs for heterogeneous traffic streams. Also, two scenarios are generated for comparison to explain the improvement in the network characteristics together with a sensitivity analysis.

Results Compared to the base scenario there could be 25-35% of AVs on the road networks based on the analysis in coming fifteen years. This increment in usage impacts the capacity of road networks positively by increasing it up to 59%.

Conclusions Results obtained after the application of the suggested model approach to the real network can be used to define a realistic method for multi-vehicle equilibrium assignment models for heterogeneous traffic streams including autonomous vehicles instead of approximating the penetration rates.

Keyword Autonomous vehicles, Penetration rate, MFD

1 Introduction

The capacity of urban networks and traffic flow has always been a topic of interest for planners, policy-makers, government authorities and statistical physicists in recent decades [1–3]. Repetitive travel patterns of commuters make it difficult to mitigate congestion as increased induced travel demand and population

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growth rapidly consume any added network capacities [4]. Traffic yields three macroscopic parameters namely speed, flow and density of vehicles on the network. These parameters generate two conditions of the traffic which either becomes saturated or unsaturated. A saturated condition is when the addition of a vehicle to the network further moves the system towards congestion decreasing the speed and flow of traffic. Whereas, in an unsaturated condition any addition of vehicles to the network also increases the flow of vehicles [5]. The critical point decides the boundary between the network's saturated and unsaturated conditions. This critical point is the capacity of the urban traffic network to yield the maximum traffic flow that can be accommodated without causing congestion. Although one-dimensional and expressway traffic flows are detailed in studies like [6], some of them [7, 8] also studied urban traffic networks.

The rapid testing of AVs and the impact of these technological advancements on transportation systems need to be investigated. In this regard, researchers [9–11] analysed and evaluated the problem of introducing autonomous vehicles into the transportation networks and highlighted the opportunities and gains that could be achieved in terms of macroscopic fundamental traffic network characteristics. Despite improved mobility and safety to the highest level expected from these technologies, concerns about their long-term impact on transportation systems are also there [12–17]. Yet, there is no evidence of quantification of the penetration rate of AVs in urban network evaluations but some predictive studies [18–22] for penetration rate are present.

Milakis et. al. conducted a scenario analysis following an intuitive logic approach around the most impactful technologies and policies towards supportive and refuting implementation of AVs. Four scenarios of AVs in stand-by, in bloom, in demand and doubt were analysed for the future developments track in the Netherlands and their potential impacts over the time up to 2030 and 2050. The analysis revealed that fully automated vehicles will be available in twenty years thus increasing the penetration rate of AVs up to 61% in 2050. This inclusion is expected to enhance the capacity of the motorway from 5 to 25% and vehicles kilometres travelled from 3 to 27%. Following the analysis, the results are validated in a logical workshop of fifteen field experts.

Litman used previous analysis to predict the market penetration of AVs for 2020-70 based on the factors like the pace of technological developments, regulatory and testing approvals, incremental costs, land usage and travel preferences at the user end, service quality and affordability, public policies for swift inclusion and safety. This theoretical analysis predicts the increase of market penetration of AVs based on improvement in performance, decrement in price and increment in user confidence such that by 2045 half of the new vehicle sales would be autonomous albeit market saturation will not be the same. This trend can result in a faster shift towards AVs in dense urban environments considering sharing services but unlikely to switch to private travel in suburban and rural areas. Although, this study predicts that AVs travel between 50 and 80% by 2060 albeit highly dependent on theoretical predictive studies.

Ben-Haim et. al. developed a qualitative approach for estimating the penetration rate of AVs for 2030-50 to evaluate their impact on travel behaviour and user activities. They used the Delphi method in combination with scenario analysis to construct two rounds of survey analysis. Again the approach of expert-based surveys was used which concluded significant progress in AV technology and usage till 2050 thus increasing the penetration of these vehicles into the traffic network. The penetration rate of AVs touches 23% by the year 2030 and jumps up to 60% by the year 2050. Similarly, Lavasani et. al. developed a market diffusion model based on the data of previous technologies adoption. Considering the adoption patterns of previous advancements, an indicator of innovation factor and imitation factor were deduced to evaluate the market penetration of AVs. The study concluded that a market saturation might occur in 35 years given that fully autonomous vehicle is available by 2025. To the best of the knowledge of the authors, no state-of-the-art quantitative method for AV penetration rate was found except for Lavasani et. al. with limited indicators considered. This certainly is a gap since without a precise penetration rate the impacts of AVs cannot be synthesized as they are not part of the real-time networks yet.

For evaluating the implications of this new technology macroscopic fundamental diagram (MFD) offers a simplified yet holistic approach to systematically examining urban traffic at both link and network levels [4]. It effectively allows determining the critical point between two traffic conditions of an urban network consequently revealing overall capacity. As [23] presents a cross-comparison of various MFD estimation methods both for a link and network level and describes its possible usage for simulation purposes. This makes it a useful tool to analyse the operation of urban transportation networks in heterogenous traffic scenarios with AVs.

The MFD gives an overall link/network capacity and corresponding critical density and flows after which the saturation starts. Later, they are used to determine the travel-time and flow relationship for the link or the entire network. Researchers [24–26] evaluated the influence of introducing this new form of mobility into urban transportation networks by using MFDs. Although they [24, 25] showed that AVs have significant impacts on traffic flow, their consequences on travel time are still missing. Also, they do not take into account the physical and functional parameters of the network links (disruption, the road bends, number of non-signalized crossings etc.) which certainly influence link and overall network performance. This generates a question to be answered via this research article: *"how do the physical and functional characteristics influence the urban road link capacity and travel time flow relationship in presence of a quantified amount of AVs?".*

This study aims to rationally quantify the number of AVs based on the socio-economic and demographical characteristics of the study area. Also, by using this quantified penetration rate, it realistically evaluates the impacts of this new form of mobility on urban road link capacity via MFD. Finally, it expresses the effect of change in urban road link capacity on the travel-time flow relationship by incorporating physical and functional characteristics of the urban road link.

