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Analysing inequity in land use and transportation models by genetic algorithm for realistically quantified penetration rate of Advanced Driving System Equipped Vehicles

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A R T I C L E I N F O

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A B S T R A C T

The continued evolutions in automated driving technologies and their rapid testing on common roads make it necessary to evaluate their impacts on land use and transportation models. It is crucial to quantify the number of advanced driving system-equipped vehicles that are going to be part of transportation networks. On the other hand, the intuitive property of these vehicles to create an induced demand can bring both positive and negative effects on the travel equilibrium costs that create inequity. To cater for the gap of realistic quantification of penetration rate and inequity evaluation on the inclusion of such vehicles; this research crafts a detailed and effective methodology. This research formulates a convex minimization problem as a lower-level part of the bi-level optimization model intending to minimize the travel equilibrium cost for all OD pairs. Also, acts as an assignment of demand to the network following the stochastic user equilibrium approach by using the Frank–Wolfe algorithm. Whereas, the upper level of the model maximizes the production of newly generated demand incorporating inequity constraints. A genetic algorithm is used to solve the multi-objective fitness function yielded from the bi-level optimization model by application of the model on a real transportation network of the city of Genoa, Italy.

1. Introduction

The concept of a person driving behind the steering was always accompanied by a vision of a car bringing its passengers to their destinations without a driver controlling the vehicle. However, the accomplishment of this vision continually remained somewhat 20 years away from becoming a reality (Wetmore, 2003). Self-driving vehicles played a vital role in visualizations of technology albeit their translation into reality largely remained pictorial until recent times.

The technological boom in the vehicle industry arose with the invention of advanced driving system-equipped vehicles (AVs) in the late 1920s (Kröger, 2016). From the first driverless car tested on McCook airforce base in Ohio, USA to the American Wonder on Broadway, New York, technically these vehicles were remote-controlled but theoretically driverless self-driving wonders (Kröger, 2016). From the period when they were called phantom auto (Sentinel, 1926) or robot cars (o, 1936) up to recent times with the development of fully automated vehicles and connected automated vehicles (CAVs), their prototypes are being tested on common roads. The latest example of which is a 22-mile long network of urban streets augmented for the self-driven vehicles testing in Turin, Italy (Car and Driver, 2019). These test runs attested to the replacement of traditional vehicles (TVs) whether they are privately or commercially owned. Furthermore, through test runs, it is revealed that introducing AVs into the system generates an evolutionary change in vehicle usage norms while at the same time impacting the transportation systems.

Given the law of physics, any new addition to the existing system shifts its equilibrium. Similarly, this new form of self-driven form of mobility raised a question of changes in transportation system equilibrium including all different classes of these type of vehicles as explained in J3016 Information Report (SAE, 2014). Albeit, it is also a fact that a complete transition and 100% shift from the TVs to AVs could take many years or a couple of decades to be true and massively reliant on huge investments from the tech giants for developing full-proof technology (Trivedi, 2018). Such a level of technological advancement makes it necessary to get done a thorough evaluation of functionalities and impacts on the user, society, and overall system. There are uncertainties associated with the large-scale inclusion and impacts of AVs, yet the ambiguities remain there unless we try to cope with them. Root-level planning is required for the people by the inclusion of people and their social dynamics. The approach taken in this study consists of more

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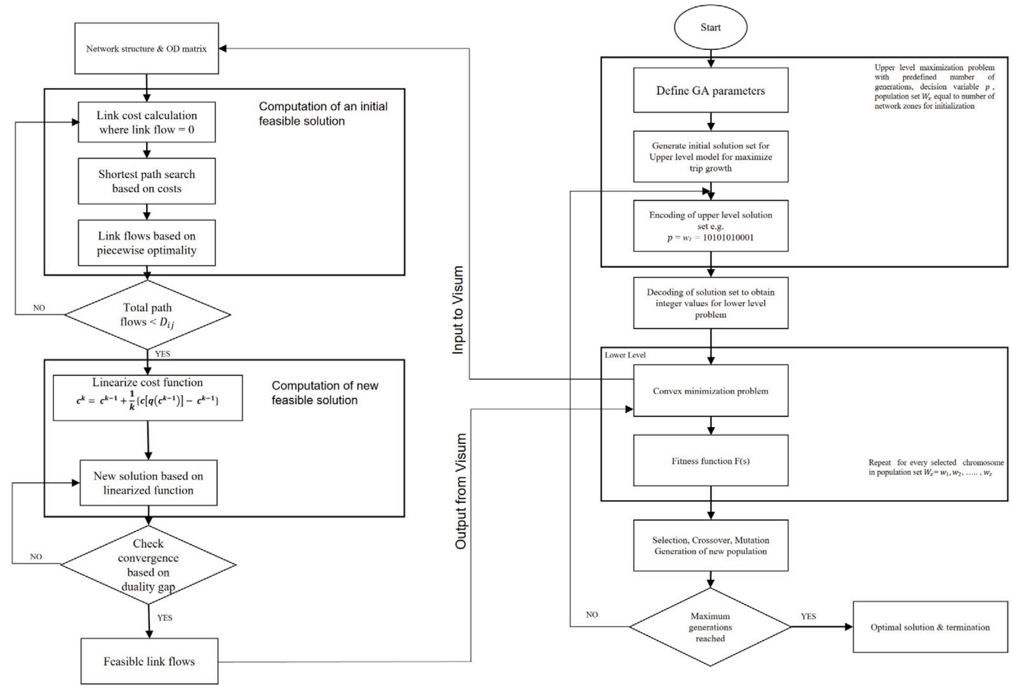
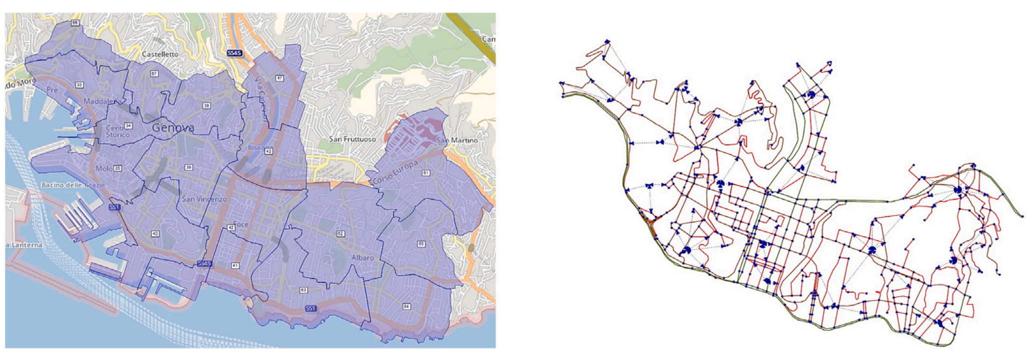


Fig. 1. Methodological framework visualization.



(a) (b)

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

than twenty social-demographic indicators representing the dynamics in social, demographic, urban, and commuter fabric. Limited to no research has been done to quantify the presence of AVs which creates uncertainty when we try to effectuate their effectiveness. This means that short as well as long-term changes that this technology is about to cast on society remain a question.

2. State of the art

From this perspective, various researchers penned down the impacts on travel and mode choices, travel behaviour, traffic patterns, environmental effects and road safety.

2.1. Environmental and land use impacts

Silva highlighted the fact that most of the scientific community is attended with revealing the environmental impacts of AVs mainly focused on evaluating energy consumption and reduction or increase in the emission levels (Silva et al., 2022). They concluded that for supporting long-term decision-making in line with sustainable urban development, more realistic and overall analyses are required. To skim out and analyse the positive and negative effects, inclusive examination for realistic and whole transport systems on the inclusion of AVs would be beneficial. Rafael in his detailed study revealed the potential gains in terms of air quality from the sequential introduction of AVs from 10% to 100% into urban transportation networks (Rafael et al., 2022). This study achieves the objective through a numerical modelling method incorporating a microscopic traffic model, a total emissions model, and an air quality assessment model. The methodology is applied to two corridors from two distinct cities of Portugal (Aveiro & Porto) having different structural and urban surrounding characteristics. The study concludes with an inverse correlation between the penetration rate of AVs and air quality benefits. High penetration of AVs decreases NO_x emissions. However, the spatial analysis of air quality shows that NO_x concentrations fall up to 69.8% for a fully automated scenario in Aveiro whereas less than 2% for the same scenario in Porto. This draws the attention of researchers to the importance of urban design, road structural characteristics, and wind directions in air quality benefits from the inclusion of AVs. Although the study evaluates some impacts on traffic performance and capacity levels too but is limited in casting a complete picture with a spatially larger traffic network. The variability in results for instance in the scenario of Porto where the queue length is decreasing but at the same time speed is also decreasing for all AVs penetration is something contrasting which reveals the importance of considering the social, user, and demographical aspects while including AVs into the network instead of introducing them sequentially keeping every other driving factor constant.

2.2. Traffic network performance and capacity impacts

As per Kockelman, a system of shared AVs reduces 10 times the number of vehicles to serve the existing travel demand as well as appreciable emission savings but suffers 11% more empty vehicle kilometres travel (VKT) to reach the next passenger (Fagnant and Kockelman, 2014). Effective roadway capacity increased three times with 100% deployment of AVs on the roads consequently incurring travel time savings (Kim et al., 2015), while Zhao and Kockelman (2018) suggests that increasing the induction of AVs with more travellers opting them over TVs and public transport will result in a 10% increase in VKT with consequent congestion and almost 3% drop in average speed. Nevertheless, Correia and van Arem (2016) concludes after solving a traffic assignment and vehicle routing problem for user optimum scenario of privately owned AVs that this new form of intelligent vehicles can serve more trips as compared to TVs while causing only a little increase in congestion regardless of extra VKT. They also concluded that if in conjunction with this technology, the user perceives a lower value of travel time this can further serve even more trips without any cost of congestion.

On the other hand, Liu revealed the increase in road capacity up from 2000 veh/h at 0% AVs to 3070 veh/h by replacing all the TVs with AVs in a transportation network that is with 100% of the penetration rate of AVs (Liu et al., 2017). Similarly, an increment of 46% in the free flow speed from 78.85 km/h to 115.20 km/h, whereas improving the critical density slightly shows the property of AVs to make the entire traffic flow stable. However, Mena-Oreja et al. (2018) shows that large safe gaps in the platoon of mixed vehicle streams reduce the impacts of AVs in the traffic. In over conservative scenario even with a 100% penetration rate of AVs the traffic flow only increases to 9.39% as compared to the scenario with no AVs in the traffic stream, whereas for aggressive and neutral gap configuration the flow increases up to 39.21% and 26.09% respectively (Liu et al., 2017). Stern in a thorough real-life experiment with a circular mixed traffic stream of AVs and TVs, claims the augmented capacity of a mixed traffic stream for a penetration rate as low as 5% of intelligently controlled AVs (Stern et al., 2018). Overall, Stern shows that deviation of velocity between vehicles in a mixed stream is reduced up to 80% and braking events from 9 events/veh/km decreased to 2.5 events/veh/km. Friedrich after macroscopic traffic flow analysis involving AVs shows a significant increase in capacity leading to the efficient use of transport infrastructure, reduction of traffic loss time and jams due to shortening of headways and higher speed at constant density in presence of AVs (Friedrich, 2016). However, Schmitz came up with a different conclusion stating that the capacity increases and the urban congestion reduce drastically in a setting of 100% AVs but a mix of TVs and AVs on the contrary reduces the capacity of an urban traffic system (Schmitz and von Trotha, 2018). They discovered that in a mixed traffic stream scenario with a 50% penetration rate of AVs, the traffic capacity decreases up to 16.3% as compared to the current capacity. This volatility in conclusions from the literature creates room for questions and still, the answers are uncertain.

Maxime explored the impacts of connected automated vehicles in a microscopic simulation environment (Maxime et al., 2018). The study analyses the impacts of various penetration rates of CAVs into the system on traffic efficiency (mean speed, mean flow, congestion, mean headway, average speed), traffic safety (time to collision, relative speed, lane change rate), and environmental sustainability. The study effectively concludes a positive impact on traffic stability with improvement in flow, speed, congestion levels, service levels, and safety. Yet the absence of application of the assessment methodology on a real-world road network is its limitation. Moreover, as the study is a part of a huge pilot project involving the assessment of the impacts of CAVs under varying penetration rates it misses out on the impacts on society as well. The present study deals with this gap by macroscopically analysing the major societal impact in terms of inequity considering numerous social indicators in devising the input of penetration rate of AVs into the system thus reflecting the most important component of the system i.e. Users. Also, Pedro analysed the effects of various combos of automated shared as well as connected vehicles at the regional scale (Pedro et al., 2021). Particularly revealing the impacts on energy efficiency, environmental (air) quality, traffic performance and emissions. The study forecasts the impacts for the year 2030 by implementing the macroscopic modelling methodology on a motorway corridor between two cities. The occupancy, as well as trip frequency values, were assumed to be coherent for the entire region. The research reveals that CAVs can pose negative consequences on emissions if only improvement in traffic efficiency is kept in mind as an inclusion objective. However, social and land usage impacts have not been studied whereas they recommended incorporating demographic and land usage factors to be included to design the demand scenarios having automated driving.

