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Mixed fleets of automated and human-driven vehicles in public transport systems: An evaluation of feeder line services

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ABSTRACT

This study focuses on the transitioning period of operating mixed fleets of both automated and human-driven vehicles for public transit services. The type of service investigated here is flexible, including elements of both fixed route and on-demand systems. The operation of the mixed fleet is optimized with analytical methods leading to models for optimal service headway and stop spacing for the two types of vehicles. Analytical models for optimal passenger capacity per vehicle and required fleet size for each type of vehicles are also derived. Four operational strategies are considered, referring to whether the two types of vehicles operate jointly or independently in terms of optimal service headway and stop spacing within the mixed fleet. Numerical analyses indicate that automated vehicles operate optimally with less frequent vehicle dispatches and more fixed stop locations compared to human-driven vehicles. They also require greater fleet size and similar passenger capacity per vehicle. The four operational strategies perform similarly in terms of total generalized costs for the input values considered here. However, sensitivity analyses showed that the operational characteristics of the two types of vehicles in a mixed fleet and the performance of the four operational strategies depend significantly on the percentage of total demand that each type of vehicle serves, as well as on the automated vehicles' speed and in-vehicle travel time cost for users. The mixed fleets represent the transitioning period towards transit fleets of automated vehicles only and it is shown to be the costliest period for both users and operators.

1. Introduction

The rapid advancements in vehicle automation technology pose the need for transit agencies to enhance their preparedness in order to introduce automated vehicles (AVs) in their fleets. The term "automated vehicle" is used in this study to describe a vehicle with any level of automation, thus including fully autonomous vehicles, as well. It is uncertain when fully automated vehicles will be able to fully replace conventional human-driven vehicles (HDVs). However, successful pilot studies around the world described in literature (e.g., Ainsalu et al. (2018)) are considered promising indicators for the beginning of introducing AVs in public transit fleets. The reduction of operating costs through reducing (or eliminating) driving costs is discussed and analyzed in various studies as a major benefit of AVs' technology. According to existing studies (e.g., Tirachini and Antoniou (2020)), operation constitutes the major type of cost for public transit. Tian et al. (2021) present also the shortage of trained bus drivers as a challenge for current HDVs, which could be eliminated by driverless vehicles. In order to make better strategic decisions about incorporating AVs into public transport, decision-makers need to explore both their innovative vehicular characteristics themselves in comparison to HDVs, as well as the associated new operational conditions that they bring within the service.

The introduction of AVs in public transit fleets is associated not only with cost-related opportunities (e.g., lower driving costs), but also with planning challenges that should be considered carefully before such vehicles are included in transit fleets. Pilot studies reveal that a safe operational speed for AVs is much lower than the speed of HDVs (Ainsalu et al., 2018), leading to significant increases of travel times, among others. In-vehicle travel time shall be perceived differently by users if they are traveling within an AV compared to HDV (Yap et al., 2016), due to safety and comfort aspects, among others. Users' willingness to use AVs is an important element for the incorporation of AVs in public transit fleets (Hwang et al., 2020). Many users might not be willing or able to switch to AVs (e.g., paratransit passengers that require human assistance). Thus, the scenario of operating AVs for public transit should be carefully planned and organized, also taking into account such challenges. A fleet with both HDVs and AVs is referred to as "mixed

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fleet" in this study. The two different types of vehicles within a mixed fleet might operate with operational characteristics that are determined either in a joint or in an independent manner, according to policies and goals. Thus, an important decision during the incorporation of AVs is the level of synergy between the two types of vehicles. The term "joint operation" in this study refers to the case that when planning the operational characteristics of one type of vehicles, parameters associated with the other type are also considered. The term "independent operation" refers to the case that the operational characteristics of one type of vehicles have been planned without considering the other type of vehicles. In this study, the decision-maker for the mixed fleet's operation is considered to be the local transit agency which is also referred to as the operator for the rest of this paper, without considering the case of contractors or sub-contractors for one or both types of vehicles considered here.

An existing body of research on AVs within public transit focuses on comparing the operation of AVs with the operation of HDVs in a service area (e.g., Liu and Schonfeld (2020)). Many studies investigate the replacement of scheduled HDVs with demand responsive AVs (e.g., Winter et al. (2018)) or the integration of fixed route HDVs with demand responsive AVs (e.g., Shen et al. (2018)), among others. Few studies focus on the early stages of introducing AVs in a public transit fleet. Hatzenbühler et al. (2020) study the transitioning period of operating both AVs and HDVs considering the gradual replacement of HDV services per line by AVs using a simulation method. Tian et al., 2021 use mixed-integer stochastic programming to investigate the operation of HDVs and AVs in the same area offering fixed route services by making necessary simplifying assumptions, as for example that all users are willing to use AVs. However, the investigation of the early introduction of AVs in public transit fleet should consider the benefits as well as limitations associated with this introduction, in the challenging case that both vehicles operate on the same line. In addition, alternative strategies of optimizing the operation of the two types of vehicles, not only independently but also jointly, need to be identified and evaluated. Regarding research methods in this field, many studies use agent-based models which do not offer explicit expressions for equations and variables (Fielbaum, 2019). Analytical models in this field mostly focus on optimizing decision variables, such as service headway and vehicle capacity and the resulting requirement for a number of vehicles, but with a focus on AVs independently from the HDVs that might operate in the same service area.

Having in mind the existing research gap, this study investigates the early introduction of AVs within an existing public transit fleet with the aim of serving a percentage of demand that is willing to use AVs, while required HDVs maintain their operation to serve the remaining of the demand. The focus is on a feeder line offering route deviation flexible services in low density areas. The expectation is that AVs operate more safely there, so their initial introduction will be smoother. Existing studies, as for example Badia and Jenelius (2020), also support that suburban areas with low demand are the potential environments for early implementation of AVs. The goals of this paper are to a) investigate the effects of introducing AVs in a mixed fleet of public transit vehicles that offers flexible services in low demand density areas, b) optimize with analytical methods the operation of AVs and HDVs within a mixed fleet considering different operational strategies, and c) compare and evaluate the performance of these strategies. The outputs include a) analytical models to optimize the mixed fleet's operation under different operational strategies, and b) insights on the role of AVs in mixed public transit fleets operation and costs. The proposed analytical models refer to optimal service headways, vehicle capacity and minimum required fleet size, as well as optimal stop spacings which are not widely studied in existing literature for AVs. Unlike most existing studies, this study considers that both types of vehicles operate in the same fleet offering the same type of services within a line. Even though existing literature mostly considers either conventional fixed route or pure on-demand services, this study focuses on flexible services with elements of both. Such services refer to rural and low demand areas which are potential candidate areas for the early introduction of AVs.

This study is structured as follows. Section 2 presents literature review on flexible transit services and AVs in public transport. The proposed process for introducing AVs in an existing transit fleet is described in Section 3. Section 4 describes the modeling setup of this study, including the description of a flexible route system with mixed fleet of HDVs and AVs, the proposed models for operator and user costs, as well as the derivation of optimal service headway and stop spacing, among others. Section 5 includes input values (accompanied by proper justification for their choice) as well as the results of the numerical analyses performed in this study. Section 6 shows the effects of considering different values for important input parameters on the mixed fleet's operation and costs. The role of service characteristics and vehicle automation in mixed fleets is included in Section 7. Conclusions, limitations, and future extensions of this study are discussed in Section 8.

2. Literature review

2.1. Previous experiences with AV deployment in public transport

The implementation of AVs has been tested and evaluated through various pilot studies. CityMobil2 was an EU-funded project that allowed the implementation of pilot studies in Europe, aiming at defining the required legal and technical frameworks in order to enable the operation of AVs as part of an automated road transport system (Alessandrini et al., 2014). Description of pilot studies using autonomous shuttle buses in urban environments is included in Ainsalu et al. (2018). Apart from testing technology, user acceptance is reported as one of these pilots' major concerns. Christie et al. (2015) report the results from AVs' demonstration in Switzerland. The authors emphasize on the positive reaction of users towards AVs. The European Road Transport Research Advisory Council (ERTRAC) in their "Connected Automated Driving Roadmap 2019" offers insights and details on pilot studies implemented in Europe, as well as on initiatives in countries around the world, such as USA, Japan, South Korea, China, Singapore, and Australia (ERTRAC Working Group, 2019). A pilot study implemented in Appelscha, the Netherlands, is described in Boersma et al. (2018). Appelscha is a city associated with declining number of inhabitants and a shrinking public transport network, so the pilot aimed at assuring region's accessibility. Among others, pilot studies of AVs offer valuable field observations that can serve as input for various modeling approaches (Narayanan et al., 2020).