The gaps identified through a rigorous review of state-of-the-art make this study highly significant to produce results in this area with fewer ambiguities. The developments in AVs technology and research on their impacts are at pace yet the uncertainties remain there. The ambivalences are not only related to the large-scale inclusion of AVs on the networks but also to their consequences on traditional vehicles specifically in scenarios of heterogeneous traffic streams. Thus this study plays its part to cope with the ambiguity of the penetration rate of AVs. The system of indicators developed in this study is an open-bound matrix that means further indicators related to the three classes (land use, user and road network) can be added thus creating more impact on quantified yet realistic input of penetration rate of AVs in network analysis. The deduced seven indices are highly applicable to the data from the stated adaptation surveys as well as flexible to be used in any region or study area. Similarly, the traffic flow relation scenarios adopted in three different scenarios with the inclusion of physical and functional characteristics of the network are adaptable for any region or study area. This simplicity yet preciseness of the approach taken in this study makes it a valuable addition to research in the domain of AVs allowing researchers to think more practically instead of testing the networks on probable penetration rates.

The paper is organized as follows: Sect. 2 describes the major assumptions, explains definitions of the notations for the socio-economic and demographical characteristics together with the quantification of the penetration rate of AVs followed by single-lane urban link formulation for MFD in Sect. 3; Sect. 4 reports the application of proposed methodology on a real city network of Genoa, Italy; finally, a concluding discussion is in Sect. 5.

2 Basic elements

This section describes the main assumptions, definitions of the constants for the quantification process and notations to be used in later sections. The major assumptions are;

1. AVs are further grouped into two categories, Level 1 to 2 in the first group and Level 3 to 5 in the second group, particularly for reaction times and deceleration rates.
2. A stable regime network is considered with stationarity conditions for the fundamental relationships.
3. A constant safety policy for AVs is considered for forming the platoon of vehicles.
4. MFD is strictly concave holding only one maximum.

It is to be noted that concerning the societal, economical and user-demographical characteristics, house maintenance and lodging costs are considered to be fixed depending upon the number of residents on a condition of a single city centre having services of interest amassed in selected zones as in the case of many European cities e.g. Genoa, Cagliari, Porto, Timisoara. Although MFD is majorly dependent upon the road network topology, choices for route and mode and signal controls [4], we are considering here uninterrupted conditions with a network topology as a major factor.

In the following sub-section, all indices for generating a quantification method for a realistic penetration rate of AVs are reported. Later this realistically derived penetration rate will be used to develop a macroscopic fundamental diagram for a realistic urban network to understand the characteristics of the heterogeneous traffic stream.

2.1 Quantification of penetration rate

This section describes the approach for the quantification of penetration rate for AVs to be used in traffic flows consequently generating heterogeneous traffic streams.

To obtain the answer to the research question defined in Sect. 1, the formulation of an indicator system is presented for evaluating a realistic amount of AVs to be introduced as a vital input for the macroscopic fundamental relationships. For the indicator system as shown in Fig. 1, twenty indicators from three different classes of user demographics, user socio-economics and road network characteristics are used to formulate seven indices. These indices are defined through seven equations and are gathered together in a converged relationship providing a single quantification index for AVs. The uncertainty of the impacts of AVs on any transportation system and its users are given in the literature to some extent but the results are based on the inclusion of this new form of