Narayan reviewed and summarized the state-of-the-art literature on the consequences of CAVs and AVs on road network capacity, traffic flow stability and safety, travel time, congestion, changes in VKT and policy recommendations for the inclusion of this new form of mobility (Narayanan et al., 2020). According to him, one of the key constraints in current literature recounts the factors and assumptions being used in the modelling studies analysing the impacts of AVs on transportation networks, users and society. Although testing of this new form of mobility is at pace; studies except (Martin-Gasulla et al., 2019) do not often take into account the real-world parameters and factors affecting the inclusion of AVs on transportation networks. Gasulla uses realistic network parameters to evaluate the impacts of AVs on traffic flow parameters using a microsimulation analysis of a simplified four-leg intersection. But do not consider any realistic parameters for the inclusion of AVs thus calculating the impacts on various penetration rates from 0%–100%. Studies (Ye et al., 2018; Zheng et al., 2019; Sagir and Ukkusuri, 2018; Anis and Csiszár, 2019; Janzen et al., 2018; Hairuo et al., 2019) used various penetration rates (either incremental values from 0%–100% or fixed values of moderate to high 0.7–1.0) to evaluate the effects of AVs in various simulative environments and effectively described the possible implications. Yet the variability in conclusions draws our attention to the limitations of studies in terms of quantification of the realistic penetration rate of AVs.

This brings us to the first objective of our research to define a methodology that extensively and realistically quantifies the penetration rate of AVs to be used in modelling and analysing traffic flow characteristics. The quantification is based on three major classes: user demographics, road network and land use that will be responsible for the adoption and consequently get influenced by the impacts of AVs. For the consistent and reliable evaluation of extracted data, different researchers (Frei, 2006; Bergström and Magnusson, 2003; Hensher et al., 2003; Ortúzar et al., 2000; Keegan and O'Mahony, 2003) used a system of indicators for evaluating the quality of services, social equity improvement, transport network assessment for pedestrian mobility, temporal and spatial comparisons. Here we grouped various indicators into already mentioned three major classes to quantify the penetration rate of AVs for the city of Genoa, Italy in the first part of our research.

2.3. Land use and equity impacts

In a scenario of a heterogenous traffic stream with TVs and AVs, the interactions on a transportation network for studying mobility patterns in polycentric urban dwellings need a comprehensive analysis of user demographics, road network characteristics and land usage. Henceforth, following realistic quantification of the penetration rate of AVs, it appears lucrative to highlight and investigate the impacts of AVs in terms of land use and transportation interaction (LUTI) for effective planning of future transportation networks. Although effective studies of spatial interactions date back to 1931 albeit the articulation of urban-dwelling models for land use and transportation interactions came into existence in the early 1950s and 1960s (Wilson, 1998). Theoretical advancements in the field of land use and transportation interaction models are comprehensively penned down by Wilson (1998). Going through the land use and transportation interaction patterns, it is observed that they are dependent on each other in a cyclic pattern. The interaction patterns are most probable and consistent with the state of the intensity of transportation services availability and land usage pattern (Wilson, 1998). Since the start of urbanization, the location of the population remained dependent on the location of their workplaces, then with the era of powered mobility, the urban population started to expand alongside the major roads, tram lines etc. (Cordera et al., 2017). In turn, land use and settlement decisions contributed towards trip generation with the continued increase resulting in congestion and consequent high trip costs.

However, some of the research (Erlander, 1977; Fisk, 1979) proved that incremental trips do not necessarily become a reason for high trip costs for all the paths in the network. Fisk showed via extensive sensitivity analysis of travel costs in Wardrop's equilibrium problem that both origin to destination and overall travel cost can be decreased for an increasing input flow but not necessarily for the same OD pair (Fisk, 1979). In such a case, the travel cost for the same network does not remain equitable for all the network users. For evaluating the amount of inequity resultant from the higher inflows in the network there have been many examinations (Meng and Yang, 2002; Rodier et al., 2010; Bills, 2013) in continuous network design problems for LUTI. Meng analysed equity after the network design project for different OD pairs of the network via continuous network design problem by implementing it on the Sioux Falls network (Meng and Yang, 2002). Rodier investigated the equity issue for different transport and land usage policies on travel time and travel costs using advanced aggregate travel models and activity-based models (Rodier et al., 2010). Bills used a regional activity-based travel model for transportation equity analysis involving distributional comparisons of individual-level equity indicators and societal scenario-based equity analysis (Bills, 2013). Similarly, Litman (2020) and Van Dort et al. (2019) detailed the disparities and unfair distributional gains of transportation systems, services and policies collectively impacting the part of communities. Not only this but providing methods for determining the inequity for various transportation enhancements. After an extensive review of current literature on AVs, Kassens-Noor et al. (2020) astoundingly identified the gaps in research on the social impacts of AVs and concluded that the challenges are being overlooked. Although there have been several interesting equity analysis on the inclusion of AVs yet the gaps in literature remains there. Dianin performed an extensive literature review of AVs impacts in terms of transport equity and accessibility (Dianin et al., 2021). Several key points were raised in this study related to the key assumptions concerning AVs. For instance, numerous studies completely overlook ownership-based mobility to the spread of ride-sharing deployment of AVs. However, the occupancy rate in the regions (specifically Europe and USA) shows contrasting results revealing that users are still more inclined towards ownership of the vehicle for their mobility needs. For example, Eppenberger developed a three-step model to showcase a relationship between accessibility and social well-being by deploying AVs as shared vehicles complementing public transport in central city districts while replacing car trips (Eppenberger and Richter, 2021). They developed a multiple linear regression model to evaluate the dependency of accessibility on social well-being indicators (yearly income, unemployment rate, educational attainment) in presence of shared AVs. Confirming that higher educational attainment is the best-performing indicator for enhanced accessibility. However, the possibility of attaining such objectives is dependent if the transportation means are operated by a single entity or highly regulated if shared services are privately owned. Instead of looking at AVs always as a ride-sharing, ride-sourcing non-owned vehicle we need to spread the research paradigm.

Also, Dianin et al. (2021) suggest including a wider range of social, spatial and regulative indicators while analysing impacts. A broader matrix of indicators is useful for social equity analysis that could not only encompass social groups but their preferences, economic conditions and living habits too. In this view, Cohn et al. (2019) used 8 scenarios with existing and future baseline conditions using the two sample t-tests method. They assessed the impacts of AVs against several performance measures including employment accessibility, trip time and distance, and mode share. They used three regional classes of indicators namely land use (households, population, population density, employment, employment density), income (slots ranging from <$50,000–>$150,000), and vehicle ownership (ranging from 0–3+). The results show that in most of the scenario combinations inclusion of AVs enhances job accessibility, and reduces the trip duration but increases the vehicle miles and distance travelled. Albeit the study is limited in terms of intra-household decisions based on the number of income earners and vehicle ownerships. The study assumes that all household owns a vehicle thus reflecting 100% deployment of AVs in all the scenarios. Moreover, it does not include any auto operating costs and willingness to upgrade or own an AV.

In a recent study (Emory et al., 2022), various policy practices from different countries are studied and characterized into classes of access and inclusion, community well-being, and multi-modal transportation. In contrast to the claim of Dianin et al. (2021) here Emory et al. (2022) urges policymakers to strap AVs to shared mobility programs to curb the increasing travel distances and emissions. Moreover, encourages responsible to consider income disparities among various households to generate a more wholesome equity policy for these low-income groups are stand to lose the most if overlooked in planning equitable developments. Likewise, invite researchers to do future work in terms of ownership models specifically considering the low-density communities for dealing with the high potential of empty vehicle trips on the inclusion of shared AVs. Another evidence of inclusion AVs into real transportation systems creating heterogeneous traffic streams for equity analysis is Bilal and Giglio (2021) that involves the analysis of an example network with independent penetration rate of AVs.

The present research study here contributes to some of the gaps identified in the literature. For instance, this research study is based on a private ownership model of an AV that serves the concern raised by Dianin et al. (2021) given the faint increase in the occupancy rate of vehicles for the past 25 years in Europe. Another point (Dianin et al., 2021) raised about the inclusion of a wider range of social, and spatial indicators is answered through this research by forming three class matrices for quantifying the penetration rate of AVs. Thus considering social, demographical and land use factors which not only incorporate economic factors of households but also the living and trip habits of intra-household mobility covering the limitation of Cohn et al. (2019) and Eppenberger and Richter (2021). Lastly, dealing with the overlooking factor of income disparity in policies and low dense communities as explained by Emory et al. (2022), the inclusion of a multiple indicator system for the calculation of the penetration rate of AVs, this study to some extent reflects the presence of such underserved areas mainly through land-owner profit, household transportation budget index and social inclusion index. That gives us the second objective of this research to extensively perform an inequity analysis on a real transportation network for the city of Genoa, Italy on the inclusion of AVs.

In summary, this research is first of its kind effort to fill two major gaps in the literature by first quantifying the realistic penetration rate of AVs and secondly introducing this state-of-the-art mobility form into the network using the realistic penetration rate, carrying out the inequity analysis on a real transportation network. The goal of this research is to identify the factors converted into indices for the inclusion of AVs into the network and to analyse the resultant change or imbalance in travel equilibrium costs. For the travel equilibrium cost analysis to determine the inequity, the Equilibrium Trip Distribution/Assignment with Variable Destination Costs (ETDA-VDC) model from Oppenheim (1995) is used. The flexibility of ETDA-VDC to allow the inclusion of various measures of attractiveness for the destination zones depicts the potential trip generation from certain zones. This property allows to inclusion of AVs as an opportunity and an enhancement of travel options in already present traffic streams. Thus reflecting the traveller's choices and giving a solution to the convex minimization transportation problem at the same time incorporating the inequity bounds. A bi-level optimization model is used to attain the objective of this research in which the lower-level assigns the travel demand to the network following the stochastic user equilibrium (SUE) approach whereas the upper level maximizes the trip generation based on quantified penetration rate, inequity constraints and physical constraints of the origin and attraction zones.

The paper is structured as follows: Section 3 describes the model setting involving main assumptions, network representation, quantification of penetration rate and convex minimization problem formulation; Section 4 presents the bi-level optimization model for the defined problem followed by genetic algorithm solution approach, in Section 5 a real network model implication is presented; finally, concluding remarks are reported in Section 6.

3. Model setting

In this section, the main assumptions, notations and definitions of the involved constants related to the model settings are presented. Moreover, realistic quantification of the penetration rate is done in this section followed by the assignment algorithm to solve the convex minimization problem. It is assumed that:

1. a macroscopic model is considered for two different classes of privately owned vehicles i.e. TVs and AVs. Initial OD demand is fixed and remains stable.
2. incremental trips generation is following the quantified penetration rate while keeping the already present demand intact.
3. the network is considered to be congested with an assignment to the network based on the stochastic user equilibrium (SUE) principle.
4. given already stored algorithms for path choice in AVs, the choice processes are assumed to be deterministic; whereas for TVs path choice is done via logit model with the least variance parameter.
5. no inter-period dynamics are considered, as steady-state conditions with only one transport mode is deemed.

In the case of socio-economic and demographical properties, fixed maintenance and rental costs based on the number of residents are considered with a single city centre having services accumulated in selected zones as in the case of many European countries' cities e.g. Krakow, Genoa, Timisoara. A visual illustration of the methodological framework is presented in Fig. 1.