2.2. User perception towards AVs

From a demand point of view, there is a significant body of research that focuses on user acceptance towards AVs (Becker and Axhausen, 2017). In Wang and Akar (2019), among other conclusions, it is highlighted that it is not expected that users' perception towards self-driving vehicles will be temporally stable. Ashkrof et al. (2019) highlight that travel distances and purposes are proved to be strong determinants of the user choices towards on-demand AVs that offer services competitive to both conventional vehicles and public transport. Yap et al. (2016) present an early study on investigating users' attitudes towards using AVs as an egress mode of train trips. In addition to travel times and costs, psychological factors, such as user trust towards AVs, are presented as important factors for determining user choices. Guo et al. (2021) conducted an experiment to investigate user preferences towards HDVs and AVs. The experiment included variables such as purpose, travel distance, and weather conditions, among others. Results indicated greater elasticity of user choices towards changes in AVs' service levels. Hwang et al. (2020) performed a focus group study to investigate the perception of elderly and people with disabilities towards AVs for paratransit services. The authors also highlighted the limited knowledge regarding the transit agencies' perception towards AVs' services. A body of research in this field focuses on studying automated technology as an innovation. The “Diffusion of Innovation” (DOI) is a term presented by Rogers (1962). Shabanpour et al. (2018) present a very detailed review on the evolution of this theory and existing studies that have used it over the years. A detailed literature review on user perception towards AVs is presented by Gkartzonikas and Gkritza (2019).

2.3. Previous research on public transport operations with AVs

There is a broad research on operating AVs as part of public transit. Ainsalu et al. (2018) present a review regarding the impact of automated buses in public service. The authors highlight the expected benefits from introducing automated buses in public transport, among which they refer to the reduction of costs for last mile transport and improvement of the service for the users. They also emphasize on the changes that transit agencies need to make in order to smoothly transition to new modes of transport and shared mobility, accounting for automated services' operational requirements and street infrastructure needs, among others. Scheltes and de Almeida Correia (2017) study the operation of a fleet of small AVs used to support last mile connection to train. The authors developed a simulation model considering the case study of the connection between a train station and a campus' location in Delft, the Netherlands. Among other findings, they refer to the importance of allowing higher speeds in the reduction of average travel times and pre-booking as a way of reducing average waiting times. In Soteropoulos et al. (2019) the authors emphasize on the importance of addressing uncertainty in modeling assumptions, as for example in the perception of in-vehicle travel time. Many studies express AVs' operating costs as a linear function of vehicles' passenger capacity, which exists in literature from the early'80s already (Jansson, 1980). Tirachini and Antoniou (2020) propose analytical models for optimal vehicle size and service frequency, among others, and use data from electric vehicles in Germany and Chile to investigate the impacts of automation. According to their findings, both operators and users should expect benefits from AVs. The operators should expect benefits in terms of reduced operational costs and the users in terms of reduced waiting times and optimal fare per trip.

An automated demand responsive transport service (ADRTS) is studied in Winter et al. (2018) as a replacement for scheduled bus services. The authors use simulation methods to investigate the effects of various parameters (e.g., demand, vehicle capacity, vehicle dwell time) on fleet size and system costs. Badia and Jenelius (2020) study when and where door-to-door services of AVs should replace existing fixed route in suburban areas using analytical methods. Their findings highlight the importance of the degree of AV technology's development, in order to make their operation door-to-door competitive to fixed route services. Leffler et al. (2020) implement simulations to investigate the comparison among different scenarios of operating on-demand and fixed services with AVs. The evaluation of services is based on user experience (i.e., waiting, travel time, denied boarding). Their results highlight that larger fleets of smaller vehicles improve quality of service. Militão and Tirachini (2021) state that AV technology is expected to reduce the costs of on-demand services and study the replacement of fixed route systems. They focus on vehicle size and fleet size and use a hybrid approach (i.e., numerical and analytical) to model these decision variables in an optimization problem that minimizes total costs. After considering different demand levels and automation related scenarios, they conclude that the operation of AVs for door-to-door shared services depends on the operational scheme. Fielbaum (2019) studies an on-demand feeder system operated by AVs and combined with a traditional trunk system, forming an AV feeder–trunk system (AVFT), using analytical methods. In their study they focus on electric AVs, fuel AVs and traditional vehicles. According to their results, traditional vehicles' costs can be 50% greater than AVs' costs, while the AV technology was found to affect significantly the vehicle sizes. An agent-based simulation is used in Shen et al. (2018) to evaluate the performance of a public transit system with integrated AVs. The latter are used as an alternative in low demand bus routes for the first-mile problem in morning peak. The authors conclude that the integrated system has the potential to improve service quality.

A study investigating the transitioning period of operating HDV and AVs is that of Hatzenbühler et al. (2020). The authors focus on fixed line-based public transit systems, and use simulation methods to determine vehicle capacity per line, service frequency per line, as well as the type of vehicle that should serve each line (i.e., either human driven or fully automated). Their findings indicate improved service as a result of operating AVs in some lines. Another study that considers both HDVs and AVs within the same fleet is included in Bergqvist and Åstrand (2017). The authors implement linear programming to identify the optimal combination of AVs and HDVs when AVs are introduced in a pre-existing bus fleet, considering only operational costs as the objective value. Results show important operation cost savings by the introduction of AVs. In Tian et al. (2021), the authors focus on uncertain transit demand and implement a mixed-integer stochastic programming approach to determine the optimal fleet size and fleet assignment in the case of AVs and HDVs offering fixed route services, assuming that all users are positive towards AVs and the two vehicles have equal travel times. In terms of user costs, waiting time is the respective cost component included in the objective function. The introduction of AVs can reduce the required fleets and total cost, according to their findings.

2.4. Modeling flexible services for HDVs

Most of the existing research on AVs in public transit focuses on either fixed route or on-demand services. The current study investigates the operation of the mixed fleet under flexible services. Flexible services operate as an intermediate system between conventional fixed route and pure on-demand services (Sipetas and Gonzales, 2021). They are thus expected to address the high user dissatisfaction of the former (Sipetas et al., 2020) and the high operational costs of the latter (Gonzales et al., 2019). Flexibility incorporated in transit services may be spatial (i.e., route deviations), temporal (i.e., time schedule deviations) or a combination of both. According to Qiu et al. (2015) deviated fixed route services are the most widely used flexible services. Zheng et al. (2018) model the operation of route deviation services and perform a comparison with point deviation services to assist decision making. Sipetas and Gonzales (2021) propose analytical models based on continuous approximation for optimal stop spacing and flexible region boundaries within a service area. Flexible services refer to route deviation. Pei et al. (2019) summarize model types implemented in existing literature for modeling flexible transit systems. The authors highlight that the most commonly minimized objective function for operating flexible systems is the system's overall cost, including both agency and user costs in most cases.

3. Process for introducing AVs into public transit operations

This study considers that a transit agency has decided to introduce AVs in its existing fleet of HDVs and is investigating the optimal way of performing this introduction. The focus is on optimal service headway and stop spacing, as well as on the resulting requirements for fleet size and passenger capacity per vehicle. A transit agency that offers services that are not purely on-demand may operate a mixed fleet of AVs and HDVs under different strategies of optimized operational characteristics of service headway and stop spacing. The following four operational strategies (referred also as “operational cases”) are considered in this study:

- Case A: The two types of vehicles operate with different stop spacings, S^{T^*}, $T \in \{HDV, AV\}$, and the same service headway, H^*.
- Case B: The two types of vehicles operate with the same stop spacing, S^*, and different service headways, H^{T^*}, $T \in \{HDV, AV\}$.

- Case C: The two types of vehicles operate with different stop spacings, S^{T^*}, T ∈ {HDV, AV}, and different service headways, H^{T^*}, T ∈ {HDV, AV}.
- Case D: The two types of vehicles operate with the same stop spacing, S^*, and the same service headway, H^*.

In Case C, the two types of vehicles operate fully independently, with the only connecting element being the percentage of total demand that each vehicle serves. The sum of the percentage of passengers served by AVs, p^{AV}, and the percentage of passengers served by HDVs, p^{HDV}, always equals 1. In Case D the two types of vehicles operate in a fully joint way. Each one of the four operational strategies is associated with different opportunities and challenges for a transit agency and deciding which one to implement depends on the agency's goals and/or existing operational characteristics. For example, a transit agency that has already established bus stop locations for HDVs and is not able to add different stops for AVs might decide to implement a strategy in which both types of vehicles operate with the same stop spacing (i.e., Case B or D). On the other hand, a transit agency that wants to ensure equity in service's waiting times among all users would implement an operational strategy in which both types of vehicles operate with the same service headway (i.e., Case A or D). As shown in the following Section, optimal service headway and stop spacing affect the optimal passenger capacity per type of vehicle, K^{T}, T ∈ {HDV, AV}, and required fleet size per type of vehicle, M^{T}, T ∈ {HDV, AV}.

