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# A simulation-based framework for quantifying potential demand loss due to operational constraints in automated mobility services

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ABSTRACT

Automated vehicles are key to unlock a more widespread on-demand service, increasing accessibility also in peripheral areas of large cities. To evaluate how the performance of these services may affect the overall demand in return, multiple dimensions of the transport problem have to be considered. Indeed, despite people may be willing to use Automated Mobility On-Demand (i.e., generating a potential demand for the service), they may be less willing to consistently replace their other travel options if they, for example, experience high waiting times (determined by the performance of the service, i.e., the supply). In this study, we propose a simulation-based framework developed by integrating an activity-based and a dynamic traffic assignment model, designed to frame absorbed and lost demand at a disaggregated level. This allows capturing how the effects of network congestion and fleet constraints may cause a certain portion of the demand to shift to traditional modes of transportation, thus improving, for example, the accuracy of business cases for mobility service design or of hidden patterns of inequality for policymakers and public authorities.

## 1. Introduction

### 1.1. Motivation

Urbanization and urban sprawl are two of the driving trends forecast to continue growing in the next decades (Behnisch et al., 2022), which pose challenges from the mobility perspective as peripheries become more distant from the city center and the city outskirts become more sparse. While strong public transportation is a prerequisite to tackle these challenges, the general consensus is that flexible mobility services, e.g., on-demand or demand-responsive, may play a key role in guaranteeing accessibility to peripheries and city outskirts (Narayanan et al., 2020b; Campisi et al., 2021; Nahmias-Biran et al., 2021b; Agriesti et al., 2022b). Still, it has been challenging to design sustainable solutions with accessible prices for the users due to the very nature of the areas to be served, i.e., involving longer trips and a more sparse demand. One of the current streams of research possibly tackling this problem focuses on Automated Mobility On-Demand (commonly referred as AMoD in literature), i.e. on-demand mobility services provided through automated vehicles (AVs) as in Tsao et al. (2019), Hörl et al. (2019b), Narayanan et al. (2020b), Oh et al. (2020) and Nahmias-Biran et al. (2021b), where the operational cost for running such services can be significantly reduced thanks to the absence of

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human drivers (Nahmias-Biran et al., 2022, 2023). Multiple works in this direction have been carried out, focusing on the effects of AVs on the transportation supply (Narayanan et al., 2020a; Oke et al., 2020; Oh et al., 2021; Mourtakos et al., 2022), on land use (Soteropoulos et al., 2019), on the willingness to use and attitudes towards AVs (Chee et al., 2020; Cartenì, 2020; Lécureux et al., 2023), and on the operations of the on-demand service (Dandl et al., 2017; Hörl et al., 2019b; Hyland and Mahmassani, 2020; Nahmias-Biran et al., 2021a; Zhou and Roncoli, 2022; Zhou et al., 2023). As the problem involves multiple transportation dimensions, each bringing different challenges, tools able to frame the complex interactions between the new demand and supply dynamics are often used in these studies, the most common being agent-based models (ABMs) as per (Boesch and Ciari, 2015; Kagho et al., 2020; Bastarianto et al., 2023). These models are able to simulate every single agent (be it user or vehicle) and are generally seen as more effective in evaluating future scenarios, for which the more traditional four-step model could be ill-equipped (Li et al., 2020; Xintong, 2021; Bastarianto et al., 2023). In fact, the four-step model relies on an aggregate analysis of the demand, based on historical patterns, thus less suitable to frame scenarios with disruptive mobility services. On the other hand, many works use ABM to answer questions about AV services and their mobility implication but may rely on some assumptions due to the many factors involved, as stated by Nahmias-Biran et al. (2022). This paper describes a simulation framework integrating state-of-the-art agent- and activity-based (demand) and traffic assignment (supply) models. Then it tests it on a real case study and evaluates two policy implementations. The results focus on the effects that more constrained AV fleets, characterized, for example, by fewer vehicles or less aggressive driving styles, may have on a disaggregated demand. These effects are referred to as *feedback effects* in this paper, by which it is meant the whole array of factors arising from the supply side that would affect the demand (and vice versa). These are, for example, the congestion patterns and their influence on waiting times, but also the scheduling process for the on-demand service or the car-following model and driving style of AVs.

### 1.2. Literature review

Integration of supply and demand models has been studied in literature and, especially in the last decade, resulted in popular simulation tools and ad-hoc architectures. Pendyala et al. (2017) categorize different integration types based on the nature of data exchange (in parallel or iterative) and the developed ad-hoc modules. Pendyala et al. (2012), for example, set up a data exchange between the two models happening every time a destination is reached, for the agents to update their behavior depending on the actual cost of the previous trip. Xiong et al. (2018) build a model that uses a behaviorally sound measure of error to predict changes in mobility choices and the dynamics of the arising traffic conditions. A similar approach is adopted in Xiong et al. (2021) to focus on traffic management strategies. The same supply model is used in Zhang et al. (2018) and its integration with a behavioral ABM is applied to analyze the effects of land use changes. A purely iterative approach with no mid-simulation data exchange is adopted in Heinrichs et al. (2018), where an ABM is coupled with a queue-base supply model. The equilibrium of supply and demand has also been explored in a two-sided market and as result of a day-to-day learning process. In this sense, it is worth mentioning works such as Djavadian and Chow (2017), in which flexible travel services are simulated from both the users and the operator perspectives to find stochastic user equilibrium. In their work, the authors expand the problem of finding an equilibrium state between the two models, as the adopted operator is responsive to the day-to-day oscillations of the demand. Market equilibrium is also used by Rath et al. (2023) to calculate the fleet size of a certain mobility service. A similar approach is followed by Kucharski and Cats (2022), in which drivers of a flexible transport service are modeled as agents to frame their choice of providing the service or not through day-to-day learning and equilibrium search. Two-sided market approaches are attractive due to their ability to potentially frame how trends in the demand arise and change across time, as in Ghasemi and Kucharski (2024) where the perception of each agent about a new service develops with time, based on service quality and marketing factors. Interestingly, not all two-sided market approaches are equilibrium based, as on-demand services may fluctuate too fast for a steady equilibrium to emerge. That is the case in Nourinejad and Ramezani (2020), where a day-to-day ride-sourcing analytical model is designed to optimize the dynamic pricing of a single platform. Overall, multiple integrated ABM solutions have recently emerged in literature and, for a wider discussion on ABMs and supply–demand modeling, we refer the reader to Bastarianto et al. (2023).

As this study focuses on the effects of a constrained AV services on the potential demand, in the following, we focus on (mostly) agent-based literature where disaggregated demand and supply are integrated to study AV services. Generally speaking, the focus on integrating (disaggregated) supply and demand modeling in the same simulation architecture stems from the need of assessing a more fluid transportation ecosystem, with incoming disruptive services and technologies promising to transform the way we move in cities (Paiva et al., 2021). That is the reason why similar modeling approaches have been applied to AV services, among others, as they are able to frame the complex array of effects and disruptions that said services would have both on the supply and the demand. In Marczuk et al. (2015), Basu et al. (2018a) and Oh et al. (2021), for example, a disaggregate demand and its variations due to AV services are fully characterized by designing a nested-logit behavioral model, namely SimMobility-MT (Lu et al., 2015). Yet, the traffic assignment tool (TA) adopted in these works does not frame all the vehicle-to-vehicle interactions that other state-of-the-art tools are capable of. To overcome this limitation, Nahmias-Biran et al. (2022) couples SimMobility-MT with another TA model, namely Aimsun (Casas et al., 2010), to increase the capabilities to account for complexities in the supply model (e.g. by framing car-following interactions). The study in Nahmias-Biran et al. (2022) is the only one (other than this work and its preliminary version (Agriesti et al., 2024)) in literature to couple the two mentioned tools (while Agriesti et al. (2023a) couples them but adopts only a macroscopic TA). This study differs from Nahmias-Biran et al. (2022) as we develop a replicable methodology to integrate the two tools. We then apply it to different scenarios to quantify the effects of different policy-oriented scenarios. In Nahmias-Biran et al. (2022), the focus is instead on operational costs and their impacts on the demand. Basu et al. (2018b) explore the implications of AV services on public transport and manage to do so while also framing network congestion and its effects on the demand. Nahmias-Biran et al. (2021b) focus on three different types of prototype cities to assess equity implications in different urban settings and with different types of AV services, succeeding in capturing the induced demand arising from these different settings and related constraints, but does not study how the AV driving style may change. (Caros and Chow, 2021) apply the two-sided market problem and the day-to-day approach to a case with AV. In their work, the authors use market equilibrium to adjust the mobility service operator's routing policy for maximum profit for a fleet of modular autonomous vehicles. The presented approach is interesting but the aim differs from this work, as in Caros and Chow (2021) the day-to-day learning is used to define an optimal configuration of the service. Maciejewski and Bischoff (2018) try instead to frame the effects on traffic flow of mixed-traffic (AV and human-driven) by using an integrated ABM, i.e. MATSim, an activity-based, extendable, multi-agent simulation framework whose equilibrium between demand and supply is explored through a co-evolutionary search (Horni et al., 2023). Maciejewski and Bischoff (2018) expand the queue model used in MATSim through a flow capacity consumption coefficient that adapts the links' throughput based on the ratio of AVs over human-driven vehicles, also stating that the queue model, while computationally efficient, entails certain simplifications such as vehicles in traffic being only tracked when entering and leaving a link. Nevertheless, the improved queue model was successfully exploited by Simoni et al. (2019) to assess the effects of congestion pricing on the demand, with on-demand and shared AV services. Bischoff et al. (2018) evaluate a pooled ride-hailing service, focusing explicitly on the effects of the service performance on the demand distribution. Still, the evaluation for an autonomous fleet is listed only as research direction. Hörl et al. (2019b) use MATSim to evaluate and compare multiple operational policies for an AV fleet, calculating indicators such as waiting times, occupancy, share of empty distance, etc. The study assumes that every trip that could be served by AVs in an agent's plan, will be and so focuses on a long-term time horizon. Yan et al. (2020) assess the impact of trip densities and parking constraints on the SAV fleet performance, calculating the resulting demand for different fleet sizes. Liu et al. (2020) develop an agent-based modeling framework to simulate the competition between human-driven taxis and SAVs, assessing modal share through a logit model. Notably (Liu et al., 2020) explore the effects of different operational speeds for SAVs on the demand, although the speed is not simulated but only estimated. Auld et al. (2019) analyze different demand scenarios to assess AVs, testing different combinations of market penetration, value of time and link capacity improvements (based on the share of AV in the traffic). Gurumurthy et al. (2021) use an integrated ABM to evaluate the effects of an AV fleet spatially constrained (i.e. constrained in the areas of Chicago covered by the service), in a fashion similar to what will be presented as one of the applications of the presented framework, later in this paper. Still, in Gurumurthy et al. (2021) the traffic at the link level is simulated macroscopically (de Souza et al., 2019). Lokhandwala and Cai (2018) focus instead on dynamic ride-sharing and the potentialities of SAVs in said context, by using the Anylogic simulation software (Grigoryev, 2018) to frame how sharing would impact the agents' attitudes towards the service. The focus on shared automated services also motivates (Segui-Gasco et al., 2019), whose work focuses on integrating MATSim with the fleet simulator IMSim to frame the impacts of different AV scenarios and fleet management strategies. Hörl et al. (2019a) focus on the fleet sizing problem with a responsive demand, concluding that the dynamic demand responding to the AV service performance results lower than the maximum static demand, unresponsive to said performance. Many works tackle the problem of simulating AVs in urban settings while relying on some wider assumptions on either the demand or the supply side. Bösch et al. (2018), for example, focus on future scenario design and policy analyses but no particular attention is dedicated to the effects of AV performance on the short-term demand, i.e., the set of day-by-day mobility choices. In ITF (2015) a similar scenario-oriented approach is adopted and different impacts related to AV driving are identified. While a bigger focus is dedicated to the effects of AVs on the transportation supply, no consideration is made on how these effects and AV fleet constraints may reflect on the potential AV demand. Zhou et al. (2025) start from a disaggregated demand while studying different routing and pricing algorithms for a fleet of shared AVs, while Nahmias-Biran et al. (2021a) focus on evaluating how different AV services may affect accessibility in different areas. Still, the effects of AV driving behavior and of fleet constraints (such as limited fleet sizes) are not discussed'in these works. Fagnant and Kockelman (2018) examine how dynamic ride-sharing and fleet sizing are intrinsically correlated, analyzing how different fleet sizes may result in different service performances and impacts. Congestion effects are considered only in relation to the vehicle-miles-travelled (VMT) indicator, as the model does not explore how AVs and their driving style may affect congestion and the demand in return. Golan et al. (2019) use an ABM to solve the fleet sizing problem but adopts a less disaggregate behavioral model and less complex car-following behavior. Similarly, the fleet sizing aspect is the main focus of the paper by Bischoff and Maciejewski (2016) but, while the modal share is reported for each scenario, no assessment is provided on the feedback effects of the fleet performance on the demand. Boesch et al. (2016) evaluate the reduction of the required vehicle fleet size for an AV fleet, given specific performance levels. Still, the different considered demands are fixed and rigid. Notably, the paper lists in the conclusions the need for a better framing of the feedback effects of the service performance on the demand, which is what this paper tries to tackle through the presented simulation-based framework. Rodier et al. (2018) integrates two simulation tools to harness the improved demand model from one and the efficient TA of the other. Still, the AV performance in different scenarios and configurations is not reassessed through the demand model. Carreyre et al. (2020) perform a cost–benefit analysis for different scenarios and AV services but fleet constraints and performances are not considered in the calculation of the demand.