3.1. Network structure

In the context of the considered scenario under the abovementioned assumptions, the traffic network is represented by a synchronic graph of nodes N and directed links L; $G = \{N, L\}$. Let $P \in Z$ and $Q \in Z$ be the set of origin and the set of destinations, respectively, for the considered network where Z is the set for all zones consisting of all the origin–destination pairs. All the links are connected by a set of paths R for all origin–destination pairs. $R_{pq} \subset R$ is the subset of all the paths connecting origin $p \in P$ to destination $q \in Q$. Moreover, an incidence matrix I is set up with all probable paths connecting any generalized origin–destination pair (pq). Each link $l \in L$ weighs depending on flow-based travel cost $c_l(q_l)$ where q_l is link flow. Deviation in flows on all the links is affecting the travel cost of a generalized link. c_l is assumed to be monotonically continuous and directly proportional to q_l. As assumed, initial OD demand is fixed and remains stable denoted as m_{pq} and distributed over the network following the SUE principle. Newly generated trips/demand m^{n}_{pq} follow the path choice process of the logit model among various destinations independent from the irrelevant alternatives. This makes the attraction cost c_q an increasing function i.e. $c_q = c_j(m^{\mathrm{n}}_{pq})$.with the increment of flow under newly generated demand.

Parameters for the quantification are defined for routes set S, activities set AC, age groups set AG and households set H. Keeping in view the proposed enhancement for AVs, ceteris paribus, a quantification equation (QE_{AV}) is defined by aggregating various parameters from three classes: user demographics, road network and land use, to generate seven indices. These indices together result in the penetration rate (PR_z) of AVs to be used in the formulated model.

Notations	
$DLP_{u,t}$	Discounted land owner profit for the land u in time t with inflation i.
$LR_{u,t}$	Rent of the land u in a time t.
$MC_{u,t}$	Maintenance cost of the land u in a time t.
$NOR_{u,t}$	Number of residents lived in land u over time t.
h_s	Household size.
RL_z	The total length of roads in a zone z.
PS_z	The total population in the zone z.
$L_{r,prt}$	Length of route r from the route set RS using a private vehicle .
$e_{tr,h}$	Total household income expenditure for transport in a month.
I_h	Total household monthly income.
B_{prt}	Binary index for private vehicle ownership. if a household owns a car it is 1 otherwise 0
$dc_{t,h}$	User discounted generalized cost for a time period t in each household h from set H for inflation i.
α_{z_2,ac_1}	Number of opportunities for activity ac_1 from set AC in z_2 from set Z.
β_{z_2}	Binary index. 1, If an opportunity to carry out an activity is available in zone z_2 or 0 otherwise.
NTR_{g,ac_1}	Number of trips by the special group g from AG for an activity ac_1 from AC
NTR_{tot,ac_1}	Total number of trips by all population of the respective zone for an activity ac_1 from AC
$AT_{\mathrm{prt},r}$	Average travel time on route r using private transport.
ΔVKT_5	Relative growth of vehicle kilometers travelled over 5 years.
ΔGTI_5	Relative growth of the total covered area by transportation infrastructure for over 5 years
ω_{NMS}	Weight for the provision of non-motorized streets such as car-free zones and streets.
ω_{SF}	Weight for the number of services in the zone such as work, leisure, education.
ω_{R}	Reliability factor
OD	Origin - Demand
GA	Genetic Algorithm

3.2. Quantification

The first part of our research objective as defined earlier is to obtain a realistic value of the penetration rate of AVs as an input to the traffic analysis model. Depending upon land usage, socio-demographical and road network classes, indicators are grouped and seven different indices equations are skimmed. These indices relate to the adaptation of AVs in a systematic and quantitative perspective instead of including a random percentage of these vehicles to identify the outcomes of introducing this new form of mobility to the urban transportation networks. Furthermore, this quantification explains the diversity of the impacts and dependence of the usage of AVs in the coming decades. Not only does it allow to indicate various influences of different urban sub-systems on the usage of AVs but also illustrates the reverse impacts. This also realistically inputs the value of AVs into the system while avoiding divergent solutions at the same time.

In terms of demographical indices, the economical prospect of land usage is of prime importance while choosing a residential location (Putman, 2015). A variance of landowner profit over a period keeping in view the inflation reveals the inequity in the vicinity type (Szeto et al., 2015). This inequity is a consequence of the population's choice to reduce the time spent getting to work and daily utilities. As Wegener explains the slow relationship between land usage and transportation activities which gives a proposition of location choice near the point of activities (Wegener and Fuerst, 2004). This gives a proposition of adaptation AVs to reduce the inequity by renting or buying at farther places yet using time of commuting for productive tasks instead of driving. We use the index from Szeto et al. (2015) to compute the landowner profit index ($LI_{u,t}$) as in (1) normalized to attain a value from 0 to 100.

$$LI_{u,t} = \sum_{u} \frac{DLP_t}{(1+i_t)^{t-1}} \tag{1}$$

$$DLP_{u,t} = LR_{u,t} \cdot \frac{NOR_{u,t}}{h_s} - MC_{u,t} \tag{2}$$

Higher population density does not guarantee a higher number of services, but higher services do guarantee higher population density (Janasz and Creighton, 1970). The density of transportation links is evaluated here by an index of transportation land usage (TI) as in (3). Land usage type and infrastructural provision are important for a new service to be welcomed as the era of the pandemic taught us and we witnessed it in the case of new electric micro-mobility provision. Also, Litman describes private vehicle ownership as being dependent on the infrastructure provision for a region as long as it remains sustainable which gives a proposition of direct relation for adaptation of AVs (Litman, 2021). An index is devised by taking a ratio of weighted road links density to the weighted population density for an area.

$$TI = \frac{1}{|Z|} \sum_{z\in Z} \frac{RL_z \cdot \omega_{\mathrm{NMS}}}{PS_z \cdot \frac{1}{\omega_{\mathrm{SF}}}} \tag{3}$$

Land coverage (LC) by transportation network infrastructure is also indexed in terms of vehicle miles travelled throughout a certain period. Indexed as in Kaparias and Bell (2011), long-term adaptation times for land usage is a property that is also common for the adaptation of AVs and them to be part of the traffic stream. The value for this index from (4) is in the range from [−100 to 100].

$$LC = \frac{\Delta VKT_5}{\Delta GTI_5} \tag{4}$$

Urban mobility index (UI) formulated by Kaparias and Bell (2011) represents the mobility condition of users within an urban transportation network by calculating travel time per kilometre. If a user is experiencing less or more precisely affordable travel time per kilometre then the probability of adaptation of AVs is less and vice versa thus giving an indirect relation for the penetration rate. This index is upgraded as in (5) by using the route reliability factor which is the percentage of travel time not more than 10% higher than the average travel time on a certain route. Also, the value of the travel time $VOTT$ parameter is induced in the index which signifies a potential loss of productive hours for the commuter.

$$UI = \omega_{\mathrm{prt}} \cdot \frac{1}{|S|} \cdot \sum_{r\in S} \frac{AT_{\mathrm{prt},r} \cdot VOTT}{L_{\mathrm{prt},r} \cdot \omega_{\mathrm{R}}} \tag{5}$$

On the socio-economic side, Nicolas et al. (2003) presented an effective index considering household transportation expenditure that is converted into household transportation budget index (HBI_t) considering the inflation rate over a certain period. The user generalized cost as in Szeto et al. (2015) is used as an inclination towards adaptation of AVs in case a household owns a private vehicle controlled by a binary operator B_{prt} in determining the economic expenditure state on transportation for a household as in (6).

$$EES_h = \frac{e_{\mathrm{tr},h}}{I_{\mathrm{h}}} \tag{6}$$

$$HBI_t = \frac{1}{|H|} \sum_{h\in H} EES_h \cdot B_{\mathrm{prt}} \left[\frac{dc_{t,h}}{(1+i_t)^{t-1}} \right] \tag{7}$$

Social inclusion index (SI_p) is explained in Kaparias and Bell (2011) through an accessibility index on a spatial level for different activities. Activities represent the opportunities to undergo a task for the commuters of one zone concerning other zones. This index is superimposed with trip propensity assumption as in (9) from Putman (2015) in form of skewed peak form with a gamma distribution, with $d_{p,q}$ is the distance between any OD pair (p,q). The difference of minimum and maximum factors can reveal vacant developable space which in terms of Wegener and Fuerst (2004) is a proposition for adaptation of AVs as a result of equitable development of land as in landowner profits inequity scenario.

$$PF_{p,q} = \frac{d_{p,q}^{-1.330}}{\sum_q d_{p,q}^{-1.330}} \tag{8}$$

$$SI_p = \frac{1}{|AC|} \sum_{a\in AC} \left(\sum_{q\in Z} \beta_q \cdot \alpha_{q,a} \cdot PF_{p,q} \right) \tag{9}$$

Similarly, Kaparias and Bell defined an opportunity index (OI) at the social level for the special group of society (elderly, disabled etc.) to quantify their movement (Kaparias and Bell, 2011). A reformed index is generated by creating weighted value concerning each age group of the special group since they rely on public transport systems having special allocations, demand responsive transit or a family member to drive them off. Quantification of mobility of a special group is checked against the mobility of all other users.

$$MSG_g = \sum_{a\in AC} \frac{NTR_{g,a}}{NTR_{\mathrm{tot},a}} \cdot \omega_a \tag{10}$$

where MSG_g is the mobility of a special group for all activities in AC.

$$OI = \frac{1}{|AG|} \sum_{g\in AG} MSG_g \cdot \omega_g \tag{11}$$

In lieu of our first objective, all the seven indices are integrated under all assumptions defined in Section 3. To obtain a quantification value of the integrated index as in (12), a linear regression is also performed 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 household transportation budget index. For instance, the data for each of the indicators included in the above-mentioned seven indices are analysed for the time t against the willingness of the stakeholders which in this case is the user to upgrade or buy a new vehicle. This suggests the importance of each of the indicators involved thus giving weightage to each of the seven defined indices. The weights $(\omega_1, \omega_2, \omega_3)$ given can be adjusted according to the area or city of application of the formulated QE_{AV}. Thus the cumulative or aggregated value of the final index can be a maximum of 600. This value is analyzed against the penetration rate according to Table 1 to be incorporated into the urban transportation network as below following quantile approach as per (Frei, 2006). The methodology of Frei (2006) is simple yet very practical to be implemented in indicator systems. In it, we made quantiles or groups of the penetration rate with an interval of 5% increment from 0 to 100%.

Table 1
Quantiles approach.

QE_{AV}	PR_z (%)	QE_{AV}	PR_z (%)	QE_{AV}	PR_z (%)	QE_{AV}	PR_z (%)
0–30	5	151–180	30	301–330	55	451–480	80
31–60	10	181–210	35	331–360	60	481–510	85
61–90	15	211–240	40	361–390	65	511–540	90
91–120	20	241–270	45	391–420	70	541–570	95
121–150	25	271–300	50	421–450	75	571–600	100

Similarly, making intervals of the formulated QE_{AV} remaining in the bound of maximum value that is 600. Thus giving us 20 quantiles. This value is analysed against the penetration rate according to Table 1 to be incorporated into the urban transportation network as below following quantile approach as per (Frei, 2006).

$$QE_{AV} = LI_{u,t} + TI + LC - UI + \omega_1 HBI_t + \omega_2 SI_p + \omega_3 OI \tag{12}$$

3.3. AVs modelling scenario

AVs are modelled in PTV Visum (a macroscopic travel deman modelling software) to create a heterogenous traffic scenario and use the resulting data for optimization purposes as illustrated in . Things to take into account while modelling a heterogeneous stream of vehicles in Visum are AVs-ready infrastructure, driving behaviour selection (normal, vigilant, aggressive) according to road category, and penetration rates. The highest level of automation is considered for this study. With a fixed initial demand according to the assumptions in Section 3, AVs are introduced into the network using the scenario management capability of Visum. The number of scenarios was equal to the quantified penetration rate calculated in Section 3.2 with each scenario consisting of 10 iterations in terms of modifications. So each scenario gives an increment of 1% of AVs in the network to assign the demand over the network following the algorithm defined in Section 3.5. In the AVs scenario, 50% of the network links are provided with an AVs-ready infrastructure modelled in scenario modifications. The characteristics of the links are updated by introducing user-defined attributes in the volume-delay (VD) function. The VD function is updated with user-defined attributes of reaction times, deceleration rate, and free flow speed for AVs using the methodology of our previous work (Bilal and Giglio, 2022). Also, the user-defined attributes for modelling heterogeneous traffic streams on the AV-ready links are based on the type of follower-leader vehicle. At the end of each assignment period, the flow-dependent link costs and zonal attraction costs are calculated given the constraint set up at a lower level as in Section 3.4. This is then passed on to the Genetic algorithm at the upper level of the model to maximize the traffic flow remaining into the inequity bounds as in Section 4. The algorithm goes on until the equilibrium is reached between volume and costs revealing the inequity values for the optimal solution at each introduced upper bound of inequity.