Fig. 1 summarizes the steps that a transit agency could follow in order to optimally introduce AVs in an existing transit fleet under the four operating cases studied here, including a summary of inputs and outputs of this study. The source code with the proposed methodology is openly available[1]. All inputs required for implementing the proposed models presented in the following Section are readily available by a transit agency, except for the percentage of passengers served by each type of vehicles. The percentage of passengers served by AVs depends on the number of passengers willing to use AVs. This input value can be determined through surveys, discrete choice models, or considering DOI, among others, as discussed in Section 2. In this study, the percentage of passengers that are served by each type of vehicle on a daily basis are considered to be known by the transit agency in advance and the way these values are derived lies beyond the scope of this study. It is noted that the percentage of passengers served by HDVs might include both passengers that are willing and passengers that are not willing to use AVs, but the percentage of passengers served by AVs should only include those who are willing to be served by this type of vehicle. A collection of input values derived from existing literature and pilot studies is presented in Section 5. The transit agencies can evaluate the outputs considering constraints associated with their decision-making process. The grey dashed line in Fig. 1 represents the iterative process that could be followed in order to derive new outputs under a constrained framework. Such constraints could be for example budget limitations, policy-related restrictions, and performance measures, but their investigation lies beyond the scope of this study. Limitations and future extensions of this study are discussed in Section 8.

4. Modeling setup

4.1. Flexible route setup with mixed fleet

This study considers a flexible route system which is also described in Sipetas and Gonzales (2021). More specifically, this study focuses on a rectangular service area of length L and width W with a rectilinear street network. According to existing literature, rectilinear distances closely approximate real-life street network movements (Quadrifoglio et al., 2008). Demand is uniformly distributed over space and time. Vehicles operate on a straight-line corridor in the middle of the service area to serve passengers at fixed stop locations with predetermined stop spacing, S, but they also deviate to serve a (%) of total demand curb-to-curb. Vehicles do not backtrack to serve passengers curb-to-curb. The expected distance between the corridor and each uniformly distributed curb-to-curb location is equal to $W/4$. Users are assumed to perform their curb-to-curb requests early enough so that vehicle routing is determined before dispatch. Passengers that will not be served curb-to-curb are assumed to walk to the nearest fixed stop.

One end of the corridor is a terminal station which is assumed to connect this service area with a major destination (e.g., city center). The terminal is always one end of each trip. Thus, demand follows a many-to-one pattern, in which all passengers board the vehicle at the terminal to alight at uniformly distributed destinations in one direction and all passengers board the vehicle at fixed stops or curb-to-curb requested locations to alight at the terminal in the other direction. The uniform demand density per direction is equal to Q passengers per area per time. Demand is not affected by the quality of service (i.e., perfectly inelastic demand). Also, no rejections are considered here.

This study assumes that there are two types of vehicles available for passenger service: a) conventional HDVs and b) AVs. Automated vehicles are assumed to operate with some level of human intervention. Passengers within the service area are assumed to select whether they are willing to use AVs or not, with both types of vehicles offering the same type of transit service (i.e., route deviation with the same level of flexibility, a). The percentages of passengers served by AVs, p^{AV}, and the percentage of passengers served by HDVs, with $p^{\mathrm{AV}} + p^{\mathrm{HDV}} = 1$, are assumed to be known well in advance. In addition to demand, other differences in the operation of the two types of vehicles are listed below:

- Each type of vehicles operates with an average speed V^{T}, T ∈ {HDV, AV}, which accounts for stops and delays. According to existing literature on pilot studies, AVs usually operate with lower speeds for safety purposes in real-life applications.
- In-vehicle travel experience is expected to differ between the two types of vehicles, leading to different in-vehicle travel time costs, a_r^{T}, T ∈ {HDV, AV}.
- Each type of vehicle is expected to have a passenger capacity, K^{T}, T ∈ {HDV, AV}, that is adjusted to demand levels and optimized vehicle headways, as shown in detail in Section 4.3.
- Operating costs per vehicle and time, c^{T}, T ∈ {HDV, AV} differ for the two types of vehicles.

Fig. 2 summarizes the operation of the system that is studied here. As shown in this figure, vehicles (either HDVs or AVs) start from the terminal and return to it after serving the uniformly distributed demand within the service area at the fixed stops and curb-to-curb. For curb-to-curb requests, they deviate by $W/4$ to serve them (either for pick-up or drop-off) and the same distance to return to the fixed corridor. Vehicles can deviate at any point on the fixed corridor in order to travel a vertical distance and serve passengers curb-to-curb. Every passenger who is served at a fixed stop walks an average vertical distance of $W/4$ and an average horizontal distance of $S^{\mathrm{T}}/4$, T ∈ {HDV, AV}.

4.2. Modeling system costs

Each type of vehicle considered here operates with a cycle time which depends on the service area, operational and demand related characteristics. A vehicle starts each trip from the terminal station and visits every fixed stop on the corridor with a total number of fixed stops equal to L/S^{T}, T ∈ {HDV, AV}. It is noted that in the following equations of Section 4.2 the notation S^T, T ∈ {HDV, AV}, refers to the implemented stop spacing based on the operational strategy that is considered. Therefore, it could be common or different between the two types

[1] https://github.com/csipetas/MixedFleetsinFlexibleTransport.git.

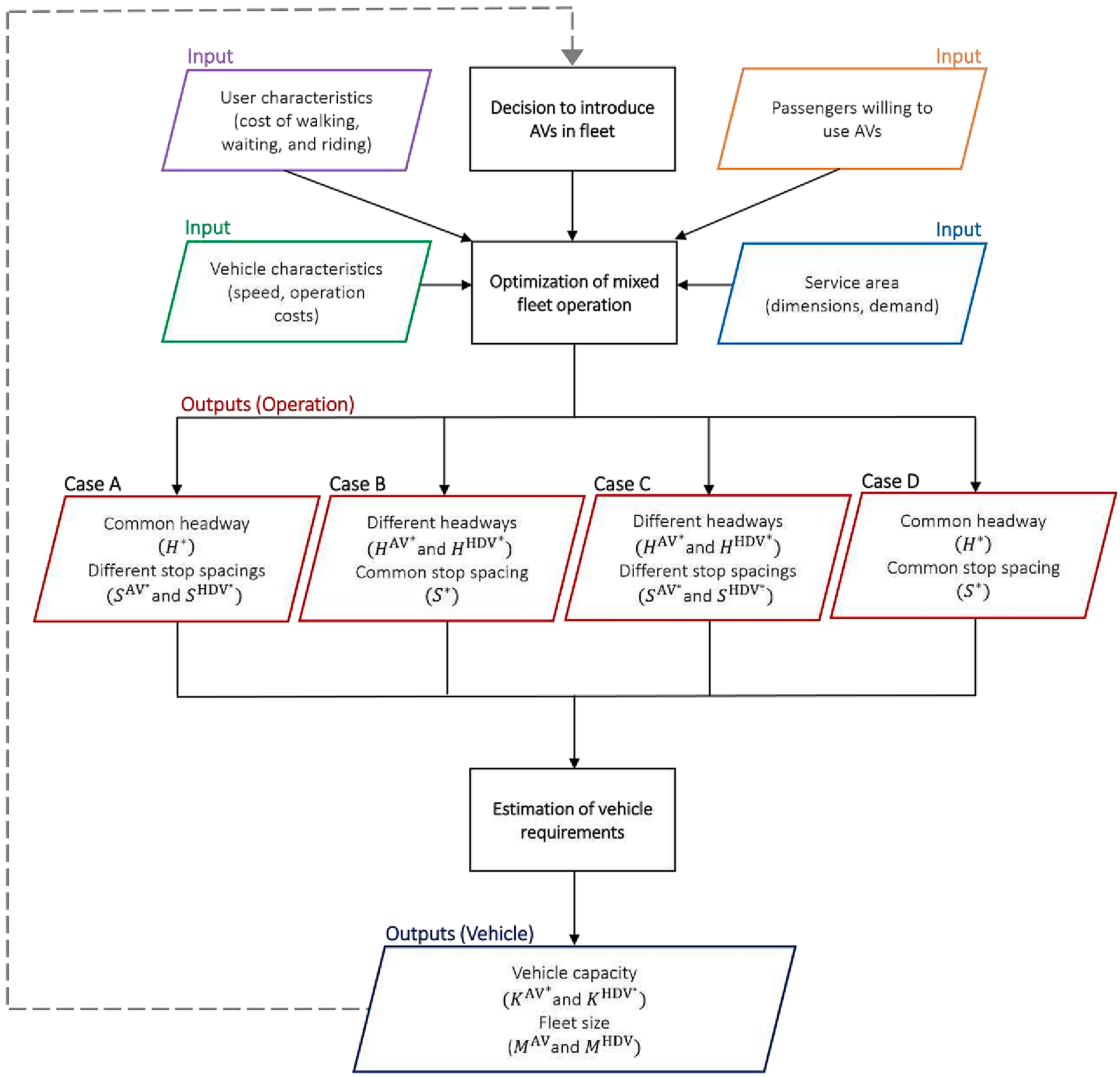

Fig. 1. Flowchart of transit agency process of introducing AVs in mixed fleets.