### 1.3. Summary of the literature

Overall, there is a rich stream of literature focusing on modeling AV services through ABMs, to frame the joint effects arising from the interactions between demand and supply. This study positions itself in the literature by coupling two state-of-the-art models while detailing the procedure step by step in a replicable fashion. The developed framework is then used to analyze two policy-oriented scenarios, designed to harness the detailed behavioral modeling and a dynamic traffic assignment (DTA) that explicitly simulates

**Table 1**
Summary of the literature review. Tools and methods are categorized as: (–) lower complexity, (o) average, and (+) state-of-the-art; in the "Type of demand" column, the choice tree refers to a logit choice structure, with a full tree encompassing all the mobility choice's level and a simplified one being limited to certain levels (such as modal split).

| Study | Type of demand | Traffic assignment tool | Supply model (car-following, queue-based, etc.) | Aim of the study |
|---|---|---|---|---|
| Basu et al. (2018a) | Full choice tree, disaggregate and elastic (+) | SimMobility Short-Term | MITSIM GHR model (o) | Impact of AVs on mass transit |
| Marczuk et al. (2015) | Full choice tree, disaggregate and elastic (+) | SimMobility Short-Term | MITSIM GHR model (o) | Fleet sizing and station location for AVs |
| Bösch et al. (2018) | Simplified choice tree, disaggregate and elastic (o) | MATSim | Queue-based (o) | Policy applications - Pricing and organization of AV services |
| ITF (2015) | Rule-based and rigid (o) | ad-hoc | NA | Impact assessment of different AV fleets |
| Zhou et al. (2025) | Simplified choice tree, disaggregate and elastic (o) | Aimsun Next | Gipps model (+) | Routing and pricing optimization for shared, on-demand AVs |
| Nahmias-Biran et al. (2021a) | Full choice tree, disaggregate and elastic (+) | SimMobility Short-Term | MITSIM GHR model (o) | Accessibility assessment for a fleet of AVs |
| Fagnant and Kockelman (2018) | Random draw (–) | MATSim | Queue-based (o) | AV fleet sizing |
| Golan et al. (2019) | Simplified choice tree, disaggregate and elastic (o) | MATSim | Queue-based (o) | AV fleet sizing |
| Bischoff and Maciejewski (2016) | Simplified choice tree, disaggregate and elastic (o) | MATSim | Queue-based (o) | AV fleet sizing |
| Caros and Chow (2021) | Random utility-based discrete choice model (o) | MATLAB | NA | AV routing policy |
| Boesch et al. (2016) | Fixed and rigid (–) | MATSim | Queue-based (o) | AV fleet sizing |
| Rodier et al. (2018) | Full choice tree, disaggregate and elastic (+) | MATSim | Queue-based (o) | Comparison of different AV services |
| Carreyre et al. (2020) | Simplified choice tree, disaggregate and elastic (o) | MATSim | Queue-based (o) | AV cost benefit analysis |
| Bischoff et al. (2018) | Simplified choice tree, disaggregate and elastic (o) | MATSim | Queue-based (o) | Analysis of service performance effects on the demand of a pooled ride-hailing service |
| Maciejewski and Bischoff (2018) | Simplified choice tree, disaggregate and elastic (o) | MATSim | Queue-based (o) | Mixed traffic assessment |
| Simoni et al. (2019) | Simplified choice tree, disaggregate and elastic (o) | MATSim | Queue-based (o) | Congestion pricing in AV scenarios |
| Basu et al. (2018b) | Full choice tree, disaggregate and elastic (+) | SimMobility Short-Term | MITSIM GHR model (o) | Implications of AV services on public transport |
| Nahmias-Biran et al. (2021b) | Full choice tree, disaggregate and elastic (+) | SimMobility Short-Term | MITSIM GHR model (o) | Equity implications with different types of AV services |
| Hörl et al. (2019b) | Simplified choice tree, disaggregate and elastic (o) | MATSim | Queue-based (o) | Comparison of different operational policies for the AV service |
| Yan et al. (2020) | Simplified choice tree, disaggregate and elastic (o) | MATSim | Queue-based (o) | impact of trip densities and parking constraints on the SAV fleet performance |
| Liu et al. (2020) | Simplified logit model (–) | NA | Estimation (–) | Effects of different operational speeds for SAVs on the demand |

(*continued on next page*)

car-following[1] and is thus able to frame interactions between all vehicles (AV *and* human driven). This work builds on Agriesti et al. (2025, 2024) by expanding the simulation-based framework and the underlying methodology, enabling to account for the disruption of an on-demand AV service. Besides, it exploits the simulation-based framework to precisely frame the feedback effects that the performance of a disruptive system would have on the potential demand, by using an activity-based model (SimMobility-MT) built over 22 behavioral models (Adnan et al., 2016) and by explicitly considering and simulating different driving behaviors for the AV fleet. The underlying complexity and capabilities of SimMobility-MT are further described in Section 3.1.

The relevant literature concerning AV and agent-based modeling is summarized in Table 1. The table reports only a subset of the discussed literature, namely the works where the chosen TA plays an important part in the study of the simulated AV service and its effects on the demand.

[1] i.e. the effects of mixed traffic on the capacity of each link are the direct result of changes in the single car-following model's parameters.

**Table 1** (*continued*).

| | | | | |
|---|---|---|---|---|
| Auld et al. (2019) | Full choice tree, disaggregate and elastic (+) | Polaris | Newell's Model (o) | Evaluation of different combinations of market penetration, value of time and link capacity improvements |
| Gurumurthy et al. (2021) | Full choice tree, disaggregate and elastic (+) | Polaris | Newell's Model (o) | Spatial constrains on the AV service and resulting VMT |
| Lokhandwala and Cai (2018) | Ad-hoc | NA | Estimated (−) | Attitudes towards sharing SAVs |
| Segui-Gasco et al. (2019) | Simplified choice tree, disaggregate and elastic (o) | MATSim + IMSim | Queue-based (o) | Impacts of different AV scenarios and fleet management strategies |
| Hörl et al. (2019a) | Simplified choice tree, disaggregate and elastic (o) | MATSim | Queue-based (o) | Fleet sizing and analysis of service performance effects on the demand |
| Nahmias-Biran et al. (2022) | Full choice tree, disaggregate and elastic (+) | Aimsun Next | Gipps model (+) | Impacts of operational costs on the demand |
| Current study | Full choice tree, disaggregate and elastic (+) | Aimsun Next | Gipps model (+) | Analysis of service performance effects on the demand |

### *1.4. Research gaps*

Many works use ABM to answer questions about AV services and their mobility implication. This work positions itself within the existing literature through the following contributions:

- Design of an integration framework through which two state-of-the-art tools not yet integrated together are coupled and tested
- Application of the proposed framework to large-scale AV scenarios in an urban setting, with a specific focus on fleets constrained either in size or in driving style, akin to public, subsidized or regulated services rather than private and unregulated ones.

Besides, the developed framework is applied to a real life case study to draw policy and practice considerations regarding:

- The unequal impacts across the population of the unserved demand, through the socio-econometric activity-based model
- Impact of different AV driving styles on the service performance, through the mesoscopic car-following model and the DTA

The work thus tackle the disaggregated assessment of an on-demand AV service from a different angle than the ones commonly found in literature (e.g. the ones in which the fleet tries to maximize either profit or performance). Indeed, it focuses on effects of given constraints that may arise in cases where the service is either subject to regulations or provided with a limited fleet (e.g. by a public authority). To do so, the presented work exploits more complex and disaggregate modeling to simulate the demand and the supply, better framing how the interactions between the two result in unabsorbed demand. It does so by exploiting the set of behavioral models in the nested logit tree defined for SimMobility-MT (Sweet, 1997) and coupling it with a state-of-the-art mesoscopic supply model able to frame car-following behavior for each vehicle. The disaggregated supply–demand interactions (specifically the feedback effects) differ greatly from more structural factors such as attitudes towards AVs (Chee et al., 2020; Cartenì, 2020; Lécureux et al., 2023) and deserve to be analyzed carefully, since, e.g., they are a key component in designing business cases for a certain fleet of AVs. Besides, they can be used by public authorities to analyze the sociodemographic characteristics of the lost potential demand and possible related social (sustainability) issues. We will show how the proposed approach allows the quantification of the loss of potential demand and its socio-demographic characteristics with a level of detail able to consider car-following specific features for AVs. This paper studies the loss of potential demand due to fleet performance by replicating the transportation equilibrium search process (Rodrigue, 2020) in a system perturbed by a new AV on-demand service. The presented work shows how it is possible to identify the potential demand that is not absorbed by a constrained AV fleet. The approach is tested on a large-scale case study, with calibrated behavioral models and realistic car-following behaviors able to frame the AV service performance across the network (and thus realistic feedback effects).

### *1.5. Paper structure*

The paper is structured as follows. Section 2 describes the simulation-based framework and the proposed solutions, detailing the underlying methodological approach and assumptions. In Section 3, a case study related to the introduction of an AV on-demand service is presented, while in Sections 4 and 5 numerical results are reported and discussed. In Section 7, the conclusions are reported, limitations are discussed, and future research directions are commented.