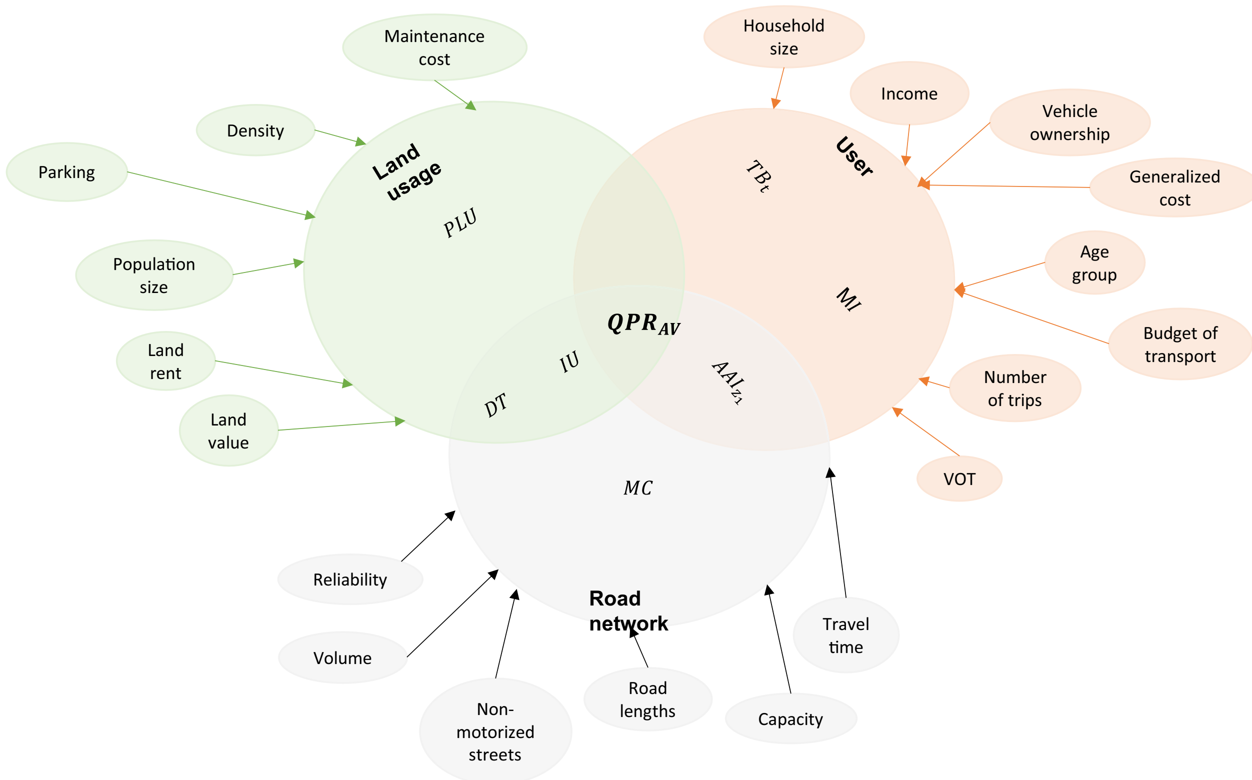

Fig. 1 Indicators Web

mobility without any concrete quantification evidence. The presented indicator system explains the adoption of AVs in an organized perspective so that the resulting outcomes and macroscopic fundamental parameters have a strong basis. Not only this but the diverse nature of indicator classes justifies the usage and inclusion of this new form of mobility in the traffic network equitably. The system is formulated in a simple way to avoid any divergence while providing a tangible value for introducing AVs into transportation models.

From the land usage class of indicators as in Fig. 2, the financial benefits in terms of land unit rentals play an important role in terms of residential location choice. According to researchers [27, 28] users choose the location not only in the proximity to their daily needs but also following the monetary condition in terms of their earnings. Yet [38] illustrates the relationship between land occupancy choices of users and activities to be in proximity to each other. This results in higher rental profits in concentrated areas resulting in inequity of landowner profits. The proposition of adaptation of AVs is directly proportional to the inequity of the land unit rentals which motivates the usage of a modified index from [28] termed as a profit of land unit (PLU) considering the assumptions of Sect. 2 as shown in Fig. 2, where $RE_{L,t}$ is the rent of the land L in a time t, $res_{L,t}$ is the number of residents living in household LU, and maintenance cost of land unit is represented by $MT_{L,t}$ considering the inflation *in*. The profit is evaluated as a variance depicting the inequity in land unit rentals. Also in Fig. 2, from the land usage class, another index is the density of transportation infrastructure (DT). The adoption of any new service is not only dependent upon the quality and comfort of the service but also the attractive infrastructure alluring the usage of this new service is important. We have seen the latest example of various European cities (Milan, Paris, Barcelona, Genoa, Malmo) providing safe and comfortable infrastructure and improvising attractive policies for people to use micro-mobility modes. Given land usage theory [29], (DT) is formulated as a ratio of the density of road network provided to the population density of the area under consideration (DRL_z and DP_z are the density of road links and population density respectively). It should be noted that the ratio for each zone z is weighted by a factor $\omega_{N,S}$, which is a ratio of the proportion of car-free streets to the average services provided in the zone. The values of DT and PLU are in direct relation with the adoption of AVs as explained by [30]. Similarly, in the land usage class, the index in the form of a ratio of the usage of transportation infrastructure in terms of change in vehicle miles travelled to the provision of infrastructure over a certain period is covered by infrastructure usage (IU) as in [31]. ΔVMT_{15} and ΔTCA_{15} are the vehicle miles travelled and transportation infrastructure provision over 15 years respectively.

Land use

$$\boxed{var\ PLU = \sum_{L} \frac{RE_{L,t} * \left(\frac{res_{L,t}}{LU}\right) - MT_{L,t}}{(1+in)^{t-1}}}$$

$$\boxed{DT = \sum_{z \in Z}^{Z} \left[\left\{\frac{DRL_z}{DP_z} * \omega_{N,S}\right\} \div |Z|\right]}$$

$$\boxed{IU = \frac{\Delta VMT_{15}}{\Delta TIP_{15}}}$$

User

$$\boxed{TB_t = \frac{\sum_{h \in HO}^{HO}\left[\left(\frac{es_h}{ins_h}\right) * \beta_h \left[\frac{gc_{t,h}}{(1+in)^{t-1}}\right]\right]}{|HO|}}$$

$$\boxed{AAI_{z_1} = \left[\sum_{at_1 \in AT}^{AT}\left\{\sum_{z_2 \in Z}^{Z} \gamma_{z_2} * \frac{x_{z_1,z_2}^{-1.330}}{\sum_{z_2} x_{z_1,z_2}^{-1.330}} * noa_{at_1,z_2}\right\} \div |AT|\right]}$$

$$\boxed{MI = \left[\sum_{g \in G}^{G} \sum_{at_1 \in AT}^{AT} \frac{ATT_{g,at_1}}{ATT_{tot,at_1}} * \omega_{at_1} * \omega_g\right] \div |G|}$$

Road network

$$MC = \sum_{r \in RS}^{RS} \left[\left\{\frac{RTT_r * VOT}{L_r * \omega_R}\right\} \div |RS|\right]$$

Fig. 2 Indices for three different classes used for quantification of penetration rate