of vehicles. At each fixed stop the dwell time is τ^f, whereas the dwell time at the terminal station is τ^t. The time that a vehicle needs to traverse the corridor in one direction is L/V^T, $T \in \{HDV, AV\}$. Vehicles also deviate to serve a (%) of passengers curb-to-curb. Assuming that each type of vehicles, $T \in \{HDV, AV\}$, operates with a service headway, H^T, the total number of passengers that will be served curb-to-curb within a cycle is $2ap^{HDV}QWLH^{HDV}$ and $2ap^{AV}QWLH^{AV}$, for HDVs and AVs, respectively. In the following equations of Section 4.2 the notation H^T, $T \in \{HDV, AV\}$, refers to the implemented service headway based on the operational strategy that is considered (i.e., it could be common or different between the two types of vehicles). The expected deviation for each trip served curb-to-curb is equal to a distance of $W/4$ to reach the curb-to-curb location and $W/4$ to return to the corridor. The dwell time at curb-to-curb stops is τ^r. The cycle time, C^T, for each type of vehicle $T \in \{HDV, AV\}$ is given in Eq. (1).

$$C^T = \frac{2L}{V^T} + \frac{2\tau^f L}{S^T} + \frac{ap^T QW^2 LH^T}{V^T} + 2ap^T QWLH^T \tau^r + \tau^t \quad (1)$$

The term $2L/V^T$ refers to the time needed for a vehicle to travel the corridor in both directions, the term $2\tau^f L/S^T$ to the total dwell time at fixed stops in both directions, the term $ap^T QW^2 LH^T/V^T$ to the total time needed to deviate from the corridor in order to serve the curb-to-curb stops and return in both directions, the term $2ap^T QWLH^T \tau^r$ to the total dwell time at curb-to-curb stops in both directions, and the term τ^t to the total dwell time at the terminal.

The minimum required fleet size for each type of vehicle $T \in \{HDV, AV\}$ depends heavily on the cycle time and is defined as:

$$M^T = \frac{C^T}{H^T} \quad (2)$$

The models for cycle time and fleet size are used as basic components for defining operating costs. Cycle time is the basis for defining riding costs for users.

4.2.1. Operating costs

Operating costs considered here are expressed as a function of ve-

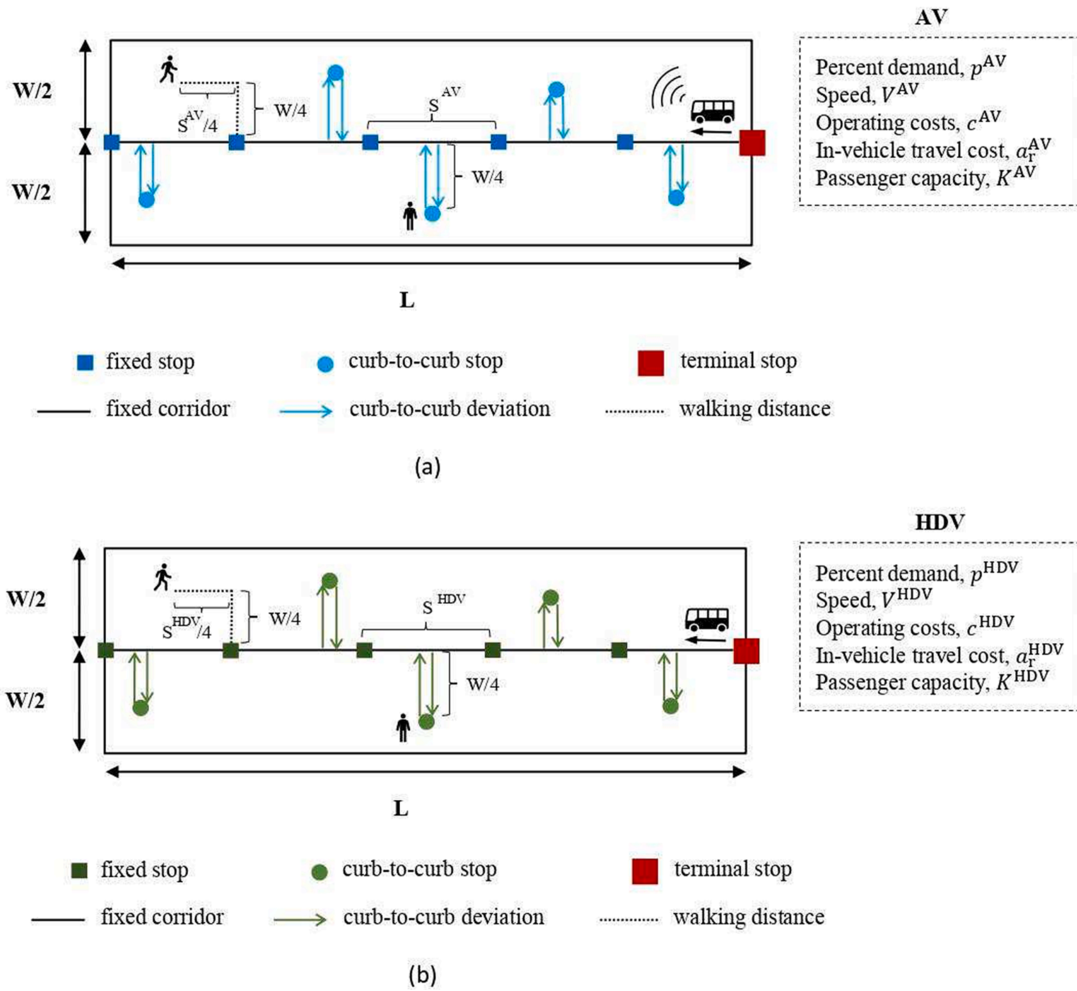

Fig. 2. Flexible route system with mixed fleet of a) AVs and b) HDVs.

hicle's passenger capacity, K^{T}, T $\in$ {HDV, AV}. The operating cost per vehicle unit and hour, c^{T}, for each type of vehicle T $\in$ {HDV, AV}, can be expressed as:

$$c^{\mathrm{T}} = c_0^{\mathrm{T}} + c_1^{\mathrm{T}} K^{\mathrm{T}} \tag{3}$$

where c_0^{T} is the base parameter of the unit cost and c_1^{T} is the marginal cost of vehicle capacity. This formulation is in line with Tirachini and Antoniou (2020), as well as other studies in this field. Considering the many-to-one demand pattern of this study, the passenger capacity requirement for a vehicle depends on the demand that is served in one direction. The assumption here is that the vehicles should have a passenger capacity exactly equal to the one directional demand within a cycle, as shown in Eq. (4), for each type of vehicle, T $\in$ {HDV, AV}.

$$K^{\mathrm{T}} = p^{\mathrm{T}} QWLH^{\mathrm{T}} \tag{4}$$

Considering the operating costs per vehicle and hour expressed by Eq. (3), the number of required fleet size presented in Eq. (2), the cycle time determined by Eq. (1) and O operating hours per day, the total operating costs per day for each type of vehicle, T $\in$ {HDV, AV}, are given as:

$$F_{operator}^{\mathrm{T}} = \left(c_0^{\mathrm{T}} + c_1^{\mathrm{T}} K^{\mathrm{T}}\right) \frac{C^{\mathrm{T}}}{H^{\mathrm{T}}} O \tag{5}$$

The term $C^{\mathrm{T}}O/H^{\mathrm{T}}$ represents the vehicle hours traveled within a day.