## **2. Materials and methods**

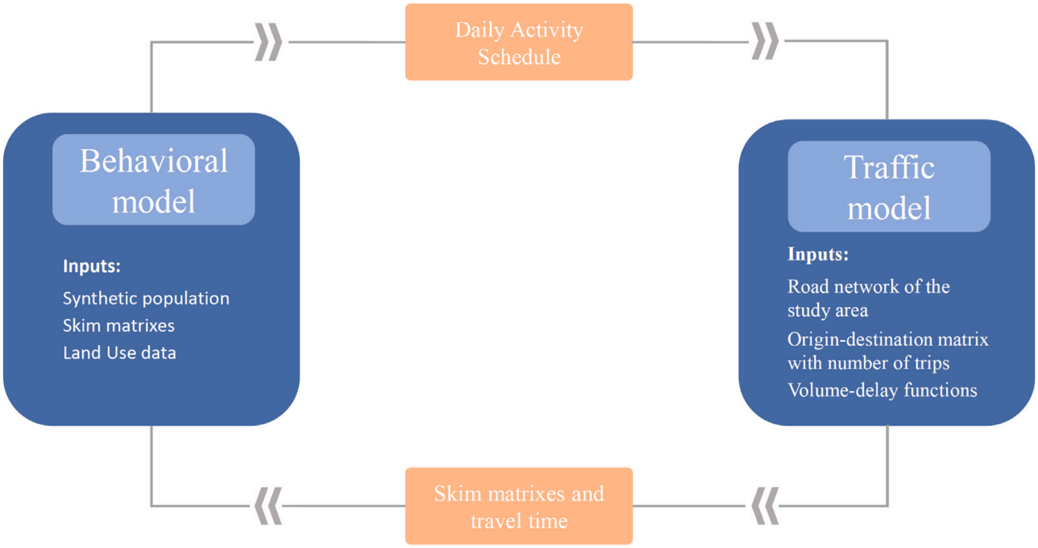


**Fig. 1.** Iteration cycle, as introduced by Agriesti et al. (2025); the daily activity schedule is a dataset including each leg of each journey carried out from the population, detailing modal choice, time of departure, destination and reason for the movement.

### *2.1. Simulation-based framework*

To investigate how a new mobility service disrupts the historical mobility patterns and where the new equilibrium between demand and supply lies, we consider an integrated simulation-based framework that comprises an activity-based model and a TA model. While the former exploits behavioral models and utility functions to determine the traffic demand, the latter carries out the traffic assignment and calculates how the AV fleet performs together with the background private traffic and the public transportation vehicles.

The underlying methodological approach has been designed to be transferable as it does not require any data exchange mid-simulation between the two models (Agriesti et al., 2023a, 2025, 2024). The two models interact in series, with the outputs of one being the inputs of the other. Besides, the approach does not require specific software as the models are treated as black boxes and the equilibrium search happens in between simulations. This, in turn, allows the usage of a multitude of TA tools, depending on the case study.

The in-series approach is based on iterations between the demand and the supply model, as shown in Fig. 1. Each iteration is one run of both the activity-based and the DTA models, with the former generating detailed activity schedules and the latter translating them into travel times (or generalized costs) across the network. All the activity schedules are aggregated in a daily dataset including each trip carried out by the population, detailing modal choice, time of departure, destination and reason for the movement. At the end of each iteration, the mismatch between the generated demand and the arising supply performance is assessed through an ad-hoc indicator (denoted later as $\Delta A$). In the following, the underlying assumptions are reported, the indicator is formulated, and the simulation-based framework is described. Besides, the methodological approach the framework relies upon is reported.

### *2.2. Theoretical background and assumptions*

The problem at hand is for the system of demand and supply (i.e., the two models) to reach an equilibrium after being perturbed by the introduction of a disruptive mobility service. For the equilibrium distribution to exist in the first place, the following is assumed:

- The number of trips $n_{od}$ and the travel time $tt_{od}$ for each OD (origin–destination) pair $od$ are inversely correlated, i.e., a decreased travel time results in a bigger number of trips. The inverse correlation between $n_{od}$ and $tt_{od}$ guarantees that there is an equilibrium point for each OD pair.
- The effect of intersecting traffic (i.e., arising from other OD pairs) on each OD pair does not change the inverse nature of the correlation between $n_{od}$ and $tt_{od}$.
- The inverse relationship between $n_{od}$ and $tt_{od}$ results in a concave search space around the equilibrium for each OD pair. This translates into the feasible equilibrium distribution lying in the same neighborhood (i.e. close distributions reflect similar demand and supply states).

For a more detailed description of the assumption and their formulation, the reader can refer to the work by Agriesti et al. (2025).

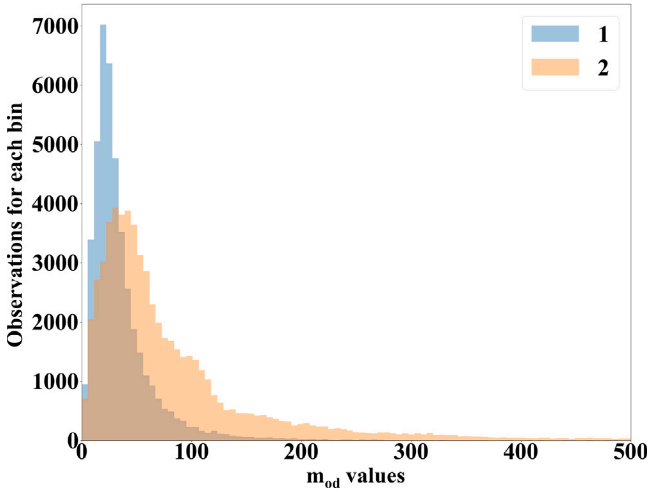


**Fig. 2.** Area comparison between iteration 1 and 2 (Agriesti et al., 2025) - each bin on the $x$-axis represents the number of cells in the OD matrix falling within a certain $n_{od} \cdot gc_{od}$ range.

### 2.3. Measure of error

To identify the distance from the equilibrium state, we introduce $m_{od} = n_{od} \cdot gc_{od}$, where $gc_{od}$ is the generalized cost for a given origin–destination pair. This quantity is broadly applicable, as any behavioral activity transportation ABM produces the number of trips (Kagho et al., 2020; Bastarianto et al., 2023) and any TA algorithm produces travel times, one of the most used measures of $gc$. Thus, we introduce our main indicator for assessing the closeness to the equilibrium state in terms of the difference in mobility patterns between consecutive iterations, according to:

$$\Delta A^i = |A^i - A^{i-1}| = \Sigma_{M_{od}} |v^i(m_{od}) - v^{i-1}(m_{od})| \quad d(m_{od}) \quad \forall m_{od}, \tag{1}$$

where $i$ is the iteration index, $od$ represents each origin–destination pair, and $v$ is the number of measurements (or cells) whose value falls in a certain range of $m_{od}$. As $\Delta A$ is designed to frame the *distance* from the equilibrium state, it is mathematically defined as the area mismatch for distributions of $m_{od}$ between iterations. Each area in Eq. (1) represents the area subtended by a $m_{od}$ distribution: two perfectly matching areas would represent two identical distributions, leading to $\Delta A = 0$. A graphical representation of two $m_{od}$ distributions and their mismatch is reported in Fig. 2.

### 2.4. Simulation-based framework

Given that the two citywide models are treated as large-scale black boxes, i.e., lacking clear mathematical formulations to describe how inputs are transformed into outputs, as illustrated in Fig. 1, finding an equilibrium solution becomes highly challenging. Consequently, we resort to using a search heuristic. The conceptual integration between the activity-based and TA models is achieved in practice through the simulation-based framework represented in Fig. 3, which details the data flow for each iteration. Each iteration involves the following steps:

- The ABM uses the cost related to each OD pair to generate demand patterns for the different modes of transportation available
- The demand patterns are translated into OD matrixes for human-driven vehicles and into on-demand requests for the AV fleet management module
- The DTA and the fleet management module are run together, with the fleet management module creating schedules for each AV vehicle in the fleet and passing the information to the DTA, which then proceeds to simulate mixed traffic
- The DTA generates in-vehicle travel times ($ivt$) matrixes for human-driven vehicles, while the fleet management module generates a log for each AV detailing every status change (idle, traveling to origin, at pickup, traveling to destination, at delivery). Unserved requests, waiting times ($wt$) and $ivt$ are then calculated for all AVs
- The travel times related to each mode of transport are used to calculate the generalized cost between each OD pair and the resulting impedance matrixes
- $\Delta A$ is calculated
- The impedance matrixes are fed back to the ABM.

The feedback effects of the impedance matrix on the demand (thicker gray line) are what is going to be framed in the paper. By impedance, it is meant generalized cost, as defined in the AV utility function in the behavioral model (as it will be explained more in detail in Section 3). The simulation-based framework is reported in algorithm form in Appendix.

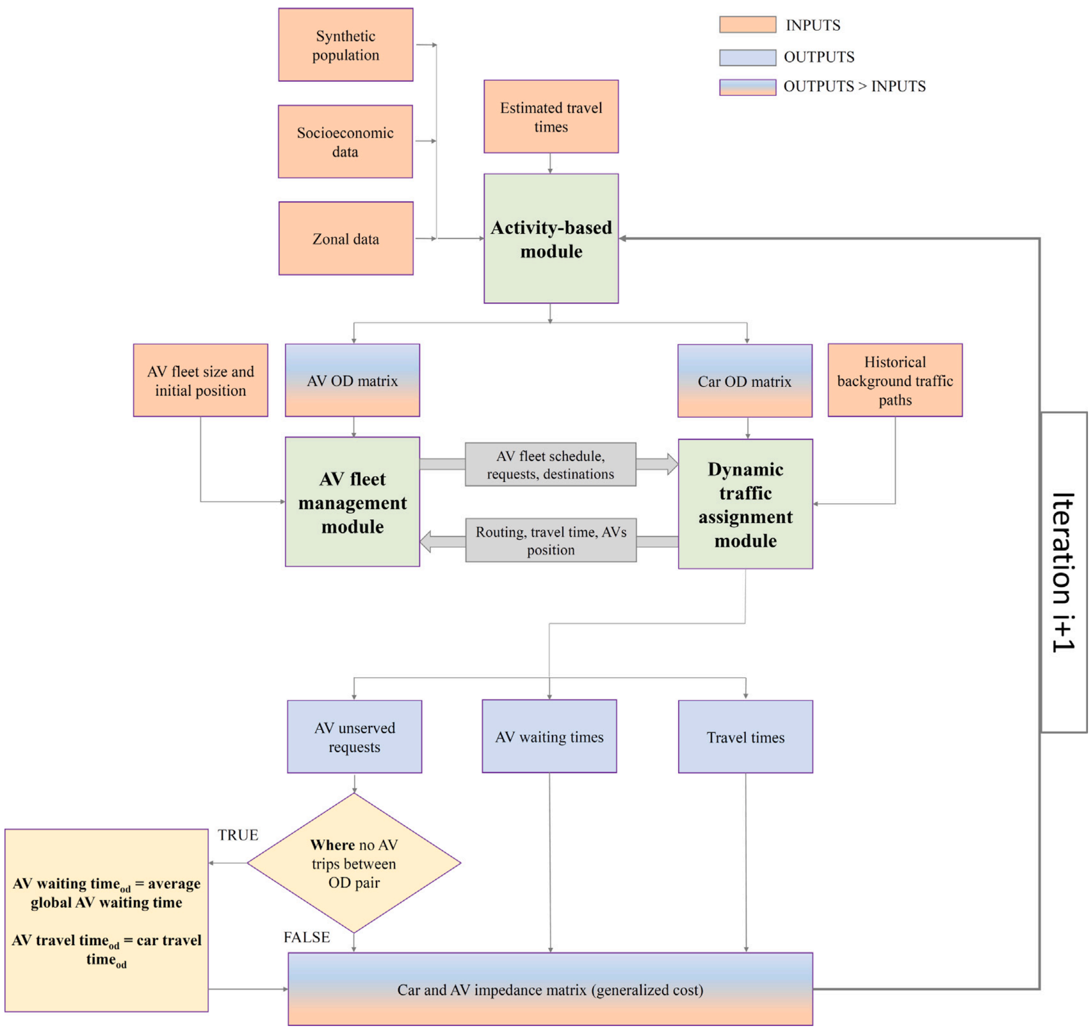


**Fig. 3.** Simulation-based framework: communication between 3 modules: Activity-based module, AV fleet management module and Dynamic Traffic Assignment module - boxes with a gradient color represents data being the output of one model and input for the other one. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

It should be again acknowledged that the iterative cycle summarized in Fig. 3 joins other similar approaches in literature (Pendyala et al., 2017; Xiong et al., 2018, 2021; Zhang et al., 2018; Pendyala et al., 2012; Heinrichs et al., 2018; Segui-Gasco et al., 2019; Briem et al., 2019; Feng et al., 2024; Ziemke et al., 2021; Nahmias-Biran et al., 2022).