From Fig. 2, the user class indicators yield a set of indices based on users' socio-economic and demographical characteristics. The budget of a household being used for transportation services to meet daily mobility needs is a significant factor. The expense indicator and generalized user costs for transportation formulated by [28, 32] are modified into the transportation budget index (TB_t) the inflation rate over the considered period and on the condition of private car ownership. es_h and ins_h are the expense on transport and the total income of the generic household h of the set of households HO. β_h is a binary operator whose value is 1 if a household owns a private vehicle and 0 otherwise. $gc_{t,h}$ is the generalised user transportation cost. Accessibility to various activities from a certain origin zone to other zones depicts the capability of commuters to carry out their daily tasks in a smooth, safe, comfortable and economical manner. In this regard, the distance to a certain activity concerning all destination zones in which that activity can be carried out can be included in the accessibility index [31] to give the activity accessibility index (AAI). Trip propensity is in the form of a distance ratio of x_{z_1,z_2} (the shortest distance to an activity in the zone z_2 from z_1) to the sum of all the distances for that particular activity in all possible zones. γ_{z_2} is a binary operator defining the presence of an opportunity to carry out a certain activity and noa_{at_1,z_2} is the number of possible opportunities for carrying out the activity at_1 in zone z_2. Similarly, in user class, another vital indicator is presented depicting the mobility of an underprivileged group of society dependent on another person to drive them off. These often include the disabled and elderly people [33]. Dividing the population under consideration into a special group represented by a set G which is further divided into subsets such that for any subset g, the mobility index (MI) is given as a ratio of average daily travel time ATT_{g_1,at_1} for a certain activity at_1 the average daily travel time of all the population ATT_{tot,at_1} for the same activity. This ratio is weighted by the type of activity ω_{at_1} and weight of the sub-group (subsets) ω_g in the total population.

Finally, in the road network class in Fig. 2**,** it is evident that the condition of the urban transportation network plays a crucial part in determining the mobility of its users according to the planned trips with the least fluctuations. If the mobility condition of a person is reasonable with affordable travel time per kilometre of a journey, then it is less likely for him to incline towards the usage of AVs. Not only this but the trust of the user in the planned route acts as an important part of making it more reliable without any potential loss of a productive hour. Under all

Table 1 Penetration rate fractiles approach

	p(%)	QPR_{AV}	p(%)	QPR_{AV}	p(%)	QPR_{AV}	p(%)
0–35	5	176–210	30	351–385	55	526–560	80
36–70	10	211–245	35	386–420	60	561–595	85
71–105	15	246–280	40	421–455	65	596–630	90
106–140	20	281–315	45	456–490	70	631–665	95
141–175	25	316–350	50	491–525	75	666–700	100

these considerations mobility condition (MC) index is formulated by modifying the mobility index from [31] with the inclusion of the value of travel time VOT and travel time reliability factor from [34]. The mobility condition is defined as the ratio of travel time RTT_r on any route r from the route set RS to the length L_r of that route weighted by the reliability ω_R of that route for a certain OD pair.

The seven formulated indices from the incorporated indicators are aggregated to form a single index giving a quantification penetration rate value (QPR_{AV}) as in (1). It should be noted that integration is done according to the assumptions presented earlier. The weights of each index in the QPR_{AV} is defined by passing the indices through a regression analysis over a choice of upgrading or buying a new vehicle. This willingness of users affects the user class indicators thus deciding the weight for each of them, particularly for the transportation budget index. Following that, 20 short fractiles are grouped based on the approach used by [35]. These fractiles give us the value for the final penetration rate p as shown in Table 1.

$$QPR_{AV}{=}\mathrm{var}PLU + DT + IU + TB_t + AAI_{z_1} + MI - MC \tag{1}$$

3 Urban link MFD set up

This section describes the equations that are proposed to produce urban network macroscopic fundamental diagrams for heterogeneous traffic streams. Later, using the capacity found from the MFD, three different scenarios for the flow travel-time relationship are established.

The second part of the objectives of this research is to generate a realistic MFD to evaluate the urban road link capacity in presence of AVs. Following the assumptions defined in Sect. 2, the analytical fundamental relationship is determined by calculating the inter-vehicle spacing of heterogeneous traffic streams. The inter-vehicle spacing as in [26] is evaluated as a weighted sum of the spacing of TVs and AVs as follows:

$$Y_{mix} = pY_{AV} + (1-p)Y_{TV}. \tag{2}$$

where

$$Y_{AV} = s{*}t_{rt,AV} + \frac{s^2}{2a_{d,AV}} + \mathrm{v}l \tag{3}$$

$$Y_{TV} = s{*}t_{rt,TV} + \frac{s^2}{2a_{d,TV}} + \mathrm{v}l \tag{4}$$

where $t_{rt,AV}$ and $t_{rt,TV}$ is the reaction time in the case of AVs and TVs respectively. $a_{d,AV}$ and $a_{d,TV}$ is the minimum guaranteed deceleration rate in case of emergency for AVs and TVs respectively. s is the average vehicle velocity and vl is the vehicle length. The governing parameters here i.e. the reaction time (a combination of human reaction time to hurdle and brake actuation time) and deceleration rate are computed as in ([25] and Transportation: Codes of Federal Regulations). Since AVs are further divided into two groups as per our assumptions in Sect. 2, two reaction times for both of the classes are calculated. Thus AV_1 and AV_2 have different reaction times. Moreover, aggregated reaction time for AVs is based on the dynamic weighted average (dw_{avg}) where weights are based on the concentration of the two sub-classes in the total amount of AVs. Calculation of the reaction time for two sub-classes of AVs is based on detailed propositions from [21]. For the first ten-year period of the futuristic scenario of the heterogeneous traffic stream, AVs of Level 1–2 (AV_1) are given the weight of 0.9 and for levels 3–5 (AV_2) the weight is 0.1. For the next 5 years of the futuristic scenario, the AVs of Level 1–2 (AV_1) are given the weight of 0.8 whereas levels 3–5 (AV_2) class of AVs is given the weight of 0.2. The weights are represented by α_1 and α_2 for AV_1 and AV_2 classes as shown below. Following (Transportation: Codes of Federal Regulations) the brake actuation time is kept constant i.e. 0.35 s considering the latest vehicle technology irrespective of automation, whereas, human reaction time to hurdle varies. The time to hurdle is the highest i.e. 0.65 s for non-automated (traditional) vehicles and zero for the fully automated ones taking into account the constant safety policy in case of a brick-wall stopping.