3.4. Convex minimization problem formulation (lower level optimization problem)

As defined in Section 3, link travel equilibrium cost $c_l(q_l)$ is dependent on the flow of that link. Following the ETDA-VDC approach (Oppenheim, 1995), this cost function is differentiable concerning flow q_l consequently leading to defining the convex minimization transportation problem. The constraints for the lower level of the optimization model i.e. convex minimization problem are defined by following the approach of Bilal and Giglio (2021). The lower level minimization function as in (13) comprises three parts; flow-dependent travel link cost, zonal trip attraction cost and path choice function based on logit parameter ρ involves in the assignment procedure.

The cumulative flow over the network is constrained in (14), which is the cumulative sum of the existing path flows from the previous iteration plus the newly generated path flows of the current iteration for all the OD pairs p, q true for all the paths r connecting them. δ_{lr} is a binary operator whose value is 0 if the link l is not included in path r for an OD pair p, q, otherwise 1 if the link is included in the path. Not only this but the existing v_r and newly generated path flows q_r are also constrained as in (15) and (16) respectively. For any OD pair p, q and path $r \in R_{pq}$ the existing path flows v_r should be equal to the existing demand m_{pq} so as the newly generated path flows q_r should be equal to the newly generated demand m^{n}_{pq}. As the newly generated demand m^{n}_{pq} from the inclusion of AVs into the system is quantified; it is constrained in (17) by the penetration rate of AVs i.e. PR_z. The boundary conditions for existing path flows, newly generated path flows and newly generated demand made sure that the network remains under stable state conditions. By defining the lower level of the optimization model it is possible to distribute demand matrix X on the transportation network keeping in view the assumptions of Section 3. After distributing the initial demand over the network following the SUE principle based on zonal attraction costs $c_q(m^{\mathrm{n}}_{pq})$, the assignment algorithm reveals the link travel costs for the user choices. So, this part of the model is responsible for assigning the trips over the network while keeping the travel equilibrium cost to minimum.

$$\min_{q,m} TC(q,m) = \sum_{l\in L} \int_0^{q_l} c_l(x)dx + \frac{1}{\rho} \sum_{\substack{(p,q)\\ p\in P, q\in Q}} m^{\mathrm{n}}_{pq}(\ln m^{\mathrm{n}}_{pq} - 1) + \sum_{q\in Q} \int_0^{\sum_{p\in P}(m_{pq}+m^{\mathrm{n}}_{pq})} c_q(x)dx \tag{13}$$

subject to:

(Cumulative Network flow constraint) $$q_l = \sum_{\substack{(p,q)\\ p\in P,q\in Q}} \left[\sum_{r\in R_{pq}} (q_r + v_r)\delta_{lr}\right],\ \forall l \in L \tag{14}$$

(Existing path flows constraint) $$\sum_{r\in R_{pq}} v_r = m_{pq},\ \forall p \in P, \forall q \in Q \tag{15}$$

(New path flows constraint) $$\sum_{r\in R_{pq}} q_r = m^{\mathrm{n}}_{pq},\ \forall p \in P, \forall q \in Q \tag{16}$$

(New demand constraint) $$\sum_{q\in Q} m^{\mathrm{n}}_{pq} = PR_z,\ \forall z \in Z, p \equiv z \tag{17}$$

Boundary conditions :

(New path flow boundary) $$q_r \ge 0,\ \forall r \in R_{pq}, \forall p \in P, \forall q \in Q \tag{18}$$

(Existing path flow boundary) $$v_r \ge 0,\ \forall r \in R_{pq}, \forall p \in P, \forall q \in Q \tag{19}$$

(New demand boundary) $$0 \le m^{\mathrm{n}}_{pq} \le PR_z,\ \forall p \in P, \forall q \in Q \tag{20}$$

3.5. Frank Wolfe assignment algorithm

As explained in the previous section, the lower-level convex minimization problem functions to assign the demand on the network while keeping the link travel equilibrium cost to a minimum. The assignment procedure follows a stochastic user equilibrium approach in which path choices for AVs are considered to be deterministic whereas for the TVs a general constrained distribution logit model is followed with logit parameter $\rho = -0.03$. Following the incidence matrix I, for each path connecting an OD pair p, q the link cost vector is calculated and passed to the minimization function. For this purpose, an updated convex combination algorithm i.e. the Method of Successive Averages – Frank Wolfe (MSA-FWA) algorithm, is used. At each iteration, the link flows are calculated based on the generalized link cost function following the

Taylor polynomial of first order yielding recursive equations thus giving the new link costs. Consequently updating the path choice probabilities at each iteration. The convergence to the solution is checked with a gap threshold of 0.001. According to the assumptions, the considered network is non-congested initially but as the iterations go on link cost and flows become mutually dependent. So, the assignment to the network is performed to obtain mutually consistent link costs and flows. Flow-dependent link costs are defined as in (21). Also, attraction costs are defined as in (22).

$$c_l = c(q_l(Q_l^p, \psi)) \tag{21}$$

$$c_q = c(m_{pq}^n, C_p) \tag{22}$$

Here Q_l^p is the capacity of link l and ψ is the vector of the link's physical and functional characteristics. Moreover, in attraction cost c_q for any destination $q \in Q$, C_p is the maximum parking capacity of the attraction zone.

4. Bi-level optimization model (upper level problem)

In this section, a bi-level optimization model is formulated specifically defining the upper-level problem for it. Concerning our research objective, we are clear that two agents are trying to optimize at the same time; first the link travel cost minimization in the lower-level of bi-model and second the maximization of the newly generated demand bounded by inequity thresholds and quantified penetration rate at the upper level. So, a multi-objective function serves the purpose.

As defined earlier, user equilibrium is reliant on two things the minimization of the total link costs based on the distribution and assignment of trips following MSA-FWA and the maximization of the newly generated trips after introducing AVs into the system among various attraction zones. The scenario for attaining two objectives simultaneously and mutually at the same time is ideal for the bi-level optimization model. In lower-level convex minimization problem, the distribution of trips over the network is dependent on $m_{p,q}^{\mathrm{n}}$ as in (17) which in turn is dependent on the quantified penetration rate PR_z. Also, $m_{p,q}^{\mathrm{n}}$ is a decision variable of the upper level of the model which is maximizing this M_z^{n}. Moreover, the distribution at the lower level is also serving as an input for inequity threshold constraint giving us Stackelberg Nash equilibrium condition (Liu, 1998). At the upper level, the maximization of newly generated trips is constrained by network physical characteristics, attraction zone and essential inequity thresholds.

In the upper level of the bi-level model, the objective function is the maximization of total newly generated trips TG which is a function of total growth vector M_z^{n}. The function in (23) is weighted by ω_z which is the weight of opportunities in a zone z i.e. if a zone has fewer service opportunities the weight will be higher showing that the generation of trips to other zones will be higher and vice versa. The weights are adjusted to shift the system towards equilibrium with the proposed development in line with the maximum potential of development keeping the constraints defined active. As in (24), the lower and upper threshold of inequity is shown by θ_U and θ_L values respectively, $\boldsymbol{M_z^n} = (M_1, M_2, \ldots, M_{|Z|})$ is the vector of total growth of trips (newly generated demand) on introducing AVs into the transportation network bounded by the quantified penetration rate for all the zones. $TC_{pq}^{\mathrm{n}}(\boldsymbol{M_z^n})$ shows the user equilibrium travel cost supplied by the lower level of the model. This cost serves as an implicit function of the vector of newly generated demand $\boldsymbol{M_z^n}$ between OD pairs (p, q). (25) depicts that the flow on any generalized link q_l must not be greater than the link's capacity Q_l^p providing sufficiency to the assumption of the non-congested network. Also in (27), the total number of trips generated from all the zones for all destinations $\sum_{q\in Q} m_{pq}^{\mathrm{n}}$, must be less than or equal to the maximum allowed growth for that zone $m_z^{\mathrm{n,max}}$. Similarly, (28) shows that the amount of newly generated demand attracted by each zone from all the origin zones $\sum_{p\in P} m_{pq}^{\mathrm{n}}$ must not b greater than the maximum attraction potential $m_q^{\mathrm{n,max}}$. This attraction potential should be less than or equal to the parking space of the attraction zone C_q as in (29). Link constraints in (25) and (26) control the convergence of solution for the formulated problem.

$$\max TG(\boldsymbol{M}) = \sum_{z\in Z} \omega_z M_z \tag{23}$$

subject to:

$$\text{(Inequity thresholds constraint)} \qquad \theta_L \le \frac{TC_{pq}^{\mathrm{n}}(\boldsymbol{M})}{TC_{pq}} \le \theta_U, \ \forall p \in P, \forall q \in Q \tag{24}$$

$$\text{(Link capacity constraint)} \qquad q_l(\boldsymbol{M}) \le Q_l^p, \ \forall l \in L \tag{25}$$

$$\text{(Link occupancy constraint)} \qquad \frac{PCE_l(g)}{Q_l^p} \le 1, \ \forall l \in L \tag{26}$$

$$\text{(Trip generation constraint)} \qquad \sum_{q\in Q} m_{pq}^{\mathrm{n}}(PR_z) \le m_z^{\mathrm{n,max}} - m_z^{\mathrm{cur}}, \ \forall z \in Z, p \equiv z \tag{27}$$

$$\text{(Trip attraction constraint)} \qquad \sum_{p\in P} m_{pq}^{\mathrm{n}}(PR_z) \le m_q^{\mathrm{n,max}} - m_q, \ \forall q \in Q \tag{28}$$

$$\text{(Attraction zone parking space constraint)} \qquad m_q^{\mathrm{n}} \le C_q, \ \forall q \in Q \tag{29}$$

Boundary conditions :

$$m_{pq}^{\mathrm{n}} \ge 0, \ \forall p \in P, \forall q \in Q \tag{30}$$

$$m_z^{max} = \sum_{q\in Q} m_{pq}^{\mathrm{n}}, \ m_z^{\mathrm{cur}} = \sum_{q\in Q} m_{pq}, \ \forall z \in Z, p \equiv z \tag{31}$$

$$m_q^{\mathrm{n}} = \sum_{p\in P} m_{pq}^{\mathrm{n}}, \ m_q = \sum_{p\in P} m_{pq}, \ \forall q \in Q \tag{32}$$

Here the point to ponder is that the constraints of link capacity, link occupancy and attraction zone can be introduced both in the lower and upper levels of the problem. Nevertheless, the reason for introducing them to the upper level along with the inequity threshold is their behavioural results. They are introduced into the upper level of the model to avoid any divergence to the solution. Since we mentioned that the upper level of the model is acting as a decision-maker for the lower level, the latter itself is acting as a major constraint for the prior (Lee et al., 2006). To solve the bi-level optimization model, a Genetic algorithm is used as explained in the next section. To summarize, the overall multi-objective fitness function of the model is given by (33)

$$\begin{aligned} FT(s) = \sum_{z\in Z} M_z - \mathcal{L} \Bigg[& \max_{(p,q)p\in P, q\in Q} \left\{ 0, \theta_L - \frac{TC_{p,q}^{\mathrm{n}}(\boldsymbol{M})}{TC_{p,q}}, \frac{TC_{p,q}^{\mathrm{n}}(\boldsymbol{M})}{TC_{p,q}} - \theta_U \right\} \\ & + \max_{l\in L} \left\{ 0, q_l - Q_l^p \right\} \\ & + \max_{l\in L} \left\{ 0, \frac{PCE_l}{Q_l^p} - 1 \right\} + \max_{\substack{z\in Z \\ p\equiv z}} \left\{ 0, \sum_{q\in Q} m_{p,q}^{\mathrm{n}} - m_z^{\mathrm{max}} + m_z^{\mathrm{cur}} \right\} \\ & + \max_{q\in Q} \left\{ 0, \sum_{p\in P} m_{p,q}^{\mathrm{n}} - m_q^{\mathrm{n,max}} + m_q \right\} + \max_{q\in Q} \left\{ 0, m_q^{\mathrm{n}} - C_q \right\} \Bigg] \end{aligned} \tag{33}$$

4.1. Genetic algorithm

To solve the formulated bi-level optimization model which is innately nonconvex, the genetic algorithm approach is followed. Since two agents are trying to obtain the indirect global optimums; minimized equilibrium costs at the lower-level of the problem and maximized newly generated trips at the upper-level; the genetic algorithm is ideal for obtaining the solution. The genetic algorithm is useful considering that link flows are nonconvex and continuous but they are non-differentiable functions concerning the newly generated trips. In a nutshell, the decision variable for the upper-level problem; the vector of newly generated trip growth is coded as finite strings and for each string, the fitness is calculated by solving the lower-level problem. The process goes on until the optimal string is found under defined constraints and boundary conditions for both upper and lower-level problems.