4.2.2. User costs

User costs are composed of the costs of walking time to access the nearest fixed stop (either HDV or AV stop, depending on their preference), waiting time to be served and in-vehicle riding time. Regarding walking, only passengers not served curb-to-curb are expected to experience walking times. The respective number of passengers per cycle is $2p^{\mathrm{AV}}(1-a)QWLH^{\mathrm{AV}}$ for AVs and $2p^{\mathrm{HDV}}(1-a)QWLH^{\mathrm{HDV}}$ for HDVs. The walking distance is $(W+S)/4$ and the walking speed is V_w. The walking time to access fixed stops per cycle, Z^{T}, for each type of vehicle, T $\in$ {HDV, AV}, is:

$$Z^{\mathrm{T}} = 2p^{\mathrm{T}}(1-a)QWLH^{\mathrm{T}} \frac{W + S^{\mathrm{T}}}{4V_{\mathrm{w}}} \tag{6}$$

Regarding waiting, all passengers are expected to wait for the type of vehicle that will serve them, irrespectively if they walk to the bus stop or are served curb-to-curb, so their waiting times depend on the respective headway. For each vehicle type, T $\in$ {HDV, AV}, each passenger waits on average half headway. The waiting time per cycle, U^{T}, for each type of vehicle, T $\in$ {HDV, AV}, is:

$$U^{\mathrm{T}} = p^{\mathrm{T}} QWL\left(H^{\mathrm{T}}\right)^2 \tag{7}$$

Regarding average riding time, it is equal to one fourth of the cycle time. Considering Eq. (1), the riding time per cycle, R^{T}, for each type of vehicle, T $\in$ {HDV, AV}, is:

$$R^{\mathrm{T}} = 0.5p^{\mathrm{T}} QWLH^{\mathrm{T}} C^{\mathrm{T}} \tag{8}$$

Considering that each day has O/H^{T} cycles of operation for each type of vehicle T $\in$ {HDV, AV}, and cost coefficients for walking time, a_z, waiting time, a_u and riding time, a_r^{T}, T $\in$ {HDV, AV}, the daily user cost for each type of vehicle, T ∈{HDV, AV}, is:

$$F^{\mathrm{T}}_{\mathrm{user}} = \left(a_z Z^{\mathrm{T}} + a_{\mathrm{u}} U^{\mathrm{T}} + a^{\mathrm{T}}_{\mathrm{r}} R^{\mathrm{T}}\right) \frac{O}{H^{\mathrm{T}}} \tag{9}$$

4.2.3. Total generalized costs

The daily generalized costs for each type of vehicle, T ∈ {HDV, AV}, are composed of operating and user costs, as follows:

$$F^{\mathrm{T}}_{\mathrm{general}} = F^{\mathrm{T}}_{\mathrm{operator}} + F^{\mathrm{T}}_{\mathrm{user}} \tag{10}$$

The total daily generalized cost of a mixed fleet resulting from the operation of both types of vehicles for both operators and users within the service area are the following:

$$F_{\mathrm{total}} = F^{\mathrm{HDV}}_{\mathrm{general}} + F^{\mathrm{AV}}_{\mathrm{general}} \tag{11}$$

It is noted that coordination costs between the two types of vehicles, if any, mostly refer to the planning process and are considered negligible in this study. The above models can be used for optimizing the service headway and stop spacing. The optimization process and the respective results are presented in the following Section.

4.3. Optimal operational characteristics

The operation of the mixed fleet flexible route system that is analyzed in this study is optimized in this Section in terms of headway and stop spacing. The effects of the optimization process on vehicles' passenger capacity and fleet size are also presented and discussed.

4.3.1. Headway

Solving the first order conditions for Eq. (10) or Eq. (11) with respect to H^{HDV} and H^{AV} leads to the optimal headway for HDVs, H^{HDV^*}, and AVs, H^{AV^*}, respectively. The term S^T, T ∈ {HDV, AV}, in the equations of Section 4.3.1 might be common (i.e., $S^{AV} = S^{HDV} = S$) or different between the two types of vehicles, depending on the strategy that is implemented. The optimal headway for each type of vehicle, T ∈ {HDV, AV}, is given below:

$$H^{\mathrm{T}^*} = \frac{1}{QWL}\sqrt{\frac{2L\frac{c^{\mathrm{T}}_0}{V^{\mathrm{T}}} + 2\tau^{\mathrm{f}} L \frac{c^{\mathrm{T}}_0}{S^{\mathrm{T}}} + \tau^{\mathrm{t}} c^{\mathrm{T}}_0}{\frac{p^{\mathrm{T}} a_{\mathrm{u}}}{QWL} + a(p^{\mathrm{T}})^2\left(\frac{W}{V^{\mathrm{T}}} + 2\tau^{\mathrm{r}}\right)\left(c^{\mathrm{T}}_1 + 0.5a^{\mathrm{T}}_{\mathrm{r}}\right)}} \tag{12}$$

As shown in Eq. (12), the optimal headway does not depend on walking costs. It is reminded that the case of $a = 0$ corresponds to fixed route systems (i.e., without vehicle deviation to serve curb-to-curb). According to Eq. (12), in such case the difference between the two types of vehicles' optimal headway depends on the difference between the demand served, the operational speeds and the base operational costs. According to Eq. (4), the vehicles' passenger capacity depends on the service headway. Replacing headway in Eq. (4) with optimal headway of Eq. (12), leads to the following equation for each type of vehicle's, T ∈ {HDV, AV}, optimal passenger capacity:

$$K^{\mathrm{T}^*} = p^{\mathrm{T}}\sqrt{\frac{2L\frac{c^{\mathrm{T}}_0}{V^{\mathrm{T}}} + 2\tau^{\mathrm{f}} L \frac{c^{\mathrm{T}}_0}{S^{\mathrm{T}}} + \tau^{\mathrm{t}} c^{\mathrm{T}}_0}{\frac{p^{\mathrm{T}} a_{\mathrm{u}}}{QWL} + a(p^{\mathrm{T}})^2\left(\frac{W}{V^{\mathrm{T}}} + 2\tau^{\mathrm{r}}\right)\left(c^{\mathrm{T}}_1 + 0.5a^{\mathrm{T}}_{\mathrm{r}}\right)}} \tag{13}$$

The service headway also affects the required fleet size for each type of vehicle, as shown in Eq. (2). Thus, combining Eq. (1), Eq. (2) and Eq. (12) leads to the required fleet size for each type of vehicles when optimal service headways are implemented. If the system of mixed fleets operates with a common uniform headway, $H = H^{\mathrm{AV}} = H^{\mathrm{HDV}}$, implemented by both types of vehicles, then Eq. (11) is optimized with respect to H. The common optimal service headway, H^*, in the case of a mixed fleet is given by:

$$H^* = \frac{1}{QWL}\sqrt{\frac{2L\left(\frac{c^{AV}_0}{V^{AV}} + \frac{c^{HDV}_0}{V^{HDV}}\right) + 2\tau^{\mathrm{f}} L\left(\frac{c^{AV}_0}{S^{AV}} + \frac{c^{HDV}_0}{S^{HDV}}\right) + \tau^{\mathrm{t}}\left(c^{AV}_0 + c^{HDV}_0\right)}{\frac{a_{\mathrm{u}}}{QWL} + a\left[(p^{\mathrm{AV}})^2\left(\frac{W}{V^{\mathrm{AV}}} + 2\tau^{\mathrm{r}}\right)\left(c^{\mathrm{AV}}_1 + 0.5a^{\mathrm{AV}}_{\mathrm{r}}\right) + (p^{\mathrm{HDV}})^2\left(\frac{W}{V^{\mathrm{HDV}}} + 2\tau^{\mathrm{r}}\right)\left(c^{\mathrm{HDV}}_1 + 0.5a^{\mathrm{HDV}}_{\mathrm{r}}\right)\right]}} \tag{14}$$

Replacing Eq. (14) in Eq. (4), leads to the following equation for each type of vehicle's, T ∈ {HDV, AV}, optimal passenger capacity in mixed fleets with common optimal headway:

$$K^{\mathrm{T}^*} = p^{\mathrm{T}}\sqrt{\frac{2L\left(\frac{c^{AV}_0}{V^{AV}} + \frac{c^{HDV}_0}{V^{HDV}}\right) + 2\tau^{\mathrm{f}} L\left(\frac{c^{AV}_0}{S^{AV}} + \frac{c^{HDV}_0}{S^{HDV}}\right) + \tau^{\mathrm{t}}\left(c^{AV}_0 + c^{HDV}_0\right)}{\frac{a_{\mathrm{u}}}{QWL} + a\left[(p^{\mathrm{AV}})^2\left(\frac{W}{V^{\mathrm{AV}}} + 2\tau^{\mathrm{r}}\right)\left(c^{\mathrm{AV}}_1 + 0.5a^{\mathrm{AV}}_{\mathrm{r}}\right) + (p^{\mathrm{HDV}})^2\left(\frac{W}{V^{\mathrm{HDV}}} + 2\tau^{\mathrm{r}}\right)\left(c^{\mathrm{HDV}}_1 + 0.5a^{\mathrm{HDV}}_{\mathrm{r}}\right)\right]}} \tag{15}$$

In the case of fixed route services only (i.e., $a = 0$) the difference between the two types of vehicles' optimal capacity depends only on the difference between the demand served by each type of vehicle. Since both types of vehicles operate with the same optimal headway, the difference between their fleet size depends on the difference between their cycle times, according to Eq. (2).