### 2.5. Methodological approach: Search space characterization

It is not sufficient to simply reassess the demand after one iteration in Fig. 3 though, as a new demand will produce a new impedance matrix and so on. In fact, the actual effects of the AV performance on the demand must be assessed in an equilibrium condition (i.e., $\Delta A \approx 0$). Therefore, the initial step involves running a first set of iterations to verify that the system does not display a diverging behavior and to identify the area where the equilibrium condition lies for $n \cdot gc$. As the AV performance is the main focus of this paper, the first iteration is run starting from a calibrated baseline at equilibrium (Agriesti et al., 2025), where the AV service is introduced as a perturbation. The same approach is replicable though for any new mobility service or technology, as long as they represent a perturbation in the considered mobility system. A new AV service is a suitable scenario in this sense, as the new service disrupts both the demand (new mode available) and the supply (different driving behavior and number of vehicles on the road infrastructure). The system itself is not guaranteed to have a strong diverging nor converging behavior, as the distributions may bounce between two extremes. Intuitively this is reasonable since we start from either an over- or an underestimation of the AV demand, as the AV service performance at the start of the first iteration is unknown and thus estimated (e.g., approximated as similar to the private traffic one). This results in either an under- or an overestimation of the performance (a higher AV demand causes

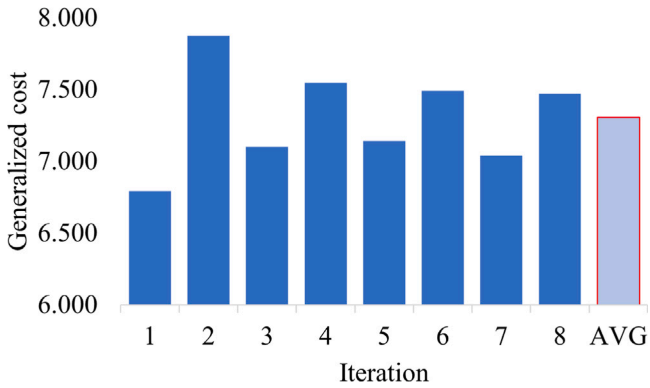


**Fig. 4.** Generalized cost across iterations in the morning peak - in light blue the average value fed back to the loop in the search for the equilibrium distribution. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

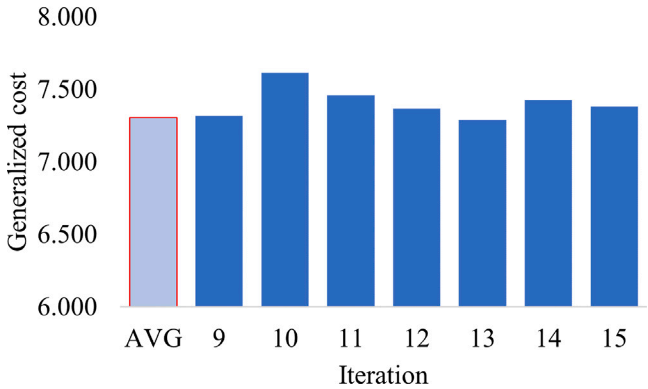


**Fig. 5.** Generalized cost after the average value is fed to the ABM model.

higher or lower travel and waiting time), which, in turn, again over- or underestimates the demand. The initial set of simulations and iterations is first employed to characterize the search space and validate the assumptions introduced in Section 2.2. If the system does not converge on its own, the search space should be explored.

### *2.6. Methodological approach: Search space exploration*

As the $n \cdot gc$ displays a symmetric behavior, i.e., an overestimation of $n$ causes an overestimation of $tt$ (and thus of $gc$), which in turn causes an underestimation of $n$ and of the following $tt$, it is possible to assume that its distribution at equilibrium lies somewhere between the identified extremes. To find it, it is possible to explore the search space by perturbing the system, i.e., introducing a new AV impedance matrix between iterations, the values of which are calculated as quantiles[2] of the values from the search space characterization. The approach is similar to what has been proposed for private cars by Agriesti et al. (2025) but has been extended to include all the generalized cost components for the AV impedance, which is calculated between each OD pair according to

$$I_{\mathrm{OD}} = ivt_{\mathrm{OD}} \cdot \beta_{\mathrm{AV\ in\ vehicle\ travel\ time}} + wt_{\mathrm{OD}} \cdot \beta_{\mathrm{AV\ waiting\ time}}, \tag{2}$$

where $ivt$ and $wt$ represent travel time and waiting time. The sum of $ivt$ and $wt$ represents the time spent for a single trip, namely both $tt$ and $gc$.

The average of the generalized costs arising from the first set of iterations (Fig. 4) is fed to the system (or rather, a matrix of averaged generalized costs, one for each OD pair). The average has been chosen as first tentative value because the system seems to display a symmetric behavior between extremes, so the exploration could reasonably start from the central area.

With the averaged generalized cost and the resulting AV impedance matrix, a new round of iterations is started to assess if the equilibrium distribution $n \cdot gc$ lies in the neighborhood of the explored portion of the area.

[2] Quantiles are cut points dividing the available observations into subsets with equal probabilities. In this work, any quantile lying between two observations is determined through linear interpolation.

The value of $\Delta A$ from the perturbed iterations is analyzed in two key aspects: reaching an acceptable threshold and, more importantly, if multiple successive iterations result in bigger values of $\Delta A$. An increasing $\Delta A$ would signal diverging behavior and thus unstable equilibrium. A stable behavior would result in similar, below-threshold $\Delta A$ values across successive iterations and flat values of the generalized cost (Fig. 5). As it will be shown in Section 3, $\Delta A$ values under a certain threshold result indeed in acceptable variation in performance indicators for the fleet of AVs (i.e., served and unserved requests, waiting and travel times). Stable values of unserved requests are the key results as they are the results of the service constraints and reflect actual agents willing to use the service (product of an elastic and, crucially, informed demand aware of the AV performance) but unable to do so (due to realistic supply constraints).

## 3. Case study: Experiment set-up

The proposed approach is tested to assess a case study involving the introduction of an on-demand AV fleet in the capital city of Tallinn, Estonia. As around 400,000 people live in Tallinn, carrying out more than 1.000.000 trips each day, the case study is a large-scale urban environment. To replicate the simulation architecture described in Fig. 3, two models have been built and calibrated: a behavioral activity-based ABM in SimMobility-MT (Lu et al., 2015) and a simulation-based traffic assignment model (DTA) in Aimsun Next (Casas et al., 2010). The base scenario focuses on the short-term implications of the deployment of a fleet of AVs, which is constrained by two main factors:

- Fleet size: The number of AV providing the on-demand service is capped at a certain value, to reflect a situation in which the city mandates a certain limit or a situation in which the service provider is not willing to carry out a bigger investment in the short term (due to regulatory uncertainties, for example).
- AV driving style: The desired speed distribution and the reaction times of the AVs are simulated as more cautious than human-driven vehicles (Stogios et al., 2019; Liu et al., 2020; Lu et al., 2021; Richter et al., 2022; Dadashzadeh et al., 2024), while being also forced to fully comply with the speed limits.

The short term scenario was chosen as the developed framework, with its degree of precision, is equipped to frame how fleet size and operational constrains will affect the transport network and the demand in return. The effects of the operational constraints specifically will be compared with results for a fleet of AVs that drives instead more aggressively than a human driver, in Section 5. In a way, the choice of a limited fleet size was made to magnify these effects and, at the same time, show the potentialities of the presented framework. It should also be noted how the hypothesis of cautious or regulated AVs is not new in literature (Hussain and Zeadally, 2018; Stogios et al., 2019; Liu et al., 2020; Lu et al., 2021; Richter et al., 2022; Dadashzadeh et al., 2024). In more regulated settings such as the European one, AV trials have very often seen mostly PT-like services and lower values of speed for the deployed vehicles (Hagenzieker et al., 2020).

### 3.1. The activity-based model

The behavioral models embedded in SimMobility-MT are a key component of our simulation experiment, as they allow to model the effects of different AV performances on the demand. A series of nested-logit models calculates the utility related to each level of each mobility choice through the day, for each Tallinn synthetic inhabitant. This is performed by computing and comparing utilities at each level of the mobility tree (Fig. 6) while exploiting the logsum concept (Nahmias-Biran et al., 2021a) to tie the utilities at the top of the tree with the ones on lower branches. As SimMobility-MT relies on 22 behavioral models and is based on a long stream of behavioral research (Sweet, 1997), it is among the most effective state-of-the-art solutions that could be adopted.

Each level of the logit tree (Fig. 6) is defined by multiple utility functions, one for each branch. The utility related to the AV modal choice, for example, is defined as

$$U_{\mathrm{AV}} = f(V_{\mathrm{case\_study}}, \underline{\beta}_{\mathrm{cons\_taxi}}, \underline{\beta}_{\mathrm{tt}}, \underline{\beta}_{\mathrm{wait\_time}}, \underline{\beta}_{\mathrm{cost}}, \underline{\beta}_{\mathrm{cost\_over\_income}}, \underline{\beta}_{\mathrm{central\_district}}, \underline{\beta}_{\mathrm{female\_num\_of\_cars}}, \underline{\beta}_{\mathrm{number\_of\_cars\_in\_hh}}, \underline{\beta}_{\mathrm{agecat\_num\_of\_cars}}), \tag{3}$$

which frames the utility that each agent perceives from the taxi modal choice, based both on the features of the trip (travel time, cost, etc.) and on the agent's own socio-demographic characteristics (income, gender, number of cars in the household, etc.). Note that each weight variable in (3) is a vector of $\beta$s, including as many behavioral variables as categories considered. For example, $\underline{\beta}$ for age category is a vector with 5 $\beta$s, since 5 are the age categories considered. As in behavioral theory, these $\beta$s are alternative specific constants framing how much each feature (of the trip or of the person) weighs towards the utility (Siyu, 2015).

The activity-based model takes as input:

- A synthetic population of $\sim$ 400,000 inhabitants (agents)
- The socio-demographic features of each inhabitant (agent)
- Cost components of each mode of transportation (e.g., monetary cost, travel time, etc.)
- A mapping of the 610 considered traffic analysis zones (TAZs)

It then calculates the daily activity schedule (Nahmias-Biran et al., 2022, 2023) of each individual, including but not limited to: time of each trip, destination, and mode of choice. Additional details about the building and calibration of the model in SimMobility-MT can be found in the work by Agriesti et al. (2022a, 2023b). Each simulation run considers a different random seed to account for stochasticity in the choice models. This can reproduce, for example, the day-to-day changes happening in real life due to external factors such as weather, day of the week, time of the year, and other external factors.