Algorithm

STEP 1 Initialization.

1.1 In initialization, encode the random population set for the decision variable of the upper-level problem $(M_1, M_2, \ldots, M_{|Z|})$ in the form of finite binary $(0, 1)$ strings representing chromosomes for the first population set. For mating (assigning values of number of trips for each zone) in initial iteration $(G_x, x = 1)$, pick the chromosomes equal to the number of zones in the network.

STEP 2 Using the technique mentioned above, decode the chromosomes in G_x to real numbers and pass it to the lower-level problem.

STEP 3 Evaluate the fitness function by solving lower-level problem.

3.1 Determine the shortest path for all OD pairs (p, q).

3.2 Calculate the link flows for the network for all OD pairs based on the piecewise optimal step size distributing all present demands.

3.3 Linearize the generalized link cost function and find the new solution following the procedure as explained in Section 3.5.

3.4 If no convergence is reached go to Step 3.2 otherwise Step 4.

STEP 4 After obtaining the solution set for the fitness values, by using the roulette wheel based method eliminates the least probable solution from the solution set and keep the solution with the highest probability and reproduce the population set G_x.

STEP 5 Perform the crossover operation on the reproduced population set by giving a crossover probability of 0.5 (Bilal and Giglio, 2021) on the encoded population set. Replace the column entries of one chromosome with others yielding new offspring.

STEP 6 Perform the mutation operation after the crossover operation on the reproduced population set by selecting random chromosome from the set based on mutation probability equal to $\frac{1}{\text{population size}}$ as per (Bilal and Giglio, 2021) and (Carroll, 1996). Replace the gene values from 1 to 0 and vice versa to generate new offspring revealing a new population set $(G_x, x = x + 1)$.

STEP 7 If the maximum number of generations for the genetic algorithm is reached the population set with the highest value of fitness results as an optimal solution otherwise go to Step 2.

The algorithm starts with random initial solutions as a population set for all the zones in the network. This population set consists of decision variables that are the maximum newly generated trips vector M comprising of $m^{\mathrm{n}}_{p,q}$ values for each OD pair within a range of quantified penetration rate $\mathcal{P} = [m^{\min}_z, m^{\max}_z]$. This initial set $\boldsymbol{M}^{\mathbf{n}}_{\boldsymbol{z}} = (M_1, M_2, \ldots, M_{|Z|})$ is encoded in the form of binary strings to form a set of initial chromosomes. For encoding, we followed (Bilal and Giglio, 2021). Here the set of chromosomes is called a population. Following that random chromosomes are picked equal to the number of zones in the traffic network for mating and decoded using binary bit conversion to decimal technique. These decoded chromosomes are passed to the lower-level problem to obtain the fitness value from the fitness function. At the lower level, a sub-algorithm is implied to distribute and assign the demand on the network following the SUE principal as described in Section 3.5. After evaluating the fitness of the current population, the genetic algorithm applies three operators to generate new chromosomes from the existing mating ones. These new chromosomes are called offsprings which replace the chromosomes they are made from. These operators are called selection, crossover and mutation. This process is a single generation of genetic algorithm. After generating a new population the process repeats until the optimum set of the population is discovered. This whole procedure is described in the $Algorithm$. It should be noted that in the fitness function in (33) a penalty function $\mathcal{L}$ is introduced to cater for the infeasibility of the solution set.

5. Real network implementation

This section describes the application of the above-detailed algorithm on the devised bi-level optimization model with SUE assignment. Also, the results obtained by applying it on a real transportation network and discussion of results are penned down.

For real network implementation, a part of the transportation network of the city of Genoa, Italy is used as can be seen in Fig. 2. The considered network is represented by a synchronic graph; divided into 17 zones with 502 nodes and 1464 links covering an area of 8 km^2. All zones in the network are origin and destination zones simultaneously with an initial fixed demand as shown in Table 2 obtained from Comune di Genova. The maximum possible growth of newly generated demand for each zone is strongly dependent on the quantified penetration rate of the AVs in respective zones which is the first objective of our research. For that socio-economic and user demographical data for the area deemed is extracted from the ISTAT (Italian National Institute of Statistics) whereas, the transportation infrastructure data is retrieved from Eurostat. Information about trips is mined from *Statista* and *Odyssee-Mure* used for the quantification of the penetration rate of AVs. The population is categorized into four groups $(15\text{–}24, 25\text{–}44, 45\text{–}64\ and \geq 65\ years of age)$. For synthesizing social inclusion and opportunity indices the activities set ACT is defined with six activities namely; Work, shopping, leisure, recreational, health and education. All seven indices are calculated for the extracted data and based on the methodology mentioned in Section 3.2; a penetration rate for AVs is obtained.

5.1. Results and discussion

Using the methodology stated in Section 3.2, the first objective of this research is attained. Utilizing the data obtained from the above-mentioned sources for the city of Genoa, values for each of the seven indices are calculated as shown in Table 3; consequently giving an integrated index from the quantification equation (QE_{AV}) as in (12). Value of the integrated index is used and the final penetration rate to be used in the model is obtained from Table 1. The quantified value which comes out to be 35% AVs into the network is evaluated based on the projected growth of the defined indices for the next 20 years.

Following the quantified penetration rate, the analysis moved to the second objective of this research to determine the inequity of the introduction of AVs into the transportation network. Trip growth generally causes an increment in travel cost and consequently yields a positive travel equilibrium ratio (Bilal and Giglio, 2021; Lee et al., 2006). So, given the assumptions in Section 3, the lower bound (θ_L) is kept equal to 1 whereas the upper bound (θ_u) is sensitively tested against different values (1.05, 1.07, 1.09 and 1.10). The aim of using close intervals for the upper bound value is to closely monitor the change in the respective optimal values for the upper and lower-level of the problem as well as the fitness function.

Looking at the fitness curves in Fig. 3 it is apparent that for all the upper bounds the fitness of GA continues to increase. However, for the upper bound of 1.09 and 1.10, the fitness sharply increases after 80 iterations of the algorithm and finally becomes stable with a relatively higher value of fitness as compared to the earlier upper bounds i.e. 1.05 and 1.07. This depicts that almost all the newly generated demand under these bounds satisfies the model thus the fitness continues to increase. An interesting thing to note is that the fitness value for the upper bound of 1.07 took the longest to get stable yet it has the lowest value. In contrast, the algorithm becomes stable only after 58 iterations in the case of an upper bound of 1.05. Comfort comes with a cost

Table 2
Network data.

Zone	Name	Originating volume	Attraction volume	Maximum production	Maximum accommodating volume
33	Prè	1145	1134	1603	1488
34	MADDALENA	657	659	920	822
35	MOLO	2079	2409	2910	3172
38	MANIN	1216	1188	1702	1463
39	S.VINCENZO	4272	4043	5980	5260
40	CARIGNANO	1363	1197	1908	1275
41	FOCE	579	605	810	747
42	BRIGNOLE	2927	2875	4097	3825
43	S.AGATA	1272	1167	1780	1333
47	MARASSI	1393	1388	1950	1643
61	S.MARTINO	2927	2875	4097	3725
62	ALBARO	2656	2394	3718	3052
63	S.GIULIANO	1311	1777	1836	2187
64	LIDO	1146	1129	1604	1280
65	PUGGIA	917	898	1283	1057
66	Oregina	1535	1489	2149	1884
67	Castelleto	1261	1319	1765	1646

Table 3
Quantification of penetration rate.

Index	Scenario A
$LI_{u,t}$	41.34
TI	56.47
LC	34.23
UI	−59.45
HBI_t	28.65
SI_p	30.85
OI	52.32
QE_{AV}	184.41
PR_z (%)	35

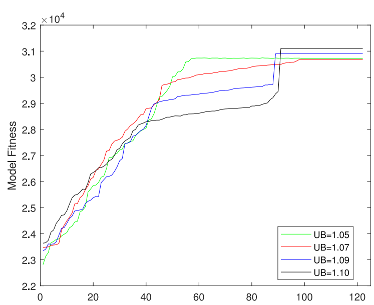


Fig. 3. Fitness curves for GA with Upper inequity bound of 1.05, 1.07, 1.09 and 1.10.

not only to an individual but also a mutual social cost. This can be verified by diving deep into the inequity analysis results. It is evident from Tables 4 and 5 that the inequity values for the newly generated demand do not increase rapidly for the increased fitness values. But as we saw in the fitness curves in Fig. 3 there is a rapid increase in the fitness values for the upper bounds of 1.09 and 1.10, this is certified by the inequity values as we can see in Tables 6 and 7 in the Appendix.

Although the new demand generated is being easily served by the network evident from the fitness curve with sharp increment in fitness; it also increases the inequity within the network thus increasing the overall equilibrium travel cost. Similarly, the change for inequity ratios for an upper bound of 1.10 is very less than the previous interval yet the fitness values increases sharply. This reveals that with higher upper bound values the inequity constraint as in (24) starts to become inactive because this excessive inequity upper bound will allow the newly generated demand to already reach the maximum values bounded by the constraint in (27) as well as the attraction constraint in (28). That also was one of the reasons to use close interval upper-bound values for inequity constraint. In the considered network three types of roads are used; highway, primary urban street, and tertiary urban street with a capacity of 2700, 1600 and 900 vehicles per hour respectively. The capacity is large enough to accommodate the maximum possible flows on the network. It must be noted that if the capacity is reduced then the inequity constraint becomes inactive for increasing iterations and capacity constraint as in (25) will control the algorithm.

Now to help understand better the situation of inequity analysis, a side-by-side comparison is shown for all the zones and all the inequity upper bounds as in Fig. 4. We can observe from Fig. 4(a), (b), (d) and (e) that despite the increase in inequity ratio due to a slight increment in the travel costs for the zones the increase in volume is appreciable which is also revealed by the fitness function except for the zones 33 and 41 which shows a minimum change. Similarly, if we look into Fig. 4(c, f) we can identify the gains in volume for a slight change in travel cost for the upper bound interval of 1.07 to 1.09 except for zone 61. This makes us choose the upper bound of 1.09 as the best possible inequity policy as above that bound the change in decision variable is very less and the bound becomes ineffective as explained earlier.

Figs. 5 and 6 show the optimal results for the lower-level problem of the bi-level optimization model. We can witness the change in costs for all the network zones for all the possible OD pairs for which the demand exists. Since in the formulated bi-level optimization model, two agents are trying to simultaneously optimize their values; it gives a chance to visualize the effect of various upper bounds and the amount of compromise in travel costs and volumes. The minimized costs are the results of the maximized volumes as can be seen in Figs. 5 and 6. The fact that for certain zones the inequity upper bound of 1.09 does not give appreciable results instead upper bound of 1.07 does. Looking closely at the optimal curves, the detailed potential of each origin zone towards each attraction zone depicts the amount of equitable development in form of the introduction of AVs.