$$t_{rt,TV} = brake\ \ actuation\ \ time + human\ \ reaction\ \ time$$

$$dw_{avg,t_{rt,AV}} = \left(\alpha_1 * t_{rt,AV1} + \alpha_2 * t_{rt,AV2}\right) \big/ (\alpha_1 + \alpha_2)$$

On integrating the quantified penetration rate of AVs into the inter-vehicle spacing relationship following the reaction time evaluation criteria mentioned above, macroscopic fundamental relationships can be defined for the heterogeneous stream of traffic. Given the conventional relationship of density of the traffic stream with inter-vehicle spacing, a relationship between the density of the traffic stream d_{mix} involving AVs is formulated as a function of velocity and penetration rate according to the spacing as in (5).

$$d_{mix} = \frac{1}{p\left(s_{mix}*dw_{avg,t_{rt,AV}} + \frac{s_{mix}^2}{2a_{d,AV}} + \mathrm{v}l\right) + (1-p)\left(s_{mix}*t_{rt,TV} + \frac{s_{mix}^2}{2a_{d,TV}} + \mathrm{v}l\right)} \tag{5}$$

Consequently, the flow as a function of the average velocity and the quantified penetration rate of AVs in the heterogeneous stream is presented in (6).

$$flow_{mix}(p, s_{mix}) = \frac{s_{mix}}{p\left(s_{mix}*dw_{avg,t_{rt,AV}} + \frac{s_{mix}^2}{2a_{d,AV}} + \mathrm{v}l\right) + (1-p)\left(s_{mix}*t_{rt,TV} + \frac{s^2}{2a_{d,TV}} + \mathrm{v}l\right)} \tag{6}$$

3.1 Travel time—flow relationship

Finally, the third part of our objective is to define the flow-dependent travel time tt_r function by incorporating the physical and functional parameters of urban road networks. Three different scenarios have been used to determine the travel-time flow relationship for an urban road network. Firstly the upgraded BPR function from [5] is used as in (7) which defines the link with a physical median so independent of the effects on the flow of the opposite direction in the traffic stream, then (8) [5] gives the travel-time flow relationship with an impact of opposite direction flows, and lastly the major function in (9) [36] which gives the travel time as a function of the flow of the heterogeneous traffic stream and the physical characteristics of the urban road network.

$$tt_{r1}\left(flow_{mix}\right) = \frac{L_x}{s_0} + \gamma_1\left(\frac{L_x}{s_c} - \frac{L_x}{s_0}\right)\left(\frac{flow_{mix}}{Q_x}\right)^{\gamma_2} \tag{7}$$

$$tt_{r2}\left(flow_{mix}, flow_{mix}^o\right) = \frac{L_x}{s_0} + \gamma_1\left(\frac{L_x}{s_c} - \frac{L_x}{s_0}\right)\left(\frac{flow_{mix} + flow_{mix}^o}{Q_{mix}^o}\right)^{\gamma_2} \tag{8}$$

$$tt_{r3}\left(flow_{mix}\right) = \frac{L_x}{29.9 + 3.59W_x - 0.58S_x - 13.86Tor_x - 10.8Dis_x - 6.38Po_x + 4.73Pv_x + \frac{-1.05\left(\frac{q^n}{W_x}\right)^2}{1+Tor_x+Po_x+Dis_x}} \tag{9}$$

In (7) and (8), L_x, Q_x, s_0, s_c are the length of the link, the capacity of the link, the free-flow speed and the critical speed for the urban road network link x; γ_1 and γ_2 are the model parameters. It must be noticed that the variation of behaviour between the human-driven vehicle and autonomous vehicle, calibrated γ_1 and γ_2 parameters are used for AVs following Esta. et. al. [37] In (8), $flow_{mix}^o$ and Q_{mix}^o represents the flow in opposite direction and overall capacity respectively. Consideration of opposite direction flow is important to be as realistic in defining the travel-time relationships as possible. As in the case of many European cities, the urban road links are influenced by the opposite direction flow due to non-median separation between the two directions. In (9), W_x is the useful road link width; S_x is the non-negative slope of the link; Tor_x is the tortuosity of the link; Dis_x is the disturbance to traffic from external factors like pedestrian crossings, irregular parking, and side entries; Po_x is the percentage of links occupied by parking; Pv_x is a pavement-type variable. The function from [36] is modified by multiplying the flow by the percentage increase in capacity from the speed-flow relationship in (6) and defined as q^n. Overall, these travel-time relationships are dependent on the flow of heterogeneous traffic streams which is, in turn, dependent upon the quantified penetration rate.