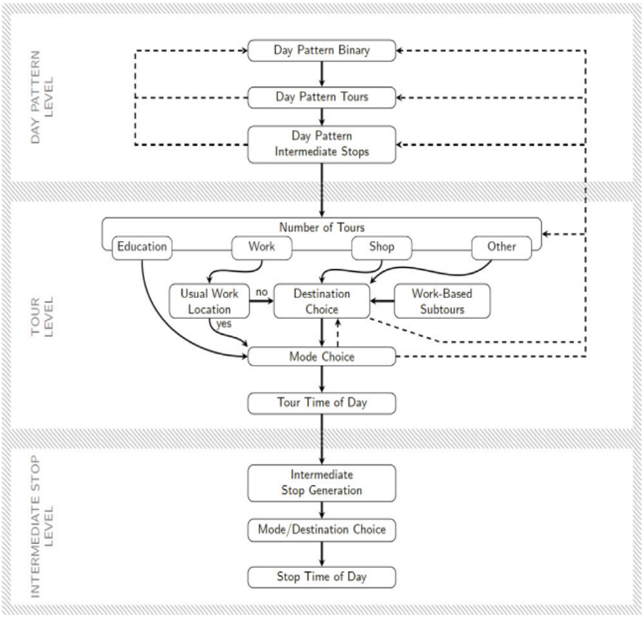


**Fig. 6.** Nested logit structure in the utility tree simulated in SimMobility-MT (Oke et al., 2019).

### 3.2. The dynamic traffic assignment model and the AV scheduling module

The DTA is tasked with assigning the human-driven vehicles and AV traffic to the road network and calculating the travel time needed to get from the origins to the destinations for each mode. The model is built in Aimsun Next, a state-of-the-art simulation-based DTA tool. As many TAZs as in SimMobility-MT have been created in the DTA, with a spatial resolution of 500 × 500 m, each being loaded with the demand generated by the corresponding one in the activity-based ABM.

While the human-driven vehicles' behavior is based on calibrated parameters (Agriesti et al., 2025), the AV fleet is characterized by a more cautious driving style, characterized by a desired speed distribution averaging 40 km/h (against 55 km/h for the human-driven vehicles) and perfect compliance with the speed limits. 3000 AVs are considered to compose the fleet, a quantity that will be kept unchanged across iterations as it is treated as a constraint affecting performance. The value of 3000 was chosen as it corresponds to roughly a 1:7 ratio between available vehicles and requests at peak demand. The ratio was intentionally chosen as lower than the optimal (Spieser et al., 2014; Narayanan et al., 2020b), to impose a constraint able to affect the demand as a feedback effect. An unserved request occurs when no vehicles (either idle or empty) are available at the time the request is made. If a vehicle is idle or empty, once it is assigned to the request, no time threshold for it to arrive to the pick-up location is imposed. This is because, through successive iterations, SimMobility-MT's behavioral demand models filter out unrealistic assignments where AVs are too far from request locations, simulating the fact that, when faced with excessive waiting times, users switch to alternative transportation modes in subsequent iterations. Waiting and travel times are recomputed at each iteration, before being fed back to SimMobility-MT. Finally, the AV fleets adopt a congestion-aware shortest path algorithm while the human-driven vehicles either follow historical paths or reroute by exploiting the Aimsun Next stochastic routing algorithm. This difference in routing is assumed to reflect the realistic features of an on-demand service more aware of surrounding congestion and more keen on avoiding it.

#### 3.2.1. The AV scheduling module - Aimsun ride

Aimsun Ride is the additional module employed to perform the AV fleet management (Narayanan et al., 2023). While Aimsun Next handles the AV routing and traffic simulation, the actual matching between available AVs and requests is performed through Aimsun Ride. Aimsun Ride has already been integrated into wider architectures to include agents' trips within Aimsun Next (Yfantis et al., 2021). Aimsun Ride considers the position of each empty AV every time a new request is submitted to the system, i.e. every time the simulation time reaches the agent departure time in the daily activity schedule from SimMobility-MT. Once the most suitable AV is assigned to the request, the AV schedule is defined by the following states: trip to the origin, pick-up, trip to the destination, drop-off. When the AV is empty again (after the drop-off event) it is either sent to the closest active request or it remains idle at the destination until a new schedule is provided (a new request arises).

As shown in Fig. 7, each AV is stationed within a virtual point called *garage*, in this state the AV is parked on the side of the road or in a station point, waiting to be assigned again. Each garage has a spatial resolution of 500 × 500 m, the same resolution as the centroids (and thus the OD and the requests). Each request is characterized by a timestamp (when the on-demand trip is actually submitted to the system by the user) and an origin centroid. The assignment process is carried out in an event-based framework, as Aimsun Ride interacts with the DTA (Aimsun Next) every time the time-stamp corresponding to a new request or a change of

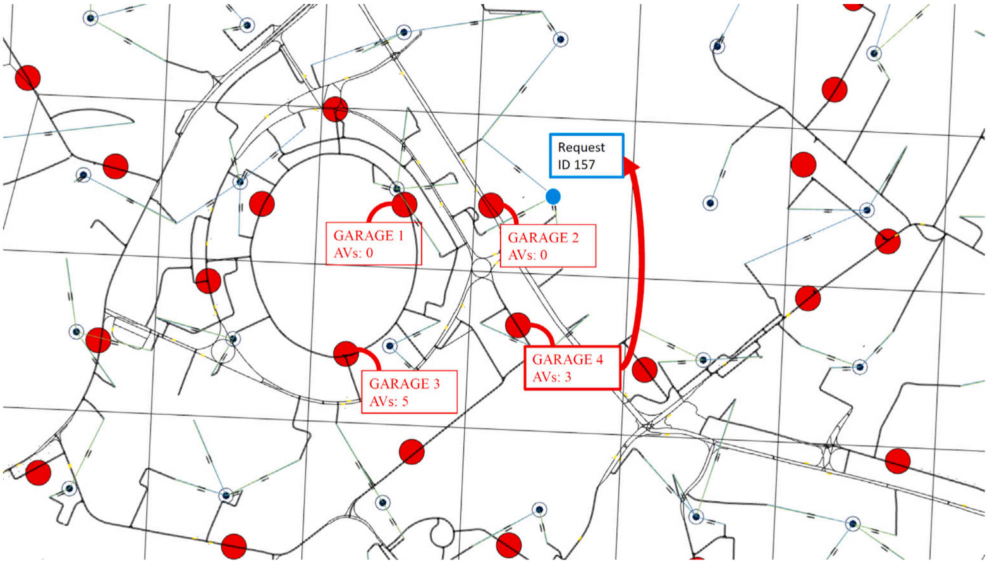


**Fig. 7.** Spatial resolution of the AV loading points (in red - garages) and assignment to the closest request (in light blue).

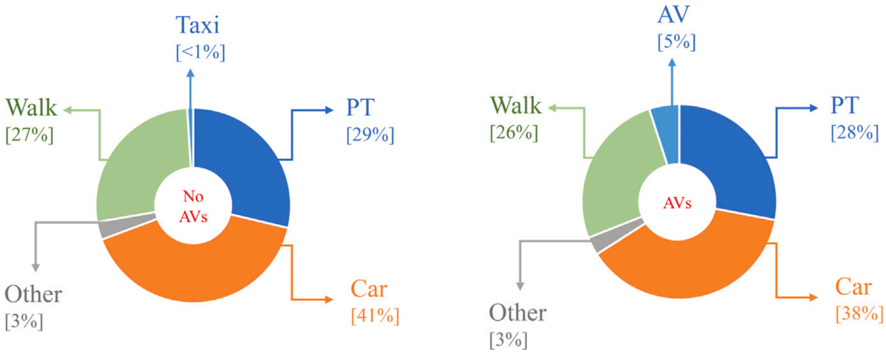


**Fig. 8.** Modal share before (left) and after (right) the introduction of AVs.

state for the AV vehicle is reached in simulation time. It does so by obtaining the position and estimated travel time for each empty AV (either idle or empty but traveling to a garage) and then selecting the one that can arrive to the pick-up point at the earliest. Requests are then assigned or rejected as soon as they enter the system, based on the availability of empty AVs. The closest empty AV vehicle is then tasked with picking up and dropping off the request to the intended destination. To have zones with an area of 500 × 500 square meters (Fig. 7) ensures that each pick-up and drop-off happens akin to a door-to-door service (minus the eventual walking distance from the actual residence to the garage pick-up/drop-off point), while bigger zones would have concentrated these steps in specific points of the network. This, in turn, guarantees that both waiting and travel time for AVs are calculated precisely, while bigger areas would have forced each AV to travel to the same point within the zone, potentially over- or underestimating the operational time needed to get there. Finally, a 500 × 500 m zone allows to include also the walking mode in the mobility choices available to the users (and thus in the modal split). Note also that, despite Aimsun Ride can simulate shared rides and pooling services, the case study for this work does not consider any form of sharing.

### *3.3. The urban scenario*

The two models have been built with the same zoning system to ensure a 1:1 correspondence between generated demand and resulting travel times. The number of trips in the baseline scenario (no AVs) is equal to 1,014,652 and the modal share is reported in Fig. 8.

As it can be noticed, the demand for taxis and other on-demand systems is virtually non-existent before the introduction of AVs. Still, once the fare of the taxi (0.6 €/km) is halved, an initial demand arises, based on an estimated impedance matrix.

The first demand of 5% is estimated by halving the cost and assuming a waiting time of 5 min and a travel time equal to the one experienced by private vehicles. The fleet of AVs is hypothesized to be equally spread across the network (i.e., among zones)

**Table 2**
AV Demand oscillation and resulting service performance - Runs 1 to 8; in red the runs where the AV demand is overestimated and the service underperforms, in blue the runs where the opposite happens.

| Runs | AV requests | Unserved requests | Average waiting time [s] | Average travel time [s] |
|---|---|---|---|---|
| 1 | 11 628 | 636 | 839 | 960 |
| 2 | 22 110 | 11 822 | 1274 | 1121 |
| 3 | 13 667 | 2548 | 960 | 1047 |
| 4 | 18 527 | 7912 | 1197 | 1108 |
| 5 | 14 756 | 3435 | 1002 | 1031 |
| 6 | 17 706 | 6993 | 1181 | 1120 |
| 7 | 14 658 | 3027 | 952 | 996 |
| 8 | 18 566 | 7745 | 1170 | 1045 |

**Table 3**
$\Delta A$ values across the iterations - in gray the first iteration after feeding an average of the generalized cost as impedance matrix.

| Iterations | AM $\Delta A$ | AM $\Delta A^{\%}$ | PM $\Delta A$ | PM $\Delta A^{\%}$ |
|---|---|---|---|---|
| 1–2 | 0.65 | 32.5% | 0.89 | 44.5% |
| 2–3 | 0.46 | 23% | 0.49 | 24.5% |
| 3–4 | 0.36 | 18% | 0.36 | 18% |
| 4–5 | 0.31 | 15.5% | 0.25 | 12.5% |
| 5–6 | 0.26 | 13% | 0.19 | 9.5% |
| 6–7 | 0.30 | 15% | 0.21 | 10.5% |
| 7–8 | 0.28 | 14% | 0.28 | 14% |
| 8–9 | 0.17 | 8.5% | 0.16 | 8% |
| 9–10 | 0.19 | 9.5% | 0.10 | 5% |
| 10–11 | 0.15 | 7.5% | 0.10 | 5% |
| 11–12 | 0.12 | 6% | 0.10 | 5% |
| 12–13 | 0.16 | 8% | 0.09 | 4.5% |
| 13–14 | 0.13 | 6.5% | 0.10 | 5% |
| 14–15 | 0.10 | 5% | 0.09 | 4.5% |

at the start of the day. This allocation constitutes another constraint, as the fleet is not optimized for the demand arising or shifting thanks to the new service.

## 4. Numerical results and the lost potential demand

In this section, the numerical results for the case study are reported and discussed. One single run of a whole iteration lasts for approximately seven hours, one hour for the activity-based model to be run on a high-performance computing cluster and six hours for the TA model running on an i5 - 8365U CPU @ 1.60 GHz $x$ 8 Dell laptop. In Section 4.1, the $n \cdot gc$ distributions for the system in its initial state are analyzed, while in Section 4.2, the same distributions after perturbation of the generalized cost are assessed and compared. The values of $\Delta A$ are monitored and the goodness of the final solution is commented upon.