From Fig. 5(a), variations in the optimization behaviour of the two decision variables at the lower and upper levels of the problem can be observed. The sharp decrement in travel equilibrium cost for trips from zone 41 to attraction zones particularly to zone 63 and zone 47 does not come at any compromise of volume as can be seen in Fig. 7(a). In fact, for zone 63 the newly generated demand continues to maximize itself with decreasing travel equilibrium cost. Similar trends are noted for origin zone 47 in which newly generated demand is increasing steadily as in Fig. 7(b) whereas, the cost continues to minimize as in Fig. 5(b). This shows the strong behaviour of constraints at the lower level of the formulated model which in turn is acting as a constraint for the upper level thus providing a balance in the production of new demand for each OD pair. The important takeaway from these optimal curves is that the increasing trips do not always increase the travel equilibrium costs yet for some OD pairs it is also decreasing the total costs. Moreover, as we mentioned earlier for some origin zones the upper bound of 1.07 performed well depicting the importance of micro-level transportation

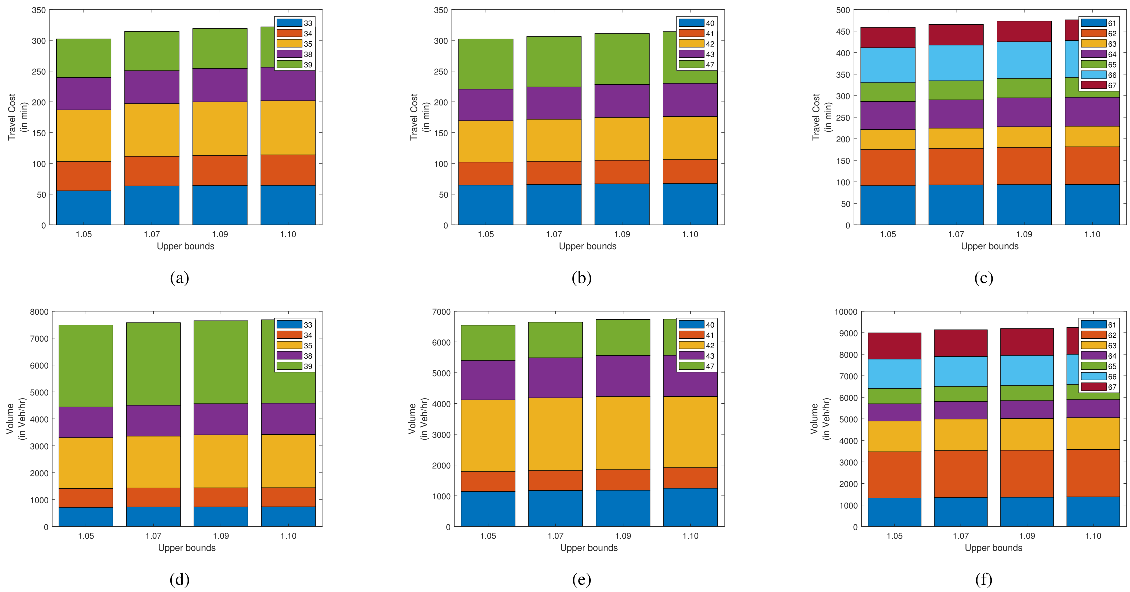


Fig. 4. (a) Change in travel equilibrium costs for different Upper bounds for Zone 33, 34, 35, 38 and 39; (b) Change in travel equilibrium costs for different Upper bounds for Zone 40, 41, 42, 43 and 47 (c) Change in travel equilibrium costs for different Upper bounds for Zone 61, 62, 63, 64, 65, 66 and 67 (d) Change in volume for different upper bounds for zone 33, 34, 35, 38 and 39 (e) Change in volume for different upper bounds for zone 40, 41, 42, 43 and 47 (f) Change in volume for different upper bounds for zone 61, 62, 63, 64, 65, 66 and 67.

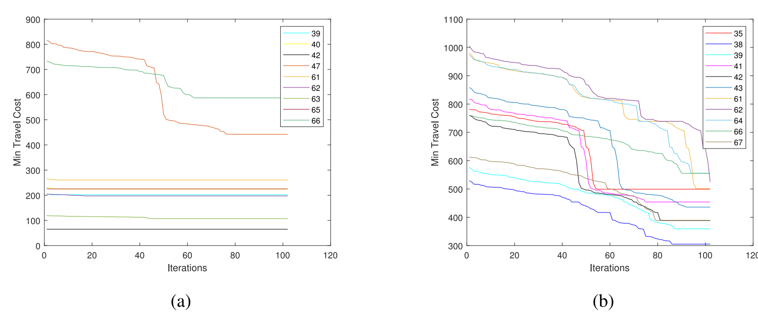


Fig. 5. (a) Optimal minimized travel equilibrium costs for origin zone 41 (b) Optimal minimized travel equilibrium costs for origin zone 47.

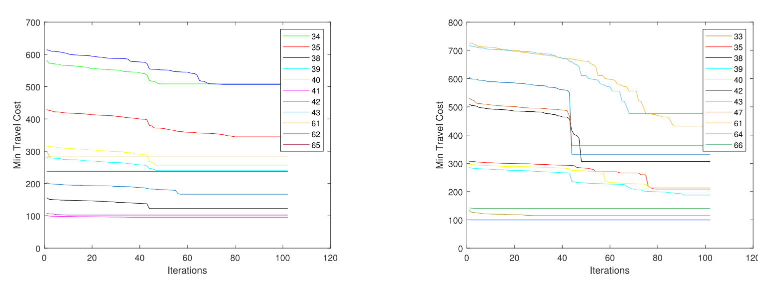
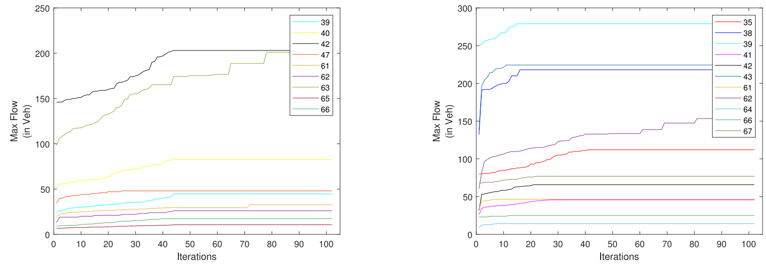


Fig. 6. (a) Optimal minimized travel equilibrium costs for origin zone 63 (b) Optimal minimized travel equilibrium costs for origin zone 67.

and land use planning revealing the possible direction of urban development. This enlightens the possibilities for different zones of the bigger network to be micro-planned for development in terms of the inclusion of new forms of mobility with variable inequity allowance. This can also open doors for the micro-mobility options to serve the needs of the user group of zones where inequity is more (see Fig. 8).

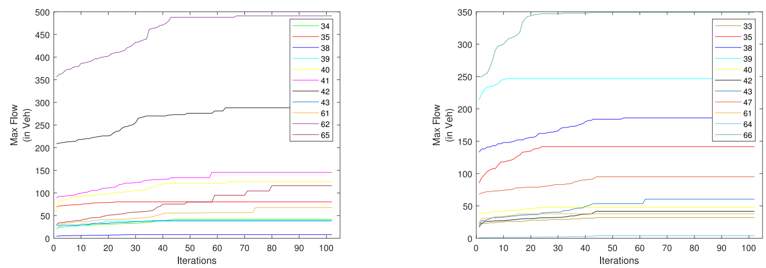
6. Conclusions

This section details the derived conclusions after the application of the formulated problem and bi-level optimization model on a real-world network. Also, the possible way forward in this regard is discussed.



(a) (b)

Fig. 7. (a) Optimal maximized trip generation for origin zone 41 (b) Optimal maximized trip generation for origin zone 47.



(a) (b)

Fig. 8. (a) Optimal maximized trip generation for origin zone 63 (b) Optimal maximized trip generation for origin zone 67.

Table 4
Inequity model results.

Zones	θ_U = 1.05																
	33	34	35	38	39	40	41	42	43	47	61	62	63	64	65	66	67
33	–	1.0294	1.0494	1.0487	1.0476	–	–	1.0461	1.0493	–	1.0379	1.0426	–	–	1.0494	1.050	1.0433
34	1.045	–	1.049	1.045	1.049	1.041	–	1.025	–	–	1.042	1.047	1.029	1.047	–	1.049	–
35	1.0488	1.0471	–	1.0472	1.0477	1.0462	–	1.0424	1.0443	1.0464	1.0195	1.0443	1.0449	1.0482	1.0426	1.0490	1.0493
38	1.0468	1.0432	1.0479	–	1.0489	1.0397	–	1.041	–	1.0435	1.0491	1.0486	1.0463	1.0478	–	1.0475	1.0481
39	1.0259	1.0373	1.0253	1.0482	–	1.0498	1.0438	1.0429	1.0418	1.0376	1.0364	1.0322	1.0413	1.0364	1.0418	1.0478	1.0492
40	–	1.0473	1.0494	1.0461	1.0499	–	1.0457	1.0477	1.0466	–	1.0352	1.0473	1.0471	1.0494	–	1.0476	1.0353
41	–	–	–	–	1.0498	1.0499	–	1.0424	–	1.0398	1.0496	1.0497	1.0472	–	1.0472	1.0484	–
42	1.0494	1.0475	1.0362	1.0303	1.050	1.0454	1.0492	–	1.0381	1.0343	1.0478	1.0397	1.0460	1.0461	1.0480	1.0438	1.0493
43	1.0498	–	1.0178	–	1.0364	1.0438	–	1.0481	–	1.0455	1.0493	1.0433	1.0440	–	1.0419	1.0406	1.0421
47	–	–	1.0469	1.0314	1.038	–	1.0494	1.0493	1.0430	–	1.0412	1.1423	–	1.0257	–	1.0414	1.0383
61	1.0352	1.046	1.002	1.033	1.046	1.0480	1.0489	1.0422	1.037	1.016	–	1.030	1.0343	1.0297	1.046	1.0148	1.0145
62	1.0493	1.0450	1.0480	1.035	1.0478	1.049	1.046	1.043	1.040	1.046	1.047	–	1.0466	1.0121	1.043	1.0370	–
63	–	1.039	1.003	1.048	1	1.0415	1.001	1.0471	1.0448	–	1.0313	1.048	–	–	1.022	–	–
64	–	1.0482	1.035	1.0180	1.030	1	–	1.003	–	1.002	1.043	1.004	–	–	1.041	–	1.049
65	1.0275	–	1.0341	–	1.003	–	1.023	1.002	1.013	–	1.0412	1.024	1.0493	–	–	–	–
66	1.0160	1.046	1.040	1	1.048	1.0462	1.049	1.002	1.040	1.030	1.045	1.001	–	–	–	–	1
67	1.016	–	1.050	1.008	1.049	1.0421	–	1.049	1.001	1.002	1.043	–	–	1.0139	–	1.05	–

Table 5
Inequity model results.

Zones	θ_U = 1.07																
	33	34	35	38	39	40	41	42	43	47	61	62	63	64	65	66	67
33	–	1.0294	1.0617	1.0690	1.0699	–	–	1.0661	1.0494	–	1.0671	1.0676	–	–	1.0613	1.0699	1.0671
34	1.0693	–	1.0643	1.0531	1.0665	1.0695	–	1.0681	–	–	1.0595	1.0606	1.0299	1.0646	–	1.0698	–
35	1.0648	1.0581	–	1.0636	1.0587	1.0537	–	1.0630	1.0591	1.0614	1.0680	1.0584	1.0450	1.0584	1.0635	1.0567	1.0633
38	1.0468	1.0627	1.0677	–	1.0696	1.0678	–	1.0611	–	1.0668	1.0592	1.0683	1.0688	1.0479	–	1.0526	1.0661
39	1.060	1.0541	1.0552	1.0694	–	1.0679	1.0665	1.0652	1.0611	1.0673	1.0619	1.0322	1.0587	1.0660	1.0601	1.0667	1.0686
40	–	1.0685	1.0694	1.0688	1.0645	–	1.0657	1.0676	1.0531	–	1.0353	1.0601	1.0695	1.0494	–	1.0593	1.0612
41	–	–	–	–	1.0686	1.0686	–	1.0425	–	1.0635	1.0679	1.0682	1.0582	–	1.0473	1.0485	–
42	1.0637	1.0613	1.0654	1.0682	1.0659	1.0649	1.0677	–	1.0614	1.0676	1.0684	1.0398	1.0647	1.0620	1.0507	1.0668	1.0550
43	1.0679	–	1.0178	–	1.0365	1.0690	–	1.0622	–	1.0543	1.0658	1.0562	1.0692	–	1.0622	1.0407	1.0672
47	–	–	1.0596	1.0520	1.0666	–	1.0495	1.0607	1.0632	–	1.0412	1.1424	–	1.0257	–	1.0549	1.0383
61	1.0679	1.0655	1.0697	1.0673	1.0580	1.0508	1.0694	1.0527	1.0634	1.0560	–	1.0302	1.0343	1.0298	1.0466	1.0148	1.0536
62	1.0682	1.0451	1.0683	1.0636	1.0616	1.0691	1.0652	1.0507	1.0579	1.0463	1.0536	–	1.0690	1.0121	1.0431	1.0370	–
63	–	1.0692	1.0584	1.0664	1.0686	1.0501	1.003	1.0472	1.0553	–	1.0313	1.0646	–	–	1.0230	–	–
64	–	1.0482	1.0503	1.0613	1.024	1.002	–	1.006	–	1.002	1.0512	1.0043	–	–	1.041	–	1.0496
65	1.0688	–	1.0342	–	1.060	–	1.0672	1.0685	1.055	–	1.0412	1.0247	1.0561	–	–	–	–
66	1.0695	1.0537	1.0404	1.048	1.0555	1.0695	1.0556	1.028	1.0407	1.0517	1.0686	1.0547	–	–	–	–	1
67	1.0695	–	1.0585	1.0089	1.0610	1.0618	–	1.0561	1.068	1.058	1.0537	–	–	1.0642	–	1.0524	–