4 Application to the urban network

This section describes the application of the methodology presented in Sect. 2.1 on a real network relevant to the city of Genoa in northern Italy; the considered area

Fig. 3 Real Network for application of formulated model

is shown in Fig. 3. The socio-economic and demographical data for the city is retrieved from the Italian National Institute of Statistics (ISTAT) and Comune di Genova (the city municipality), whereas, the transportation infrastructural data is obtained from Eurostat. Moreover, trip information is extracted from Statista and OD matrices are provided by Comune di Genova. This data is utilised to quantify the penetration rate for AVs according to Scenario "0" (the present time scenario) and Scenario "A" (futuristic heterogeneous traffic stream scenario after 15 years) as well as for the sensitivity analysis in the form of maximum bounds. The considered area is divided into four zones whereas the population is categorized into four groups (15–24, 25–44, 45–64 and > 65 years of age). For synthesizing social inclusion and opportunity indices the activities set AT is defined with six activities, namely work, shopping, leisure, recreational, health and education.

To attain the first objective of this research, in Scenario "0", all seven indices are calculated based on extracted data for the year 2022 and subsequently considered as a base scenario with no AVs available to the general public. The values for the different indices are shown in Table 2. For Scenario "A", the related growth rates are utilised to predict the socio-economic, demographical, trips and transportation infrastructural conditions in fifteen years to be used in calculating all the indices. The growth rates are extracted based on the analysis of the projections

Table 2 Penetration rate according to calculated indices

Index	Scenario 0	Scenario A
PLU	12.55	50.28
DT	47.83	64.86
IU	14.48	38.03
MC	29.60	49.60
TB	5.72	34.93
AAI	15.89	21.725
MI	76.44	48.83
QPR	158.59	232.72

of land usage and user demographics for the period of 2020–2040 presented by ISTAT. For the indicator classes of the road network, the relative growth rates are calculated based on past 15-year trends for included indicators as mentioned in Fig. 1. The growth rate for maintenance cost, population size, land unit rentals household size, household income, age group, transportation expenditure and travel time are computed (they are 19.41%, -1.4%, 6.23%, 3.13%, 10.47%, 9.23%, 3.14% and 4% respectively). It must be noted that the growth rates for household size and age group are computed according to the division of age groups mentioned earlier. These new values are then used to quantify the penetration rate of AVs in fifteen years keeping in view the base year penetration rate is zero. Table 2 shows the values for indices and quantified index values for both scenarios. It must be noted that the quantified index as in (1) is not a simple summation of all the indices instead its value is based on the weights given to each of the seven indices through regression. The highest weights are given to the mobility index and activity accessibility index (they are 1.2 and 1.5, respectively), under the proposition of usage of AVs by the group of society who were previously unable to mobilise themselves on their own. From the fractiles approach discussed in Sect. 2.1, the penetration rate in Scenario "A" results at 35%, following the values reported in Table 2.

4.1 Sensitivity Analysis for a penetration rate

To identify the model uncertainties one of the best tools is sensitivity analysis. To keep things simple we assume the profit of land usage and infrastructure usage is kept constant over the analysis period. Whereas, all other 5 indices are tested over the range of values to evaluate the impact of their variation on the QPR_{AV} and consequently on the final penetration rate of AVs. Considering the trends of growth for the involved indicators the maximum possible bounds of each of the indices is tested to see the effect on penetration rate thus giving us a range of penetration rate instead of a single value.

In terms of density of transportation (DT), the QPR_{AV} is computed for a range of 20–26% for the road network of the considered area. All things kept constant this index has a moderate impact on the quantified penetration rate for its maximum possible bounds. For the mobility condition index (MC), the model is tested for the bounds from 18 to 40% however the variation in QPR_{AV} is a mere 6%. In the case of the transportation budget index (TB), activity accessibility index (AAI) and mobility index (MI) the change in QPR_{AV} is 4%, 4% and 13% respectively for the sensitivity bounds of 16–83%, 23–55% and 36–47%. However, the collective change for all the indices has an appreciable variation in the value of QPR_{AV} that is up to 29% for all the sensitivity bounds included as shown in Table 3. Now considering the fractiles approach as discussed in Sect. 2.1, the penetration rate according to the sensitivity analysis gives us a range from 25 to 35% following the values reported in Table 3. This range is incorporated in further fundamental relationships for explicitly revealing the impacts of AVs on the traffic network fundamentals.

4.2 Results and discussion

After the quantification process of AVs, this penetration rate range (25–35%) is used as a percentage of AVs on an urban road network to generate a heterogeneous traffic stream. For the generation and initial accuracy testing of fundamental relationships, a representative link is used from the network. After which the derived fundamental relationships are applied to the small network consisting of 100 links as shown in Fig. 3. To represent the prevailing traffic conditions in both scenarios, a speed-density relationship is obtained using (5) as shown in Fig. 4b revealing the decrement in traffic stream speeds as the density is increased. Eventually, traffic will reach a block flow situation at jam density when the speed reaches zero. However, for the same densities of traffic on the network, the heterogeneous stream is showing a range of higher speeds (area between the blue and green curves)

Table 3 Sensitivity analysis results on the penetration rate of AVs

Index	Scenario 0	Scenario A	MI	AAI	TB	DT	MC	All
PLU	12.55	50.28	50.28	50.28	50.28	50.28	50.28	50.28
DT	47.83	64.86	64.86	64.86	64.86	51.42	64.86	51.42
IU	14.48	38.03	38.03	38.03	38.03	38.03	38.03	38.03
MC	29.60	49.60	49.60	49.60	49.60	49.60	58.72	58.72
TB	5.72	34.93	34.93	34.93	29.1	34.93	34.93	29.1
AAI	15.89	21.725	21.725	18.12	21.725	21.725	21.725	18.12
MI	76.44	48.83	26.32	48.83	48.83	48.83	48.83	26.32
QPR	158.59	232.72	202.67	224.27	223.85	216.24	220.56	168.87
p(%)	25	35	30	35	35	35	35	25