### 4.1. Runs 1 to 8

This iteration cycle starts with an impedance AV matrix estimated by halving the operational cost of human-driven taxis in the city (Nahmias-Biran et al., 2022) and the resulting initial AV demand is fed to the simulation-based framework in Fig. 3. Table 2 reports the oscillations between higher and lower numbers of requests and the corresponding performance of the 3000 AVs, trying to satisfy a potential demand that is too high to be completely absorbed by the new service. Table 2 refers to the morning peak hours, as they are the more critical in terms of demand and congestion.

As it can be noticed, when not at equilibrium the quantity of requests that remain unserved features strong oscillations, resulting in a standard deviation equal to 3700. It should be also stated that the unserved requests are not simulated in the DTA (e.g., modal shift to private vehicle) until the following iteration, with the underlying hypothesis that travelers would either cancel the trip or shift to public transport.

### 4.2. Runs 9 to 15

The previous round of iterations, while failing to identify an equilibrium state, does define a search space within which the solution is assumed to lie. As it can be noticed from Table 2, both the number of requests, the unserved ones and the waiting times all oscillate between higher and lower values in a bounded manner. By averaging the generalized AV cost for each OD pair (as reported in Section 2 and in Fig. 5), a new AV impedance matrix is fed to the models before running iteration 9.

**Table 4**
AV Demand oscillation and resulting service performance - runs 9 to 15.

| Iterations | AV requests | Unserved requests | Average waiting time [s] | Average travel time [s] |
|---|---|---|---|---|
| 9 | 15 335 | 4385 | 1056 | 1094 |
| 10 | 16 226 | 5499 | 1139 | 1086 |
| 11 | 15 741 | 5151 | 1103 | 1096 |
| 12 | 16 271 | 5610 | 1161 | 1073 |
| 13 | 15 834 | 4832 | 1066 | 1053 |
| 14 | 16 854 | 5979 | 1130 | 1045 |
| 15 | 15 963 | 5089 | 1118 | 1041 |

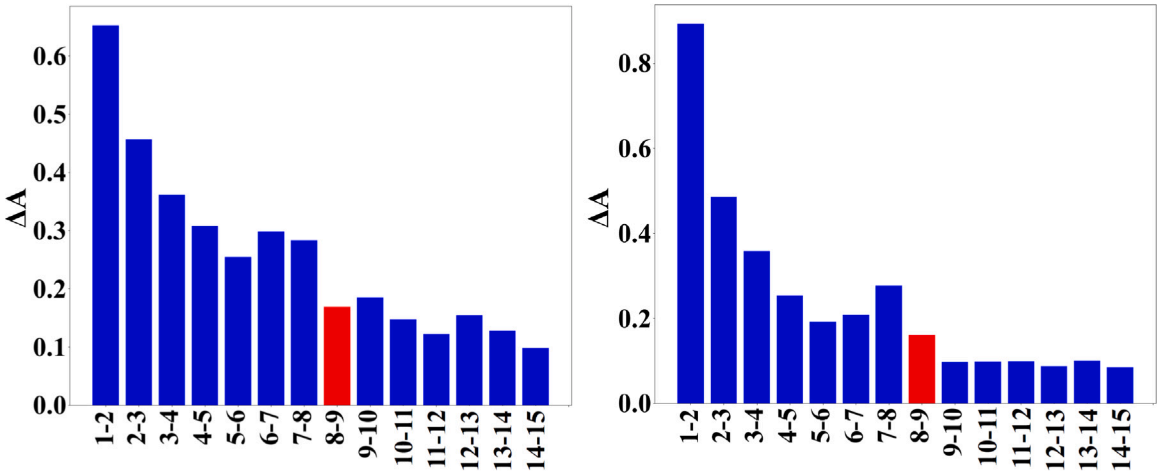


**Fig. 9.** $\Delta A$ values across iterations for the morning (left) and afternoon (right) peaks - in red the iteration fed with the average of the generalized cost for AV travel.

**Table 5**
AV Demand oscillation and resulting service performance in the afternoon peak - runs 9 to 15.

| Runs | AV requests | Unserved requests | Average waiting time [s] | Average travel time [s] |
|---|---|---|---|---|
| 9 | 14 226 | 1675 | 550 | 811 |
| 10 | 15 139 | 1879 | 572 | 767 |
| 11 | 14 619 | 1758 | 571 | 782 |
| 12 | 14 846 | 1780 | 548 | 790 |
| 13 | 14 430 | 1429 | 534 | 788 |
| 14 | 15 399 | 2419 | 585 | 783 |
| 15 | 14 549 | 1675 | 559 | 792 |

As it can be seen from Table 3, $\Delta A$ then settles around 0.10, corresponding to a $\Delta A^{\%} = 5\%$, as its numerical value can range between 0 (perfect match and $\Delta A^{\%} = 0\%$) and 2 (complete mismatch between the two areas under the $n \cdot gc$ distributions and $\Delta A^{\%} = 100\%$). More importantly, once close to equilibrium, the iterations produce remarkably stable values of $\Delta A$. It should be stressed that 0% is in practice not achievable as long as different random seeds are exploited for different iterations but, to include stochasticity through random seeds allows to test the stability of the found solution against random noise. As shown in Table 4, the system settles in an equilibrium state characterized by much smaller variations in both demand and service performance.

Furthermore, it emerges from Table 4 that the iterations corresponding to a 5% $\Delta A^{\%}$ boast a much lower noise around the equilibrium state. The standard deviation for unserved requests drops from 3700 to 529 for the morning peak, with a mean value of 5221. This means that, in this equilibrium state, the AV fleet constraints (i.e., fleet size, AV driving style, and spatial distribution) make it so that 5221 requests on average are lost in the morning peak period (07:00–10:00). These requests are potential demand for the on-demand AV, resulting from the ABM behavioral models, which would be absorbed if some of the constraints were relaxed (e.g., a bigger fleet). On the other hand, the fleet attracts 16 038 requests on average, with a standard deviation of 483. These values are important as they would allow to build different business cases, corresponding to different investment requirements (i.e. fleet size) and to specific levels of earnings (as the behavioral functions account for the AV fares and generate potential demand accordingly). The stability of the found equilibrium is evidenced by the low values of $\Delta A$, as reported in Fig. 9.

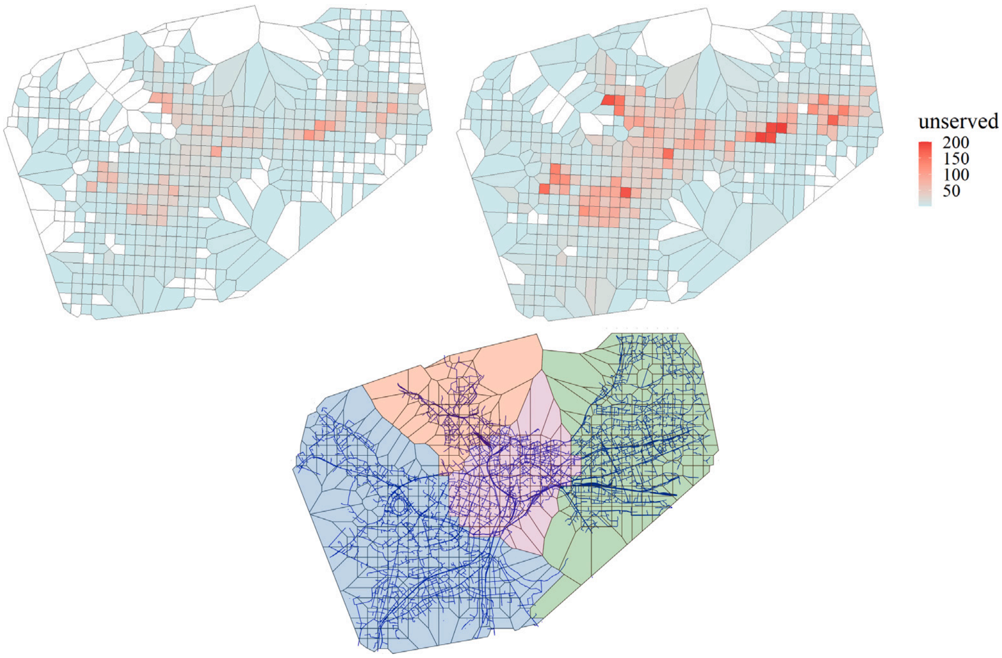


**Fig. 10.** Map of morning peak unserved requests at equilibrium (left) and in run 2 (right - configuration with the maximum potential demand unserved); Traffic analysis zones (bottom) color coded to highlight the central business district in light pink. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

### 4.3. Afternoon peak hours

It is also important to verify the stability of the equilibrium by investigating the AV service performance in the afternoon peak hours, for runs 9 to 15 (Table 5). As it can be noticed, other than a small oscillation between runs 13 and 14 (reabsorbed in run 15), the unserved requests stay flat across the afternoon iterations with a standard deviation of 306 and a mean value of 1802. Waiting times and travel times with AV also do not show any meaningful variation, suggesting that the system is at equilibrium on both the demand and the supply side. Indeed, $\Delta A^{\%}$ for the afternoon is below the 5% value which, as in the morning, shows stable behavior, as reported in Table 3. The value of 0.10 has been used as threshold value for $\Delta A$ for the baseline scenario, but the accepted mismatch between $m_{od}$ distributions should be assesses on a case by case basis, as the system has to show stable behavior for both the demand and the supply at equilibrium (i.e. small variance in $n$ and $gc$ across iterations).

### 4.4. Spatial analysis

The obtained results can also be analyzed in their spatial component, as the identified service at equilibrium results in different shares of unserved requests across the city. This could inform a service provider, for example, where an increase in the AV fleet may yield the biggest increase in earnings by intercepting the lost potential demand and comparing said increase with the investment cost.

As it can be seen in Fig. 10, the distribution of the unserved requests in the morning is uneven at equilibrium (left), with the highest values in the most dense areas (e.g. city center). The comparison is done against run 2, which is the situation where the maximum potential demand is lost (Fig. 10 - right). The choice is motivated by the fact that run 2 represents the AV demand share resulting from a previous iteration where the effects of the service constraints are the weakest (iteration 1, the one with the least unserved requests). Indeed, the comparison highlights the areas where the AV service loses the most demand due to performance constraints. It is noticeable that the spatial pattern does not change between the peak in run 2 and the situation at equilibrium, this is probably due to the initial configuration of AVs, which are spread equally across the city at the start of the simulation (5 AVs for each zone). This initial spread magnifies the fleet constraints where the potential demand is the highest (Fig. 10 - right). This bigger effects of the constraints on the potential demand is also reflected in the huge drops happening in the red zones, while few light blue area see meaningful changes. This happens again because the fleet starts equally spread across the network, which results in worse performance where the potential demand is the highest. Yet even in the central areas (i.e. the traffic analysis zones in light pink in Fig. 10 - bottom) the potential demand lost is uneven (with brighter red spots unevenly distributed), suggesting that there are different margins of improvements that can be framed with a precision of 500 m (it should highlighted that each grid covers a spatial area of 500 × 500 m). Finally, it is important to highlight how considering a rigid and unresponsive demand incurs in the risk of being locked in a peak situation like run 2 (Fig. 10 - right), while the feedback effects of the service performance would in reality affect the end results in a considerable manner (Fig. 10 - left).