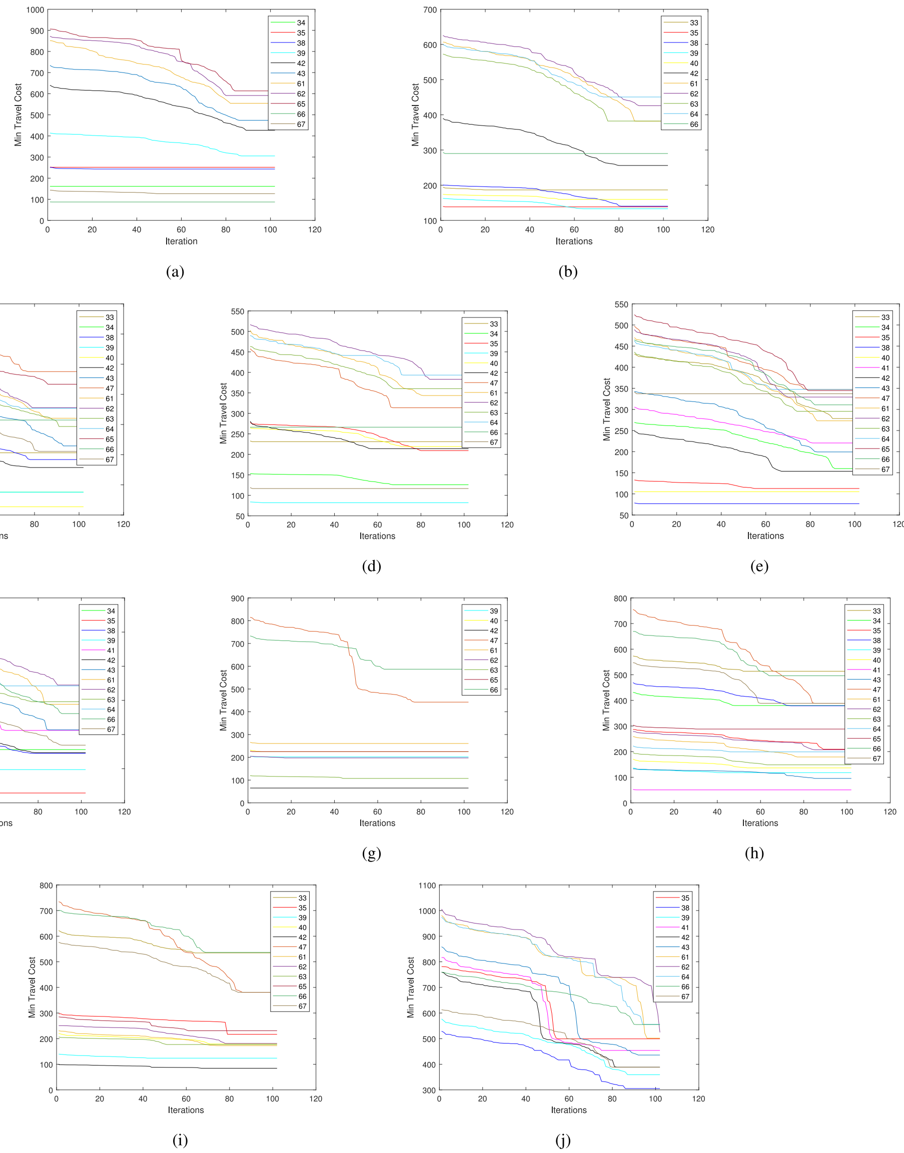
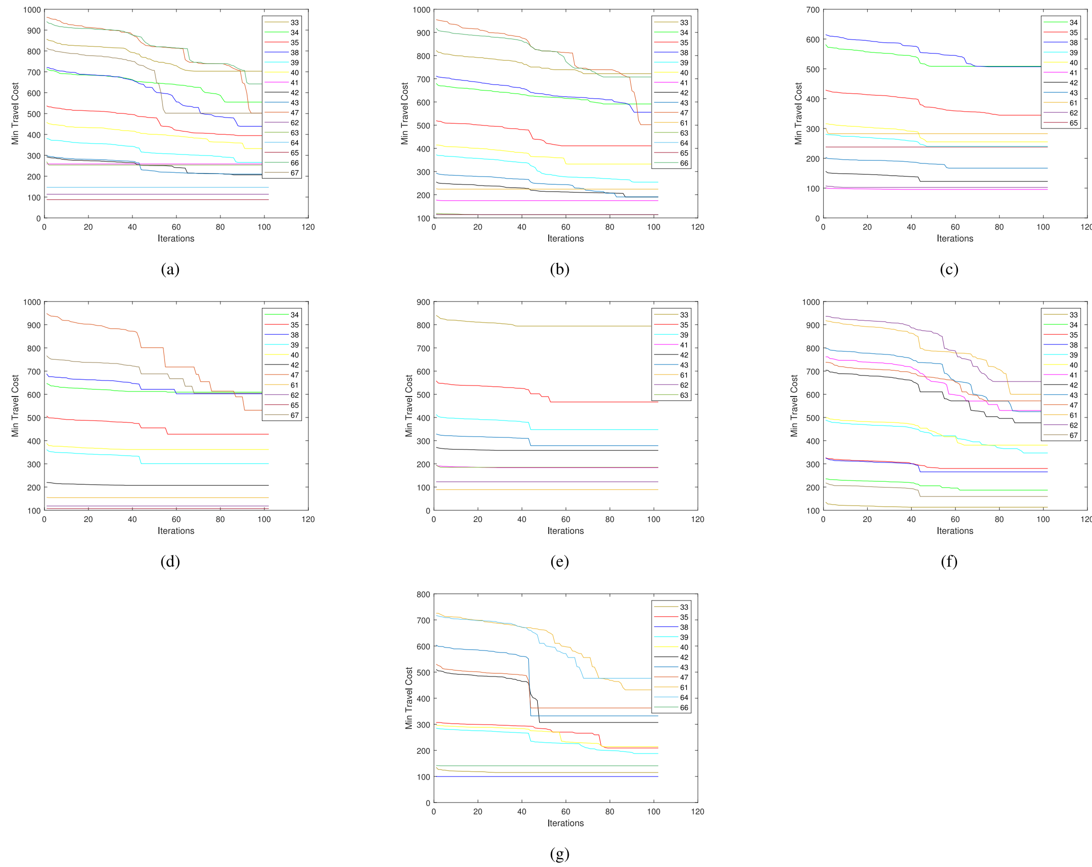


Fig. 9. (a) Optimal minimized travel equilibrium costs for origin zone 33; (b) Optimal minimized travel equilibrium costs for origin zone 34 (c) Optimal minimized travel equilibrium costs for origin zone 35 (d) Optimal minimized travel equilibrium costs for origin zone 38 (e) Optimal minimized travel equilibrium costs for origin zone 39 (f) Optimal minimized travel equilibrium costs for origin zone 40 (g) Optimal minimized travel equilibrium costs for origin zone 41 (h) Optimal minimized travel equilibrium costs for origin zone 42 (i) Optimal minimized travel equilibrium costs for origin zone 43 (j) Optimal minimized travel equilibrium costs for origin zone 47.

Table 6
Inequity model results.

Zones	θ_U = 1.09																
	33	34	35	38	39	40	41	42	43	47	61	62	63	64	65	66	67
33	–	1.0294	1.0617	1.0896	1.0699	–	–	1.0893	1.0779	–	1.0842	1.0676	–	–	1.0754	1.0800	1.0850
34	1.0859	–	1.0887	1.0531	1.0881	1.0834	–	1.0891	–	–	1.0752	1.0780	1.0771	1.0898	–	1.0795	–
35	1.0752	1.0891	–	1.0824	1.0897	1.0886	–	1.0868	1.0870	1.0892	1.0863	1.0731	1.0900	1.0892	1.0786	1.0860	1.0860
38	1.0468	1.0789	1.0776	–	1.0872	1.0878	–	1.0877	–	1.0832	1.0895	1.0898	1.0883	1.0479	–	1.0526	1.0867
39	1.0873	1.0762	1.0870	1.0806	–	1.0679	1.0796	1.0776	1.0783	1.0817	1.0619	1.0854	1.0716	1.0805	1.0861	1.0830	1.0820
40	–	1.0892	1.0884	1.0886	1.0890	–	1.0884	1.0898	1.0531	–	1.0353	1.0814	1.0892	1.0863	–	1.0593	1.0791
41	–	–	–	–	1.0799	1.0870	–	1.0425	–	1.0764	1.0861	1.0863	1.0890	–	1.0473	1.0862	–
42	1.0859	1.0787	1.0654	1.0882	1.0865	1.0871	1.0769	–	1.0837	1.0840	1.0816	1.0841	1.0828	1.0880	1.0880	1.0809	1.0550
43	1.0842	–	1.0178	–	1.0880	1.0690	–	1.0868	–	1.0882	1.0847	1.0807	1.0692	–	1.0758	1.0838	1.0848
47	–	–	1.0596	1.0892	1.0666	–	1.0706	1.0769	1.0873	–	1.0813	1.1424	–	1.0831	–	1.0735	1.0383
61	1.0892	1.0655	1.0872	1.0797	1.0580	1.0508	1.0882	1.0894	1.0899	1.0560	–	1.0302	1.0343	1.0298	1.0466	1.0148	1.0536
62	1.0876	1.0890	1.0871	1.0636	1.0616	1.0816	1.0886	1.0507	1.0579	1.0866	1.0536	–	1.0866	1.0121	1.0431	1.0857	–
63	–	1.0846	1.0894	1.0898	1.0868	1.0782	1.0896	1.0472	1.0553	–	1.0313	1.0853	–	–	1.0230	–	–
64	–	1.0884	1.0703	1.0847	1	1.0896	–	1.0878	–	1.074	1.0512	1.0043	–	–	1.041	–	1.0496
65	1.0881	–	1.0706	–	1.063	–	1.0882	1.0881	1.044	–	1.0412	1.0247	1.0746	–	–	–	–
66	1.0879	1.0537	1.0886	1.075	1.0822	1.0890	1.0556	1.0783	1.0892	1.0878	1.0703	1.0859	–	–	–	–	1
67	1.0879	–	1.0803	1.0089	1.0842	1.0796	–	1.0561	1.049	1.058	1.0734	–	–	1.0642	–	1.0524	–



(a) (b) (c) (d) (e) (f) (g)

Fig. 10. (a) Optimal minimized travel equilibrium costs for origin zone 61; (b) Optimal minimized travel equilibrium costs for origin zone 62 (c) Optimal minimized travel equilibrium costs for origin zone 63 (d) Optimal minimized travel equilibrium costs for origin zone 64 (e) Optimal minimized travel equilibrium costs for origin zone 65 (f) Optimal minimized travel equilibrium costs for origin zone 66 (g) Optimal minimized travel equilibrium costs for origin zone 67.

Table 7
Inequity model results.