4.3.2. Stop spacing

If each vehicle type operates with different stop spacing along the corridor, then the stop spacing for each type of vehicle, T ∈ {HDV, AV}, is optimized through solving for the first order conditions for Eq. (10) or Eq. (11) with respect to S^{HDV} and S^{AV}, which leads to the following optimal stop spacing for each type of vehicle, T ∈ {HDV, AV}:

$$S^{\mathrm{T}^*} = \sqrt{\frac{2V_{\mathrm{w}}\tau^{\mathrm{f}}\left[2\frac{c^{\mathrm{T}}_0}{H^{\mathrm{T}}} + p^{\mathrm{T}} QWL\left(2c^{\mathrm{T}}_1 + a^{\mathrm{T}}_{\mathrm{r}}\right)\right]}{(1-a)a_z p^{\mathrm{T}} QW}} \tag{16}$$

It is noted that the term H^T, T ∈ {HDV, AV}, in the equations of Section 4.3.2 might be common (i.e., $H^{AV} = H^{HDV} = H$) or different between the two types of vehicles, depending on the strategy that is implemented. As shown in Eq. (16), the optimal stop spacing does not depend on waiting time costs. Also, it increases as the percentage of passengers served curb-to-curb, a (%), increases. For the extreme case that all passengers are served curb-to-curb (i.e., $a = 1$), then stop spacing goes to infinity, since there is no need for fixed stops. If both types of vehicles operate at the same fixed stops with a common stop spacing, $S = S^{\mathrm{AV}} = S^{\mathrm{HDV}}$, the optimal stop spacing results from solving the first order conditions for Eq. (11) with respect to S. The optimal stop spacing, S^{*}, for the operation of the mixed fleet flexible route system studied here is presented below.

$$S^{*} = \sqrt{\frac{2V_{w}\tau^{f}\left[2\left(\frac{c_0^{AV}}{H^{AV}} + \frac{c_0^{HDV}}{H^{HDV}}\right) + QWL\left(2p^{AV}c_1^{AV} + 2p^{HDV}c_1^{HDV} + p^{AV}a_r^{AV} + p^{HDV}a_r^{HDV}\right)\right]}{(1-a)a_{z}QW}} \tag{17}$$

The required fleet size in Eq. (2) depends on the cycle time, which includes stop spacing, so the optimal value for stop spacing calculated through Eq. (16) or Eq. (17) can be used in combination with Eq. (1) and Eq. (2) to determine the required fleet size for each type of vehicle considered here as a result of optimized stop spacing.

For both Eq. (16) and Eq. (17), the closed form for optimal stop spacing includes service headway. Similarly, the closed form for optimal headway in Eq. (12) and Eq. (14) includes stop spacing. Thus, in cases where only one of the two operational characteristics requires optimization, the other can be determined easily through the respective equation. For example, in some service area the mixed fleet flexible route system operates on a pre-existing corridor with established fixed stop locations where both types of vehicles operate, but the transit agency has decided to implement optimized headways for each one of the two vehicle types. In this case stop spacing is pre-determined leading to only optimizing service headways through Eq. (12). The more challenging case in terms of computation is when both the service headway and the stop spacing need to be optimized. For example, if a transit agency decides to optimize the service headway and stop spacing for each type of vehicles separately, then the resulting problem includes two systems with two equations and two unknowns. Each system refers to a type of vehicles, T ∈ {HDV, AV}, and is solved separately.

Table 1
Notations and input values.

Parameter/Variable	Value	Units
Percent of Curb-to-Curb Demand, a	0.50	unitless
Riding Cost Coefficient for AV, a_r^{AV}	5	€/h
Riding Cost Coefficient for HDV, a_r^{HDV}	7.5	€/h
Waiting Cost Coefficient, a_u	10	€/h
Walking Cost Coefficient, a_z	15	€/h
Cycle Time for AVs, C^{AV}	—	h
Cycle Time for HDVs, C^{HDV}	—	h
Operator Cost per Vehicle and Hour for AVs ($=c_0^{AV} + c_1^{AV}K^{AV}$), c^{AV}	—	€/veh-h
Operator Cost per Vehicle and Hour for HDVs ($=c_0^{HDV} + c_1^{HDV}K^{HDV}$), c^{HDV}	—	€/veh-h
Base Parameter of Unit Operator Cost for AVs, c_0^{AV}	11.24	€/veh-h
Base Parameter of Unit Operator Cost for HDVs, c_0^{HDV}	17.93	€/veh-h
Marginal Cost of Vehicle Capacity for AVs, c_1^{AV}	0.28	€/veh-h-pax
Marginal Cost of Vehicle Capacity for HDVs, c_1^{HDV}	0.25	€/veh-h-pax
Generalized Costs per Day for AVs, $F_{generalized}^{AV}$	—	€
Generalized Costs per Day for HDVs, $F_{generalized}^{HDV}$	—	€
Operator Costs per Day for AVs, $F_{operator}^{AV}$	—	€
Operator Costs per Day for HDVs, $F_{operator}^{HDV}$	—	€
User Costs per Day for AVs, F_{user}^{AV}	—	€
User Costs per Day for HDVs, F_{user}^{HDV}	—	€
Common Service Headway, H	—	h/veh
Service Headway for AVs, H^{AV}	—	h/veh
Service Headway for HDVs, H^{HDV}	—	h/veh
Passenger Capacity per Vehicle for AVs, K^{AV}	—	pax/veh
Passenger Capacity per Vehicle for HDVs, K^{HDV}	—	pax/veh
Length of Service Area, L	5	km
Fleet Size for AVs, M^{AV}	—	veh
Fleet Size for HDVs, M^{HDV}	—	veh
Operational Hours, O	8	h/day
Percentage of Demand Served by AVs, p^{AV}	0.50	unitless
Percentage of Demand Served by HDVs, p^{HDV}	0.50	unitless
Demand Density, Q	5	pax/sq. km/h
Riding Time per Cycle for AVs, R^{AV}	—	h
Riding Time per Cycle for HDVs, R^{HDV}	—	h
Common Stop Spacing, S	—	km/stop
Stop Spacing for AVs, S^{AV}	—	km/stop
Stop Spacing for HDVs, S^{HDV}	—	km/stop
Waiting Time per Cycle for AVs, U^{AV}	—	h
Waiting Time per Cycle for HDVs, U^{HDV}	—	h
Cruising Speed for AVs, V^{AV}	15	km/h
Cruising Speed for HDVs, V^{HDV}	30	km/h
Walking Speed, V_w	5	km/h
Width of Service Area, W	1.5	km
Walking Time per Cycle for AVs, Z^{AV}	—	h
Walking Time per Cycle for HDVs, Z^{HDV}	—	h
Dwell Time at Fixed Stops, τ^{f}	0.008	h/stop
Dwell Time at Curb-to-Curb Stops, τ^{r}	0.005	h/stop
Dwell Time at Terminal Stop, τ^{t}	0.010	h/stop

5. Numerical analyses

5.1. Inputs

Table 1 presents the input values that are considered in this study in order to perform a numerical analysis of the proposed models. Regarding user cost coefficients, it is assumed here that walking costs, a_z, are the greatest, followed by waiting, a_u, and riding costs, a_r^{HDV} and a_r^{AV}. The in-vehicle travel time cost for AVs, a_r^{AV}, is arbitrarily considered lower than the respective cost for HDVs, a_r^{HDV}. Although Yap et al. (2016) state that riding time in AVs is experienced more negatively than riding time in HDVs, the assumption in our study is that advancements in technology regarding monitoring the interior of AVs in combination with the comfort of a modern vehicle can lead to lower riding time costs for AVs. The effect of this parameter on the results obtained from implementing the proposed models is investigated in Section 6. The magnitudes selected here are in accordance with those presented in previous studies, such as Wardman (2004).

Regarding vehicle speed, AVs operate with low speeds in existing pilots in order to assure safety. According to pilot descriptions, automated buses usually operate with an average speed of maximum 12 km/h, although in some cases they can travel with a speed up to 20 km/h (Ainsalu et al., 2018). The value used in this analysis is equal to 15 km/h, which was the average speed for AVs in a pilot study conducted in Appelscha, The Netherlands (Boersma et al., 2018). According to Ainsalu et al. (2018), AVs should operate in areas where the speed limit is 30–40 km/h, in order to assure acceptable relative velocity between the AVs and other vehicles. The HDVs' speed in this study is considered equal to 30 km/h.