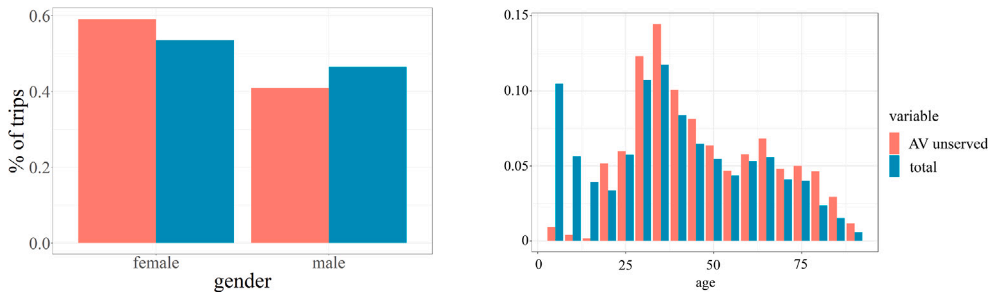


**Fig. 11.** Comparison between the whole traveling population and the one affected by an unserved request - gender (left) and age (right) distributions.

### 4.5. Socio-demographic analysis of the results

The iterative nature of the architecture makes it so that the choices of the agents are always based on the service performance from the previous iteration(s), which is akin to a learning day-by-day process. This is especially true at equilibrium, when the agents willing to choose the AV service are aware of its performance in terms of waiting and travel times (from the previous iteration). This knowledge can then be used by the activity-based module to estimate the features of the agents more likely to use the AV service, while the output of the DTA model can be used to analyze the features of the agents that suffer from an unserved request due to service constraints. This improvement allows us to fully harness the state-of-the-art activity-based model, as the AV service performance influences a set of choices wider than the modal one (as per Fig. 6). In the presented results, at equilibrium, each agent chooses to travel, the destination, time of the day and if using an AV or not, based on the generalized cost and their perceived acceptable dis-utility; each individual has therefore her/his own personalized acceptability threshold, beyond which they may shift mode, number of trips through the day, destination or simply decide to stay at home. While other demand-oriented ABMs exist in literature, our approach exploits a DTA that frames vehicle to vehicle interactions through a state-of-the-art car-following model (Table 1), thus being particularly suitable to reproduce the effects of service constraints. It is then relevant to analyze how the socio-demographic features of agents unable to carry out their preferred trip through the day differ from the statistics of the overall population, as it allows to characterize the features of the potential lost demand, which in turn would open considerations such as equity impacts but also economic analyses from the service provider's perspective (e.g. based on the income distribution of agents unable to travel through the AV service). Before that, it should be highlighted that in the present study there is no direct simulation of attitudes towards AV based on sociodemographic features, as such data is still unavailable for the city of Tallinn (e.g. the propensity of younger rather than older people towards AV). The behavioral model relies on the components of the generalized cost (waiting/travel time, monetary cost) and on the behavioral items in the upper levels of the logit tree (for example, the utility related to each reason for the tour as in Fig. 6). What the framework is able to frame, instead, is how the spatial distribution of the unserved requests results in uneven impacts on the population. Namely, the framework can capture the effects of a constrained fleet on the population living in the outskirts, for example, but cannot frame the propensity of said population towards AVs. The results reported in the following are thus more focused on the equity implications than on a market analysis.

Fig. 11 compares the gender and age distribution between the general population traveling during the morning peak hours in iteration 15 and the share of the population unable to do so due to the AV service constraints.

As can be noticed, despite the negative impact of gender is not too severe, women are more affected by a constrained AV service. The age distribution also boasts some differences, with the impacts of unserved AV requests being much higher for older travelers. This is directly related to the reason for the trip, as reported in Fig. 12, as education-based trips are almost unaffected by the AV service constraints. This may be due to the modeling hypothesis that minors are not allowed to use AV services on their own[3]; still, further analyses are needed to assess if older people might be unevenly impacted by shortcomings in the AV service performance. Another finding is that, as could be expected, less time-sensitive trips are the ones in which agents are more willing to suffer an unserved AV request, with tours dedicated to leisure (others) and shopping being the most affected.

Uneven effects arise also depending on the household size of the agents, with smaller households being more prone to suffer from an unserved request. This may reflect multiple socio-demographic characteristics, from a higher number of owned private cars in bigger households to smaller households carrying out fewer tours for education or enjoying a more flexible schedule across the day, less prone to possible delays and waiting times of the AV service.

Finally, the income levels of travelers and agents affected by unserved requests are analyzed. From Fig. 13, it is possible to conclude that constraints in the AV service do not disproportionally affect vulnerable shares of the population. On the contrary, it is people with higher incomes who suffer more from unserved requests. This is probably due to a higher propensity of high earners to use the AV service in the first place, as it has to compete with a free public transportation service in the city of Tallinn.[4] There

[3] This modeling assumption has been enforced through a disutility weight towards AVs for minor one order of magnitude higher than for the rest of the population. Still, as this is not a boolean switch turning off the alternative for minors, a small % error - minors choosing AVs - can still be seen in Fig. 11-right.

[4] https://www.tallinn.ee/en/tasutauhistransport/about-free-public-transport-tallinn.

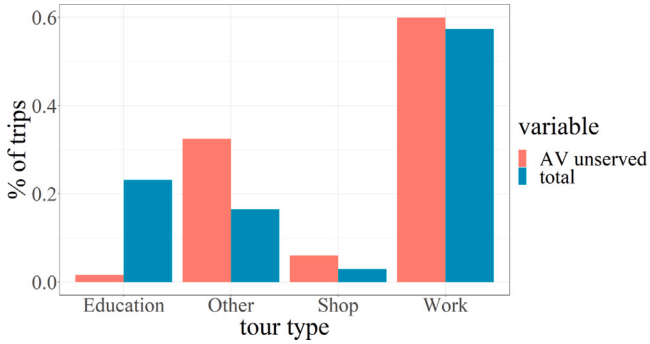


**Fig. 12.** Reason for the tour distribution - a tour is a set of trips starting and ending in the same zone.

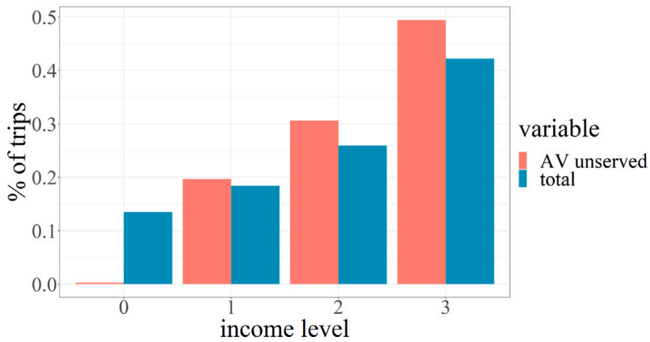


**Fig. 13.** Income distribution of agents traveling with any mode and agents affected by the unserved requests in peak hour - qualitative scale from lower (0) to highest (3) income.

is also a spatial component involved, as the AV service suffers more from constraints downtown, where people with higher income tend to live (Agriesti et al., 2022a), so it is possible that the even distribution of AVs across the network may guarantee a better service for people with lower incomes.

## 5. City imposed strategies

In this section we apply the modeling framework to evaluate two different policy scenarios: the ban of intrazonal AV trips in the city center and the completely unregulated driving style for AV. The latter scenario is framed from the regulator point of view but could arise also from a technological development able to guarantee safety without compromising on performance. As the scenario is framed as short term though, a certain compromise between performance and safety is still assumed (Hussain and Zeadally, 2018; Stogios et al., 2019; Liu et al., 2020; Lu et al., 2021; Richter et al., 2022; Dadashzadeh et al., 2024).

### 5.1. Ban of intrazonal AV trips in the city center

In this scenario, the AV service is conceived and implemented as a feeder from the outskirts to the city center (and vice-versa). In this scenario the city is strictly regulating the deployment of the service, acting on both the fleet size and the area of service, which can happen either by being the service operator itself or by imposing limitations when granting operating permits to private operators. The policy is implemented by banning intrazonal trips in the central area (the pink colored one in Fig. 10 - bottom), but still allowing trips starting or ending in said area. The aim of the policy is to improve the accessibility in the outskirts of the city, by forcing the AV fleet to start and/or end each trip outside the city center.

The framework described in Section 2 is applied to this new situation and a new equilibrium is identified $\Delta A^{\%} \approx 7\%$. The new service performance is summarized in Table 6.

As it can be noticed, the intrazonal ban intuitively results in a lower share of requests to be served and in fewer unserved ones. As a result, the average waiting time reduces, albeit not in a way that completely upends the modal share. While the average travel time seems to increase, this is more the result of banning shorter trips with AVs (intrazonal) then a degradation of the service performance. Please note that the percentage of unserved requests in the morning peak is purposefully higher than it would be

**Table 6**
Performance indicators - The unserved requests are reported for both AM and PM peaks, while the waiting and travel times are reported only for the more congested AM peak.

| | Intrazonal ban in the city center for AVs | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *Total requests AM* | *Total requests PM* | *Unserved requests AM* | *Unserved requests AM [%]* | *Unserved requests PM* | *Unserved requests PM [%]* | *Average waiting time AM* | *Average travel time AM* |
| Baseline (regulated) scenario | 16 038 | 14 744 | 5221 | 32% | 1802 | 12% | 18.5 [min] | 17.8 [min] |
| City center ban | 15 659 | 13 717 | 4705 | 30% | 1131 | 8% | 17.32 [min] | 20 [min] |

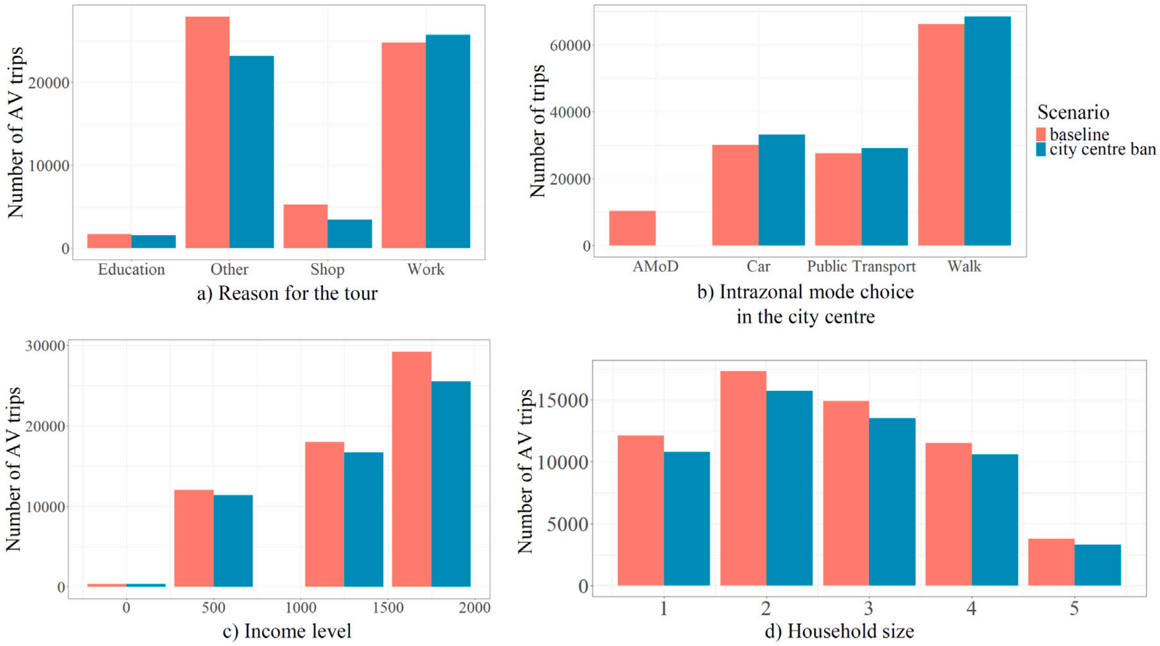


**Fig. 14.** Aggregate comparison of the daily served requests in the baseline scenario (Section 4) and with the intrazonal ban in the city center; (a) Reason for the tour, (b) modal share in the city center, (c) income level of the AV users across the city, (d) household size of the AV users across the city.

with an AV fleet sized for example to maximize profit, as the aim of the scenarios is to assess the effects of constraints on the demand (e.g. driving style but also limited fleet size). The scenarios are thus conceptually closer to ones where for example the AV on-demand service is provided by the municipality, in a subsidized manner or as complementary to the public transport offer (and therefore subject to other constraints such as budgeting). Overall, the ban results in only marginal improvements in the AV fleet performance and thus may fall short of the intended objective (i.e. improving the service for requests outside the city center).