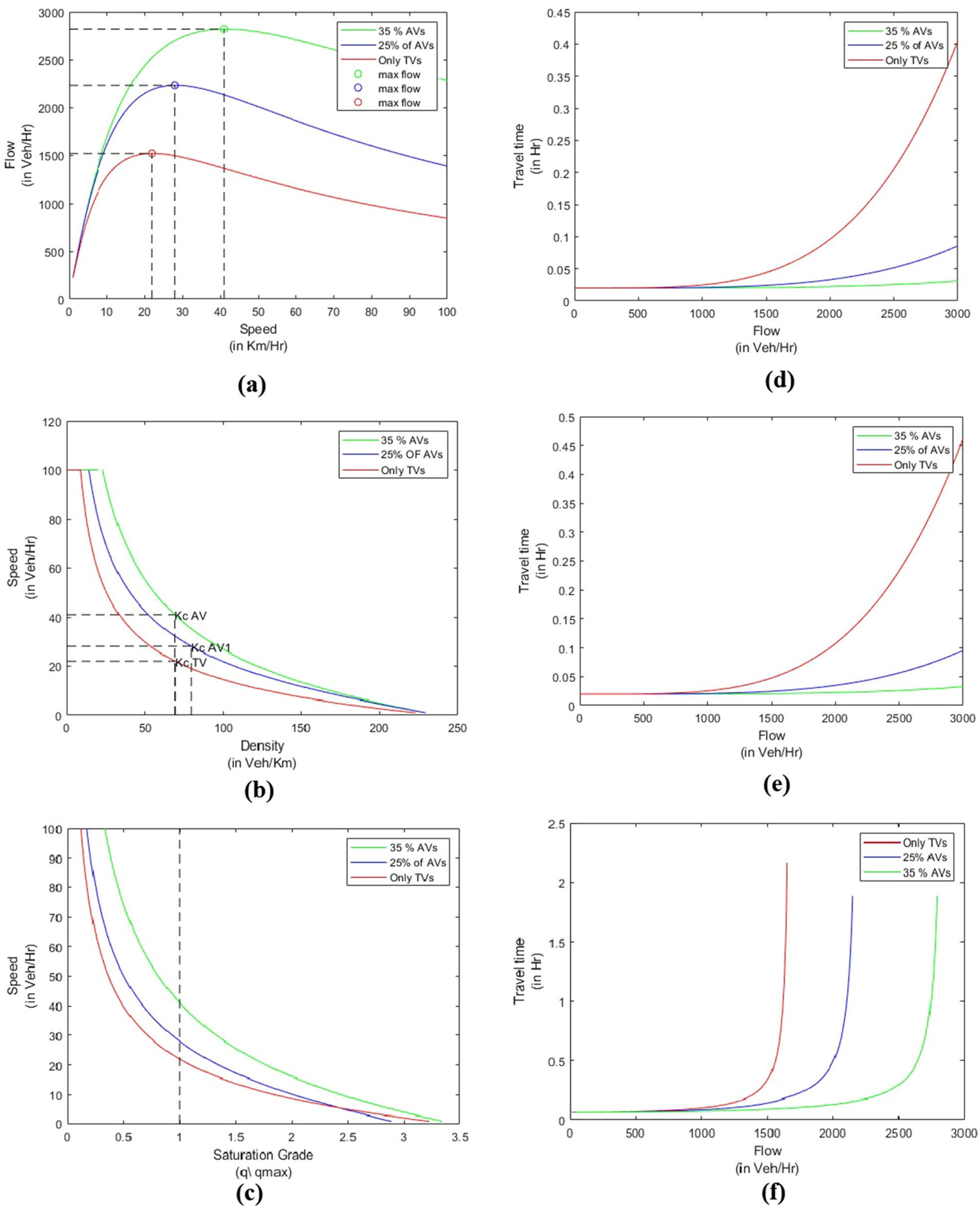

Fig. 4 **a** Speed-flow relationship for Scenario 0 and scenario A under sensitivity range of AVs; **b** Speed-Density relationship for Scenario 0 and scenario A along with critical densities under sensitivity range of AVs; **c** decrement in vehicle speed with respect to Saturation grade; **d** Travel-time flow relationship with a link having physical median and no influence of opposite direction flow under sensitivity range of AVs; **e** Travel-time flow relationship without a link having physical median and influence of opposite direction flow under sensitivity range of AVs; **f** Travel-time flow relationship with physical and functional characteristics of links affecting travel time under sensitivity range of AVs

as compared to the only TVs scenario that's where the effective time to hurdle in the case of AVs comes into play. The corresponding range of capacity of an urban road network is calculated from the speed-flow relationship from (6) as shown in Fig. 4a. It is evident that in a heterogeneous traffic stream, the capacity of the network increases efficiently with most of the parts yielding un-saturated traffic conditions in range areas of blue and green curves. Gains in flow rate are significant as long as the traffic state is un-saturated i.e. before the critical density is reached in both scenarios. It would be prudent to obtain the traffic stream conditions with higher flows by increasing the free-flow speed however, the traffic stream will be more saturated and unstable. Also, the urban link congestion can be dealt with by keeping the topology intact and making it a heterogeneous stream with the inclusion of the desired percentage of AVs remaining under acceptable and realistic limits. Albeit safety and driving behaviour will be the question that is out of the scope of this research. The trend of saturation grade is also shown in Fig. 4c which is again yielding higher speeds of the stream for the same saturation level as compared to the only TVs traffic stream against the critical densities obtained. Although the trend for saturation grade at a lower penetration range of 25% is quite closer to the TVs scenario yet giving an improvement in the speed at which saturation achieves.