Zones	$\theta_U = 1.10$																
	33	34	35	38	39	40	41	42	43	47	61	62	63	64	65	66	67
33	–	1.0294	1.0617	1.0997	1.0966	–	–	1.0893	1.0975	–	1.0994	1.0676	–	–	1.0754	1.0800	1.0978
34	1.0999	–	1.0887	1.0946	1.0960	1.0956	–	1.0991	–	–	1.0752	1.0983	1.0771	1.0919	–	1.0905	–
35	1.0985	1.0990	–	1.0824	1.0897	1.0993	–	1.0976	1.0902	1.0992	1.0965	1.1000	1.0900	1.0968	1.0957	1.0989	1.0927
38	1.0468	1.0981	1.0945	–	1.0968	1.0984	–	1.0997	–	1.0832	1.0982	1.0898	1.0883	1.0908	–	1.0526	1.0867
39	1.0873	1.0762	1.0991	1.0934	–	1.0679	1.0943	1.0915	1.0783	1.0989	1.0977	1.0958	1.0941	1.0976	1.0861	1.0830	1.0820
40	–	1.0972	1.0994	1.0990	1.0982	–	1.0951	1.0930	1.0531	–	1.0353	1.0814	1.0999	1.0863	–	1.0984	1.0944
41	–	–	–	–	1.0990	1.0961	–	1.0425	–	1.0981	1.0911	1.0996	1.0890	–	1.0473	1.0999	–
42	1.0980	1.0903	1.0901	1.0908	1.0960	1.0970	1.0769	–	1.0938	1.0840	1.0816	1.0841	1.0971	1.0973	1.0999	1.0910	1.0550
43	1.0921	–	1.0178	–	1.0995	1.0938	–	1.0868	–	1.0989	1.0946	1.0976	1.0940	–	1.0953	1.0978	1.0954
47	–	–	1.0596	1.0929	1.0965	–	1.0953	1.0769	1.0941	–	1.0813	1.1424	–	1.0995	–	1.0735	1.0383
61	1.0960	1.0942	1.0964	1.0797	1.0580	1.0508	1.0882	1.0985	1.0998	1.0560	–	1.0302	1.0986	1.0298	1.0466	1.0148	1.0536
62	1.0980	1.0984	1.0984	1.0936	1.0999	1.0816	1.0952	1.0507	1.0579	1.0866	1.0536	–	1.0973	1.0121	1.0431	1.0917	–
63	–	1.0908	1.0953	1.0938	1.0868	1.0952	1.0971	1.0472	1.0553	–	1.0956	1.0991	–	–	1.0230	–	–
64	–	1.0991	1.0703	1.0847	1.084	1.0915	–	1.0950	–	1.079	1.0512	1.0043	–	–	1.041	–	1.0496
65	1.0992	–	1.0706	–	1.0953	–	1.0990	1.0978	1.088	–	1.0412	1.0247	1.0746	–	–	–	–
66	1.0993	1.0537	1.0977	1.091	1.0980	1.0997	1.0556	1.0783	1.0925	1.0993	1.0703	1.0978	–	–	–	–	1
67	1.0993	–	1.0803	1.0089	1.0945	1.0796	–	1.0561	1.074	1.078	1.0734	–	–	1.0642	–	1.0524	–

In this research, a thorough and effective methodology is provided to fill the gaps in the existing literature related to the inequity impacts on the current users of the network upon the introduction of AVs. Concerning the stated objectives as in Section 1, a quantified penetration rate of AVs is derived from a multiple indices system to synthesize seven different indices using user demographical, land usage and socio-economic characteristics. Then by the quantile approach, the realistic value of AVs is determined which comes out to be 35% keeping in view 0% AVs in the current year and projection for the indices for the next 20 years. Later, this quantified penetration rate of AVs is used in the formulated convex minimization problem which is a lower-level of the bi-level optimization model. The lower-level problem distributed the trips onto the network following the SUE approach using the Frank–Wolfe algorithm. This lower-level problem itself acts as a constraint for the upper-level of the bi-model. The presented bi-level optimization model is solved using a genetic algorithm that addresses the inequity among the travel zones on the introduction of AVs into the network by sensing the deviation in travel equilibrium costs for each OD pair. Also, governs the maximum amount of new demand that can be produced by each origin zone.

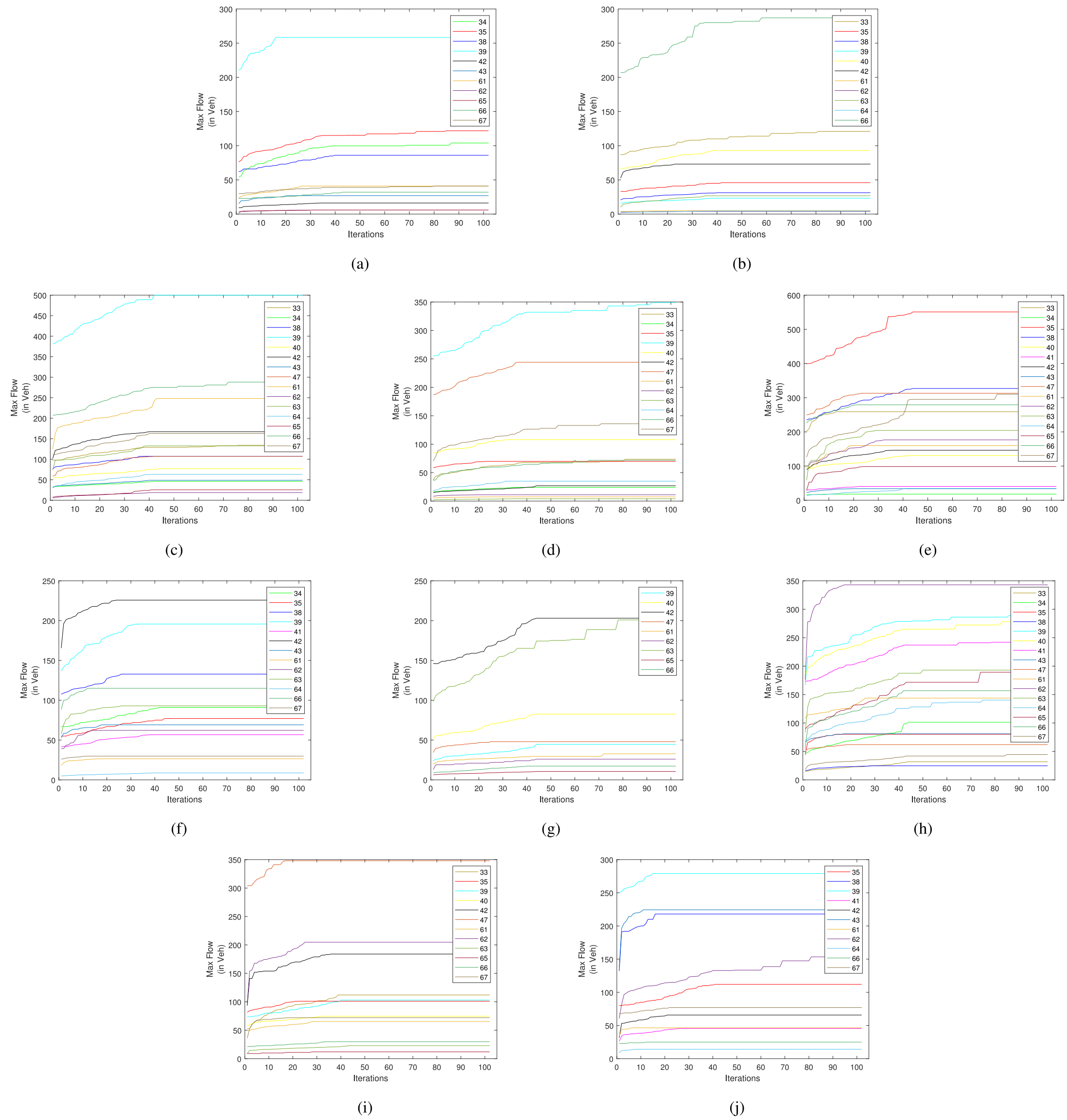


Fig. 11. (a) Optimal maximized trip generation for origin zone 33; (b) Optimal maximized trip generation for origin zone 34 (c) Optimal maximized trip generation for origin zone 35 (d) Optimal maximized trip generation for origin zone 38 (e) Optimal maximized trip generation for origin zone 39 (f) Optimal maximized trip generation for origin zone 40 (g) Optimal maximized trip generation for origin zone 41 (h) Optimal maximized trip generation for origin zone 42 (i) Optimal maximized trip generation for origin zone 43 (j) Optimal maximized trip generation for origin zone 47.

Results from the implementation of the presented methodology on a real-world network showed impressive directions. The inequalities in the form of travel equilibrium cost ratios indicate the possible induced demand that can be contained and served by the prevailing transportation networks. Under different upper bounds for inequity, it was found that the most optimal travel equilibrium costs and newly generated demand are for the upper bound of 1.09. Not only this but a detailed analysis of the optimal curves for each origin zone and every OD pair explicitly shows that with a steady growth of trips, there is a possibility of decrement in travel equilibrium costs for different zones. Also, not every zone shows the optimal values for a single upper bound of inequity. This reveals the importance of micro-level planning for urban and transportation development. The proposed methods highlight the importance of planning for each zone to the extent that it grows to its maximum potential without causing an imbalance in the travel equilibrium costs when AVs are introduced into the network. This research provided a tool for modelling inequity in transportation and land-use models by keeping an eye on and avoiding the negative impacts on the existing user group when this new form of mobility i.e. AVs is introduced. This can serve as an effective tool for transportation planners. Future work is underway for the evaluation of the network with other new forms of mobilities that are in boom nowadays specifically micro-mobility options during this period of a pandemic.

As elaborated earlier, eliminating or keeping the inequity to its minimum itself is a major societal goal that needs to be addressed while developing any policy guides for future scenarios of heterogeneous traffic streams. Although uncertainties are there yet development in technology and testing is at a pace too, coming back to the basic and grass root level planning is of uttermost importance. It is the people no matter from which group for whom the planning and policy-making should be carried out. Inequity is directly related to the social goal of access, inclusion and community well-being. AVs are supposed to contribute to serving the underserved community but at the same time can cause network imbalances too by increment in travelled miles thus it is of prime importance to reveal how much our current networks allow to digest without causing harm to any group of people. That is what we achieved through our extensive analysis. Not to forget, that

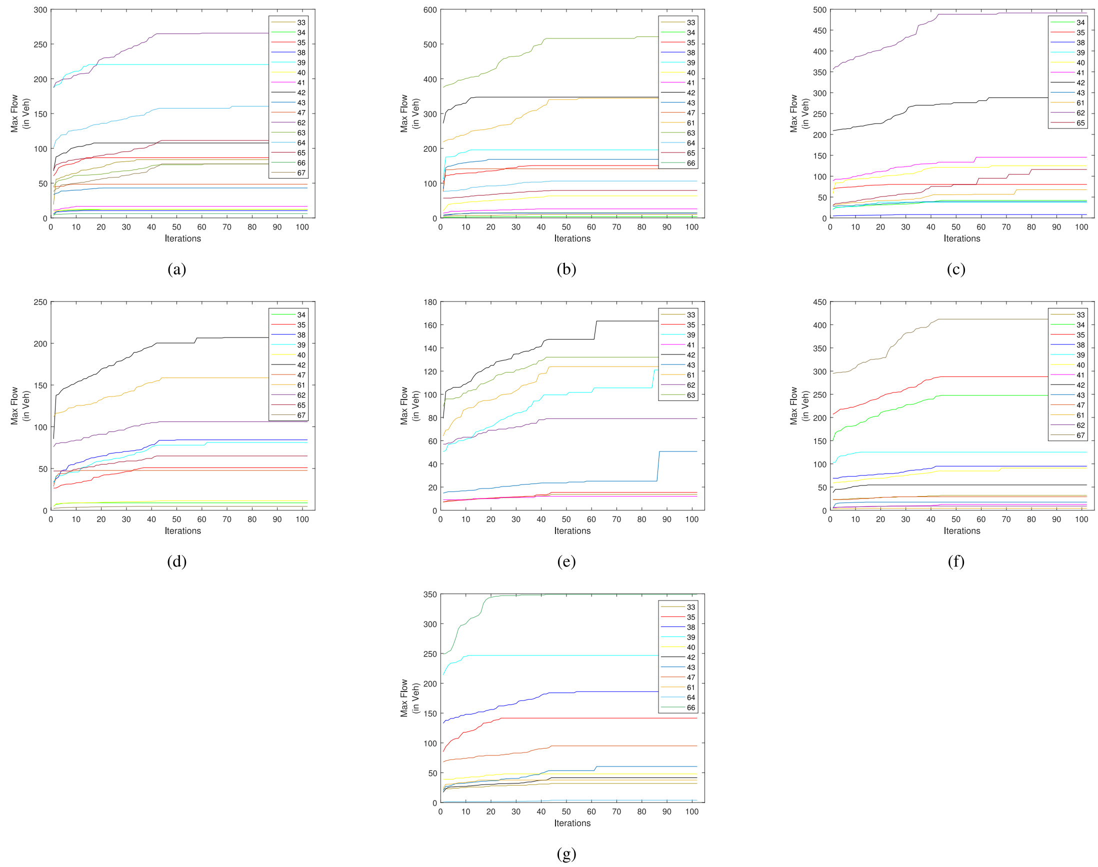


Fig. 12. (a) Optimal maximized trip generation for origin zone 61; (b) Optimal maximized trip generation for origin zone 62 (c) Optimal maximized trip generation for origin zone 63 (d) Optimal maximized trip generation for origin zone 64 (e) Optimal maximized trip generation for origin zone 65 (f) Optimal maximized trip generation for origin zone 66 (g) Optimal maximized trip generation for origin zone 67.

there were exceptions in our results where the same inequity bound was not good for some of the analysis zones. This marks the significance of micro-level planning, also revealing that policy cannot treat every zone in the same way.

CRediT authorship contribution statement

Muhammad Tabish Bilal: Conceptualization, Methodology, Analysis, Visualization, Software, Writing – original draft. **Davide Giglio:** Conceptualization, Supervision, Reviewing, Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

See Figs. 9–12 and Tables 6 and 7

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