The cost coefficients for AVs and HDVs operation, c_0^{AV}, c_0^{HDV}, c_1^{AV} and c_1^{HDV}, are based on the respective values presented in Tirachini and Antoniou (2020) for electric vehicles in Munich (Germany) and for AVs in which the cost of human driving is not completely saved. These values are estimated considering vehicle capital costs, driver costs, and running

Table 2
Operational characteristics of optimal service headway, H^* (h/veh), optimal stop spacing, S^* (km/stop), optimal passenger capacity, K^* (pax/veh), required fleet size, M^* (veh), and cycle time, C^* (h) for mixed fleet.

Case	AV					HDV				
	H^*	S^*	K^*	M	C	H^*	S^*	K^*	M	C
A	0.19	0.80	3.56	5.12	0.97	0.19	0.98	3.56	2.80	0.53
B	0.19	0.90	3.54	5.08	0.96	0.18	0.90	3.44	2.92	0.54
C	0.19	0.80	3.56	5.12	0.97	0.18	1.00	3.38	2.92	0.52
D	0.19	0.89	3.56	5.06	0.96	0.19	0.89	3.56	2.84	0.54

Table 3
Daily costs of operation, walking, waiting, and riding (€) for mixed fleet.

Case	AV				HDV			
	Operation	Walking	Waiting	Riding	Operation	Walking	Waiting	Riding
A	501.43	258.26	285.00	364.93	421.35	279.18	285.00	299.09
B	497.56	270.00	283.29	360.12	438.29	270.00	275.53	301.24
C	501.43	258.26	285.00	364.93	437.93	280.87	270.00	295.23
D	495.76	269.27	285.00	360.80	427.72	269.27	285.00	303.61

costs. The daily hours of operation, O, are considered equal to 8 h. Reasonable values for dwell times at different types of stops, as well as for the walking speed, are adopted here. Demand density considered in this study is $Q = 5$ pax/sq.km/h per direction. Regarding service area dimensions, a width of $W = 1.5$ km and length $L = 5$ km are considered here. The length of the corridor is close to the maximum values of route lengths of completed pilot studies reported in Boersma et al. (2018).

5.2. Results

Table 2 presents in detail the operational characteristics of the mixed fleet as a result of implementing each one of the four operational cases considered here. The input values are as presented in Table 1. Regarding optimal service headway, when it is not common between the two vehicle types (i.e., Cases A and D), it is greater for the AVs, meaning that they operate optimally with less frequent vehicle dispatches compared to HDVs. Regarding optimal stop spacing, AVs have lower values, which means that they operate optimally with more fixed stop locations compared to HDVs. Even when optimal service headway is not common (i.e., Cases B and C), the AVs' required passenger capacity is still very close to HDVs'. In all four cases, the required fleet size of AVs is greater than the fleet size of HDVs, which can be primarily attributed to the fact that AVs operate with much greater cycle times than the HDVs.

Table 3 presents the daily costs as a result of the operation of the mixed fleet within a day. According to this table, operational costs for all required AVs are always greater than the respective costs for all required HDVs in this analysis. It is noted that a single AV's operation cost is ~ 98 Euro, which is less than a single HDV's cost which is ~ 150 Euro in all four cases, as resulting from dividing operational costs of Table 3 with the respective fleet size of Table 2. Regarding walking, it is observed that HDVs have their lowest costs when common stop spacings are implemented for both types of vehicles (i.e., Cases B and D). In contrast, AVs have their greatest walking costs when common stop spacings are implemented. Regarding waiting, HDVs have their lowest costs when optimal service headway is different for both types of vehicles (i.e., Cases B and C) and AVs when the two types of vehicles have the same stop spacing and different headways (i.e., Case B) although the difference with the other three cases is very small. Regarding riding, AVs are always costlier than HDVs. Summing up the values in each row of Table 3 leads to the total generalized cost of the mixed fleet, which for Cases A, B, C, and D equals 2694.24 €, 2696.03 €, 2693.65 €, and 2696.42 €, respectively. It is noteworthy that the difference in total generalized costs is very small for the four operational cases considered here.

Table 4 offers valuable insights on the magnitude of the costs per passenger type that result from the operation of the mixed fleet. Walking times per passenger refer only to passengers served at fixed stops. Passengers served by AVs at fixed stops are associated with the greatest and passengers served by HDVs curb-to-curb with the lowest travel times. The total time spent by a passenger in the flexible system with AVs is greater than the time spent if HDVs are used. Thus, transit agencies should identify proper incentives for users to choose AVs for their daily service.

6. Sensitivity analyses

The input values included in Table 1 are selected to represent real-life conditions at the greatest possible extend, considering pilot studies on AVs operation and flexible service area characteristics. In this Section, the effects of important input values on system's costs (i.e., operator, user and generalized) and operational characteristics (i.e., service headway, stop spacing, passenger capacity and fleet size) are investigated. The input parameters studied in this Section refer to percentage of passengers served by AVs, ratio of AV speed over HDV speed, and in-vehicle travel time cost.

Table 4
Daily time of walking, waiting, riding, total travel time (for pax served at fixed stops and curb-to-curb) per pax (min/pax) for mixed fleet.

Case	AV					HDV				
	Walking	Waiting	Riding	Total (stop)	Total (curb)	Walking	Waiting	Riding	Total (stop)	Total (curb)
A	6.89	5.70	14.60	27.18	20.30	7.44	5.70	7.98	21.12	13.68
B	7.20	5.67	14.40	27.27	20.07	7.20	5.51	8.03	20.74	13.54
C	6.89	5.70	14.60	27.18	20.30	7.49	5.40	7.87	20.76	13.27
D	7.18	5.70	14.43	27.31	20.13	7.18	5.70	8.10	20.98	13.80