The travel-time flow relationships are plotted in Fig. 4d–f following the defined equations in Sect. 3.1 using (7), (8) and (9). It is clear from Fig. 4d, e that opposite-direction flow has an impact on the travel times of an urban link. The increase in travel time is in the range of 7–10% if no physical median is present between opposite links as seen in the area between blue and green curves which are common in urban street networks of the considered realistic network of Genoa. It is important to mention that 60% of the links in our considered network were consisting of a physical median between opposite directions.

Moreover, to attain the stated objective, the travel-time flow relationship is plotted as shown in Fig. 4f by using (9) with the influence of the network's physical and functional characteristics. The increase in capacity of an urban network as deduced from the speed-flow relationship in Fig. 4a by introducing AVs has an appreciable impact on travel times as can be seen in Fig. 4f. The large area between the two penetration curves is revealing the fact of improved traffic conditions with the inclusion of AVs. In the considered network, useful road link width and the percentage of links occupied by parallel parking had a direct impact on the flow relationship. With an increment in parallel parking and decrement in useful road length, the travel time increased for both TVs and AVs. However, the increment was higher in TVs as compared to the heterogenous stream with AVs. Given the topography of the considered area tortuosity and the non-negative slope were very less except for the southern part of Corso Italia, thus not affecting the results as much. Whereas the pavement type was the same for all the roads in our considered network. Another factor affecting the travel time and flow characteristics was the number of uncontrolled pedestrian crossings and side entries which again was mainly inducing an impact on the southern part of the considered area on Corso Italia.

5 Conclusions

In this research, a simplified yet effective methodology is provided to fill the gaps in the existing literature on urban networks' capacity in heterogeneous traffic streams as explained in Sect. 1. Concerning our three objectives (quantification of the penetration for AVs, formulation of macroscopic fundamental diagram with quantified penetration and impacts of physical and functional characteristics of urban road link on travel time flow relationship), this research attempts to seek the answer of the defined research question. For quantification of penetration rate, a multiple indices system was used to synthesize seven different indices using socio-economic and demographical characteristics. Using a quantile approach, the realistic value of AVs is used as an input for the formulation of fundamental relationships to produce MFDs. Speed density and speed functions are formalized following a constant safety policy for AVs. These are dependent on reaction time and deceleration rate for the two categories of vehicles in the traffic stream. An increment in the capacity of an urban road network is used to evaluate the effect of AVs on travel-time flow relationship in three different scenarios, network links with physical median, without physical median and with the effect of physical and functional characteristics.

Results show that keeping the present year as a base scenario with no AVs being used by the public there could be almost 25% to 35% of these vehicles using the road networks in the coming fifteen years based on vehicle ownership and readiness to buy a new vehicle. The QPR_{AV} value for the devised indicators comes out to be approximately 158 which corresponds to 25% of the penetration rate of AVs in the current scenario (scenario 0) theoretically however the current value of these vehicles is not up to 25% but less than that. Since many vehicle manufacturers are providing Level 1 and 2 automation capabilities (vehicles with ACC, steering assistance, vehicles with ADAS, lane keeping assistant etc.) in their high-class vehicles and are available to the general public. However, their exact amount of usage for validating the theoretically calculated amount is quite tricky to obtain from the concerned Vehicle Registration department which is also one of the limitations of this study. Albeit, this limitation is tried to get over by using a dynamic weighted average for the two defined classes of AVs i.e. AV_1 and AV_2 as described in Sect. 3 that different weights have been used in the computation of the dynamic weighted average of reaction time by further dividing the 15 years timeline into two parts (10 years + 5 years). Thus the improvements being reported are not exact 25% to 35% of fully automated vehicles but a mixture of the two classes.

This increment in usage of AVs generates a heterogenous traffic stream increasing the capacity of an urban network by 35% to 59% as compared to the only TVs scenario. However, any induced demand to occupy that capacity will reduce the critical speed but prolong the un-saturated condition of the network. As can be seen from saturation grade in heterogeneous stream vehicles are moving with higher critical speed. This increment in capacity has a positive impact on the travel time of vehicles where the travel time to cover the urban road network is reduced in presence of a heterogeneous traffic stream.

Although this research has appreciable findings it is limited in terms of user choices of movement and mode and also for signal controls. This can be an effective way forward together by analysing a full network to see how the capacity of the whole network is affected. Moreover, data from user adaptation surveys can be incorporated to quantify the penetration rate in a more synchronized manner.

List of symbols

$RE_{L,t}$	Rent of a land unit
$res_{L,t}$	Number of residents living in a household
$MT_{L,t}$	Maintenance cost of the land unit
DRL_z	The density of road links
DP_z	Population density
$gc_{t,h}$	Generalised user transportation cost
x_{z_1,z_2}	Shortest distance to an activity
noa_{at_1,z_2}	Number of possible opportunities
ATT_{g_1,at_1}	Average daily travel time
ATT_{tot,at_1}	Average daily travel time of the population
a_d	Deceleration rate
$\omega_{N,S}$,	The ratio of car-free streets
ΔVMT_{15}	Vehicle miles travelled
ΔTCA_{15}	Transportation infrastructure provision
es_h	Expense on the transport of a household
ins_h	Total income of a household
ω_{at_1}	Weight of type of activity
ω_g	Weight of age group
RTT_r	Route travel time
L_r	Route length
t_{rt}	Reaction time
d_{mix}	The density of the traffic stream

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Declarations

Competing interests
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