Still, policy-wise, such a ban would be assessed also on its impact on the moving population, to evaluate unintended ripple effects. It can be seen in Fig. 14 how the composition of the agents served by AVs changes in this scenario.

As from Fig. 14(a), the main change in the reason for moving with AVs is a drop in leisure trips (categorized as “others” in the model). This confirms the trend in the baseline, in which less time-sensitive trips are the most susceptible to vary following changes in the AV service’s features. No clear trend arises in the modal shift concerning trips in the city center, with every mode gaining a small share of the AV intrazonal trips when these are banned. Similarly, the effects of drops in AV trips across household sizes seem to be mostly even. Still, from this scenario, an important consideration arises based on income, as in Fig. 14(c), with agents with higher income being the most affected by the ban of intrazonal trips (the main drop being the one between income levels 1500–2000). This kind of outcome may indeed guide the policy-makers, depending on the current aims and objectives.

### *5.2. Unregulated driving style*

The baseline reported in Section 3 assumes a more cautious driving style for AVs, to comply with the short-term time horizon adopted in the study. In the following experiments, we alter the car-following model implemented in the DTA to assess the impact of

**Table 7**
Operational parameters for the AV vehicle.

| | Operational parameters | | | | |
|---|---|---|---|---|---|
| | *Reaction time* | *Average desired speed* | *Speed limit acceptance* | *Maximum desired speed* | *Fleet size* |
| Baseline (regulated) scenario | 1.2 [s] | 40 [km/h] | Perfect compliance | 50 [km/h] | 3000 |
| Unregulated scenario | 0.7 [s] | 55 [km/h] | Not always compliant | 65 [km/h] | 3000 |

**Table 8**
Performance indicators - The unserved requests are reported for both AM and PM peaks, while the waiting and travel times are reported only for the more congested AM peak.

| | AV performance | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *Total requests AM* | *Total requests PM* | *Unserved requests AM* | *Unserved requests AM [%]* | *Unserved requests PM* | *Unserved requests PM [%]* | *Average waiting time AM* | *Average travel time AM* |
| Baseline (regulated) scenario | 16 038 | 14 744 | 5221 | 32% | 1802 | 12% | 18.5 [min] | 17.8 [min] |
| Unregulated scenario | 19 362 | 17 531 | 7458 | 38% | 2952 | 17% | 17.5 [min] | 16.8 [min] |

operational parameters for AVs unconstrained by regulations instead. In practice, this would reflect a scenario in which regulators (or the car-makers themselves) do not limit the AV driving style to ensure safety, as long as the driving code is implemented.

Table 7 compares the driving style in this scenario against the one implemented and tested in Section 3. The chosen values are meant to frame two different driving styles but it is understood that literature still lacks a consensus on how similarly to human-driven vehicles AVs will actually drive (Hussain and Zeadally, 2018; Narayanan et al., 2020b; Dadashzadeh et al., 2024). This kind of analysis is intended to help regulators assess the effects of possible policies. The equilibrium between the activity-based and TA models is achieved by following the steps of Section 2 until reaching $\Delta A^{\%} \approx 5\%$. Table 8 shows how the performance of the AV service changes between the two scenarios.

The results from Table 8 are interesting as they may appear counterintuitive at first. The number of unserved requests for a more unregulated service (i.e. a service where AV has a more aggressive driving style to maximize service performance) increases instead of decreasing, both in the morning and in the afternoon peak. Still, this is explained by the higher number of agents that become willing to use the AV service, as the total requests increase due to lower waiting and travel times. While the fleet is fixed, the increased driving aggressiveness results in a higher number of served requests (in the AM average, 11903 against the 10817 of the baseline). Through the proposed framework it is possible to capture the effects of different car-following behaviors and speed distribution, which result in a 10% increase in efficiency (i.e. served requests) in the morning peak hours of the day. Similarly, in the afternoon the served requests increase by 13%. On the other hand, the total number of requests (i.e. the potential demand for the AV service) increases by 21% in the morning and by 19% in the afternoon, suggesting that the improvement in the AV service has a bigger effect on the potential demand than on the quality of the service performance. Indeed, the unserved requests increase by 6% in the morning and 5% in the afternoon peak.

Finally, it can be seen from Fig. 15 how, without increasing the fleet, the AV service is able to absorb more demand across most of the city. Still, Fig. 15 may also raise some concerns in regulators, as a driving style more dangerous to vulnerable road users results in an increase of requests in more densely populated areas of the city (which are also the ones where better public transport connections and services are located), while the improvements in the outskirts are lower.

## 6. Limitations and future research directions

The presented work has some limitations that could be addressed in future developments. First, the AV on-demand fleet is neither optimized nor repositioned to maximize the served requests and more efficient algorithms could decrease the effects of fleet constraints on the unserved demand. Moreover, the matching algorithm does not allow requests to be queued to wait until an AV becomes empty. Another limitation is that an unserved request does not carry a penalty in the following iteration, for which the demand is calculated based on the impedance matrix. In reality, not being able to find a ride to satisfy the user's mobility needs would probably be significant enough to attach a negative connotation to the reliability of the service and thus to the perceived utility. To properly integrate a penalty element for unserved requests, a calibration effort to quantify its weight against other modal choice factors should be carried out (i.e., how much the reliability of the service weighs against waiting and travel time or cost). In such a scenario, the utility of the AV modal choice would be determined by two conflicting factors, as fewer served requests entail lower waiting times with a fixed fleet, but higher penalty related to the perceived lower reliability of the service. Future works could explore the sensibility of the equilibrium to these conflicting factors. Another research direction would be, for example, to exploit the

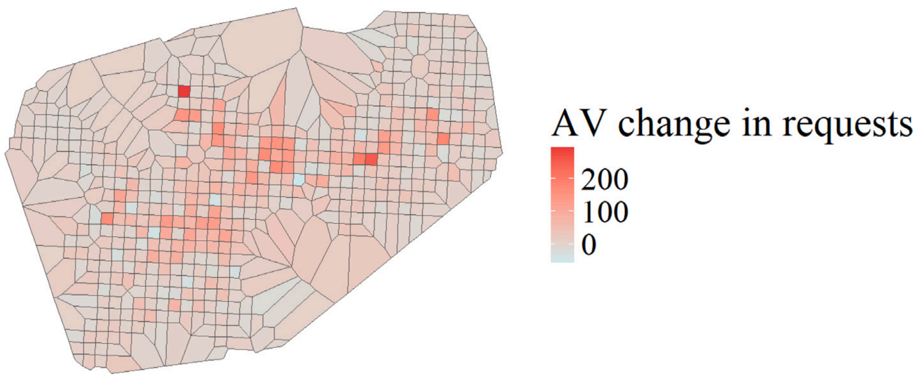


**Fig. 15.** Difference in **daily** request number in each areas - calculated between two iterations, one at baseline equilibrium and one at equilibrium with a more aggressive driving style.

multilevel (meso- **and** micro-) simulation capabilities of the Aimsun software (Casas et al., 2010) to incorporate fully microscopic simulations in the framework. Besides, the developed simulation framework could be adapted to explore multiple equilibrium states and scenarios in a two-sided market, by allowing the operator to adapt the service in response to the arising demand or even by including two or more operators, competing for slices of the potential demand. Finally, while the public transport vehicles are simulated in the supply model, the effect of their performance is not reassessed through the activity-based model (where the generalized cost is considered schedule-based instead). This modeling simplification could be addressed to better frame the effects of AVs in mixed traffic on the public transportation performance.

## 7. Conclusions

The paper analyzes the problem of framing the lost potential demand due to the performance of a newly introduced AV mobility service, by proposing a simulation-based framework to investigate this feedback effect and allow a precise analysis of the influence of the service performance on the demand. The problem is tackled by integrating two state-of-the-art modeling tools and a dedicated fleet scheduling module within the same simulation-based framework. The integration is accomplished by expanding an equilibrium searching methodological approach. The proposed simulation-based framework is then tested on a city of 400.000 inhabitants and the numerical results demonstrate the effectiveness of the proposed solution. The presented work allows to simulate what is the loss in user share corresponding to specific fleet's capabilities, with a degree of precision which is high enough to capture impacts on different socio-demographic strata of the population but also fluctuations arising from different AV driving styles. It does so while considering both an elastic and informed demand and a state-of-the-art supply model able to frame in detail the service performance. Future applications of the proposed framework could consider designing business cases while exploiting to the fullest the demand model (e.g., by assessing the impacts of investments related to the expansion of the AV fleet). For public bodies, the proposed framework could be used to assess equity impacts of policies restricting the AV fleet size and/or service area. Besides, the model can be improved by considering sociodemographic attitudes towards AVs, incorporating results from dedicated surveys and exploiting the models to carry out precise market analyses that would account both for the service performance and for the personal attitudes of each agent. Finally, explicitly tying the demand to the aggressiveness of the AV driving style allows to study the effects of AV driving styles on the demand, possibly allowing to test multiple control algorithms and technologies (ACC, CACC, etc.).

## CRediT authorship contribution statement

**Serio Agriesti:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Claudio Roncoli:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Bat-hen Nahmias-Biran:** Writing – review & editing, Supervision, Software, Conceptualization.

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## Appendix

The simulation-based framework's steps are formalized in the following algorithm.

**Algorithm 1** Framework's modeling steps adapted from Agriesti et al. (2023a) - $M_1()$ is the activity-based model and $M_2()$ is the DTA model, the parentheses include the inputs to each model; IT is the number of initial iterations for the search space characterization, $\tau$ is the $\Delta A$ threshold and quantile() is a function calculating a new impedance matrix corresponding to the average generalize cost across iterations

**Define:** IT, Impedance Matrix[], $\tau$, $List\Delta A$[]<br>
i ← 0<br>
**for** i in (1,IT) **do**<br>
    Trip List[i] = $M_1$(Impedance Matrix[i-1])<br>
    Impedance Matrix[i] = $M_2$(Trip List[i])<br>
    Impedance Matrix List.append(Impedance Matrix[i])<br>
    **Calculate** $\Delta A$ via (1) using Trip List[i], Impedance Matrix[i]<br>
**end for**<br>
**if** $\Delta A \leq \tau$ **then**<br>
    **return** $\Delta A$<br>
**else**<br>
    new Trip List ← []; new Impedance Matrix ← []<br>
    new Imp ← quantile(mean(Impedance Matrix))<br>
    new Trip List[0] = $M_1$(new Imp)<br>
    **for** l in (1,3) **do**<br>
        new Impedance Matrix[l] = $M_2$ (new Trip List[l-1])<br>
        new Trip List[l] = $M_1$(new Impedance Matrix[l])<br>
        **Calculate** $\Delta A$ via (1) using new Trip List[l], new Impedance Matrix[l]<br>
        $List\Delta A \leftarrow \Delta A$<br>
    **end for**<br>
**end if**<br>
**return** $list\Delta A$

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