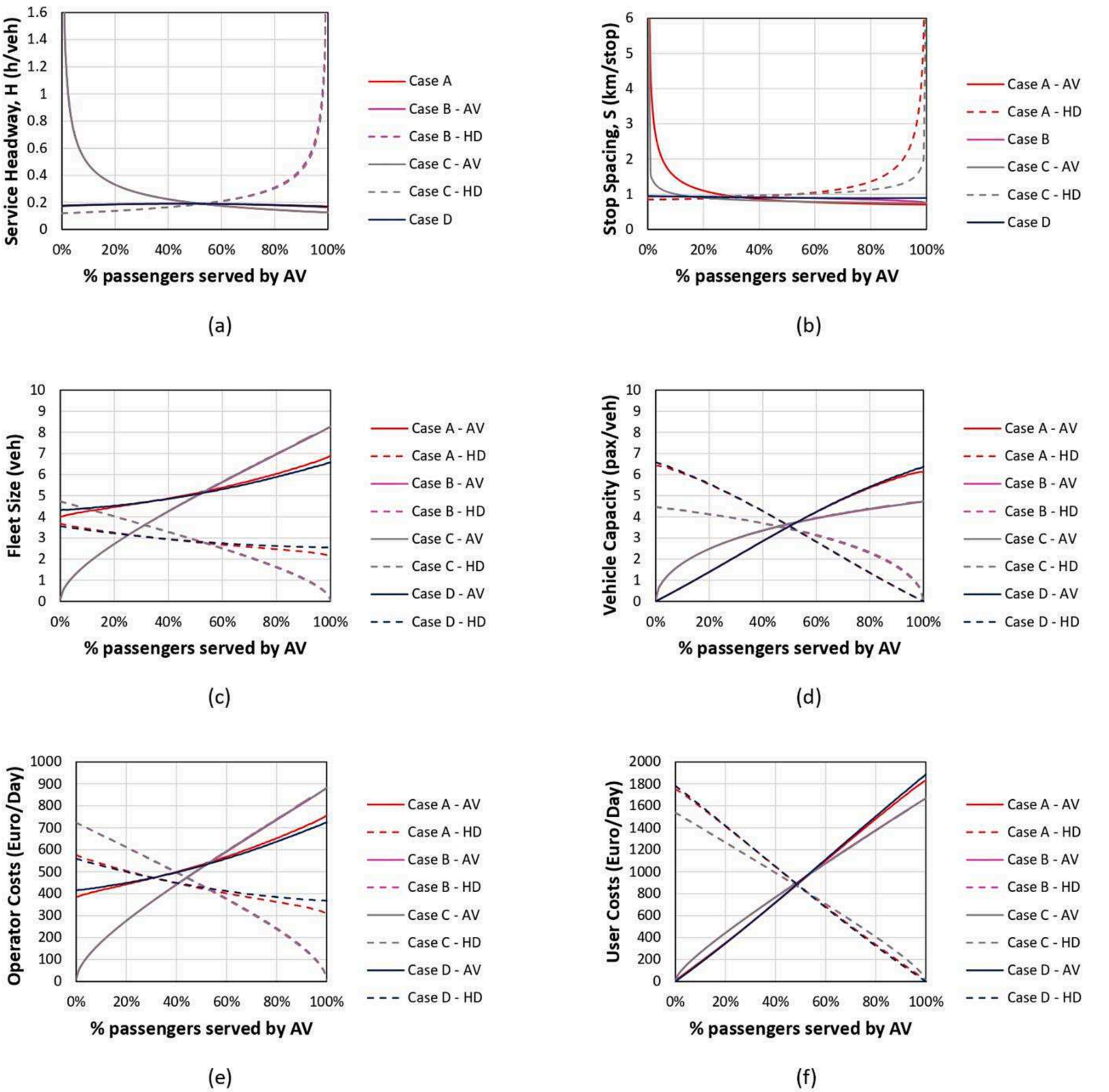

Fig. 3. Effect of percentage of passengers served by AVs, p^{AV}, on a) optimal service headway, b) optimal stop spacing, c) fleet size, d) vehicle capacity, e) operator costs, and f) user costs.

6.1. *Percentage of passengers served by AVs*

Fig. 3a shows that Cases A and D (i.e., where common headway for both types of vehicles is implemented) have almost equal values of optimal service headway. The same holds for Cases B and C (i.e., different service headways for the two types of vehicles). Thus, the effect of different stop spacings on service headway is not significant. The service headways for Cases A and D are almost unaffected by the changes in p^{AV} values. The vertical axis in Fig. 3a reaches a major value of 8 h/veh, which is the maximum possible service headway in this study, but it was cut to a lower value for better representation of the patterns that occur here. Stop spacings in Fig. 3b for Cases B and D (i.e., common stop spacing in both types of vehicles) are almost not affected by the changes in p^{AV} values, whereas Cases A and C follow similar patterns. Regarding Fig. 3c, although for $p^{AV} = 0$ there is no need for AVs (and for $p^{HDV} = 0$ no need for HDVs), the models proposed here still lead to vehicle requirements because the vehicles operate on the fixed corridor. Cases A and D refer to common headways for both types of vehicles, so their values are not adjusted to each type of vehicles' demand. Combined with the low speed and the great cycle times of AVs, these headways lead to a requirement for AVs when $p^{AV} = 0$ and HDVs when $p^{HDV} = 0$ according to Eq. (2). Fig. 3d indicates that all four cases lead to the same capacity for both types of vehicles when $p^{AV} \approx 0.50$. According to Fig. 3e, for Cases A and D, the operator costs of AVs in the mixed fleet become greater than HDVs' operator costs faster (i.e., at $p^{AV} \approx 0.30$) compared to the Cases B and C (i.e., at $p^{AV} \approx 0.50$). Fig. 3f presents the user costs, which are equal for all cases and both types of vehicles when $p^{AV} \approx 0.50$. In all sub-figures except for Fig. 3b, Cases A

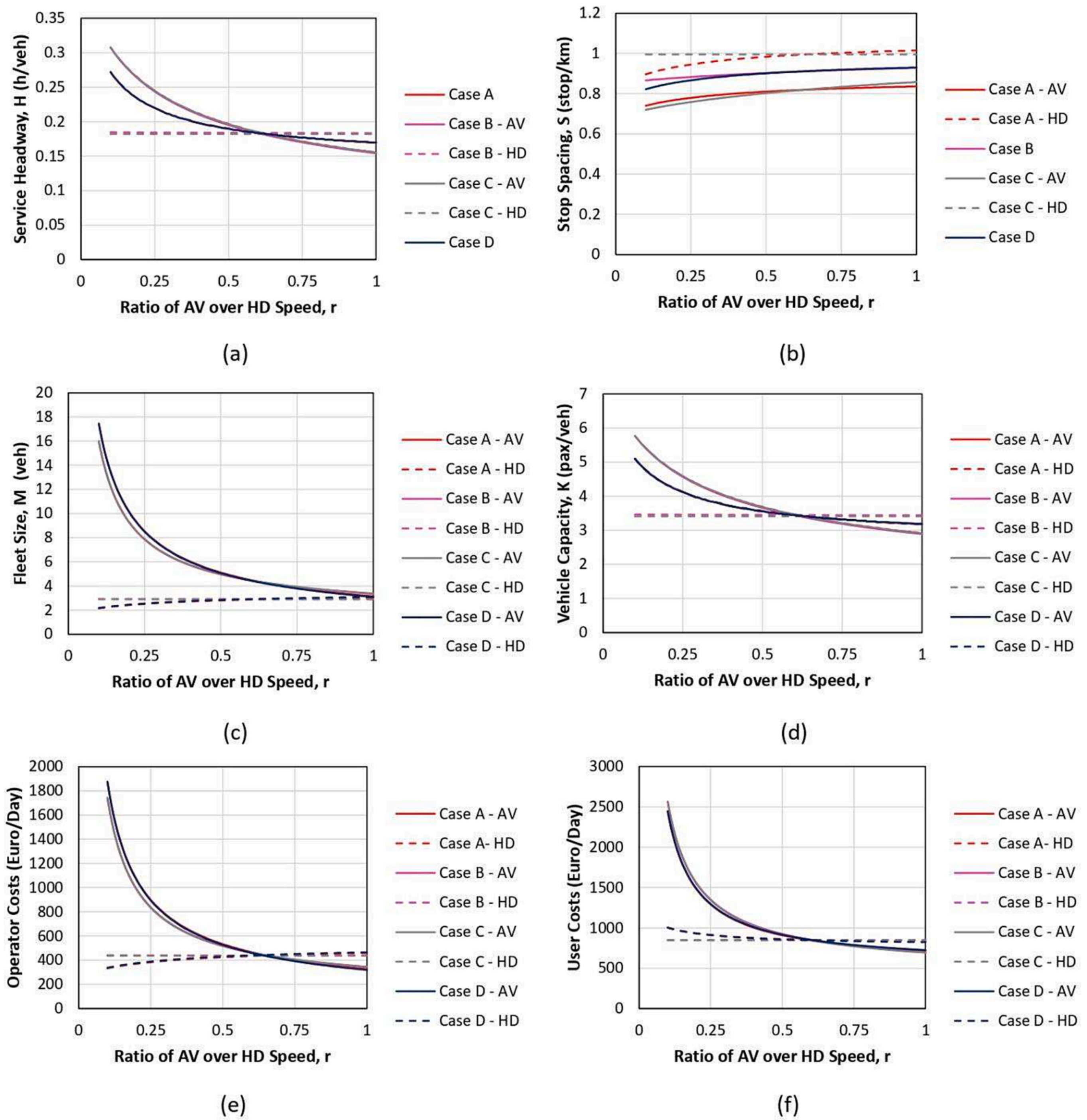

Fig. 4. Effect of AV over HDV speed ratio, *r*, on a) optimal service headway, b) optimal stop spacing, c) fleet size, d) vehicle capacity, e) operator costs, and f) user costs.

and D perform similarly. The same holds for Cases B and C.

6.2. Vehicle speed

Fig. 4 presents the effects of considering a ratio, r, of AVs' speed over HDVs' speed equal to values that range from 0.1 to 1, with 1 meaning that the two types of vehicles operate with the same speed. Similar to Section 6.1, in all sub-figures presented here Case A overlaps with Case D, while Case B overlaps with Case C. The exception is Fig. 4b. Fig. 4a, shows that in Cases B and C (i.e., different headways for the two types of vehicles) HDVs operate with lower headways until $r \approx 0.6$. The smaller the r, the greater the difference between the two vehicles' service headways. The effect of AV speed on HDVs' headways is small when the vehicles operate with different headways (i.e., Cases B and C). According to Fig. 4b, when the two types of vehicles operate with different stop spacing (i.e., Cases A and C), the HDVs will always require greater stop spacings than the AVs. In Fig. 4c, all four cases present a similar pattern, with great AV fleet size requirements for low AV speeds, which drop significantly before $r = 0.5$. Higher requirements are always met for AVs compared to HDVs, even when their speeds are equal. Fig. 4d shows that in Cases B and C the HDVs have lower capacity requirements than AVs when $r < 0.6$. For $r \geq 0.6$, HDVs have greater requirements in passenger

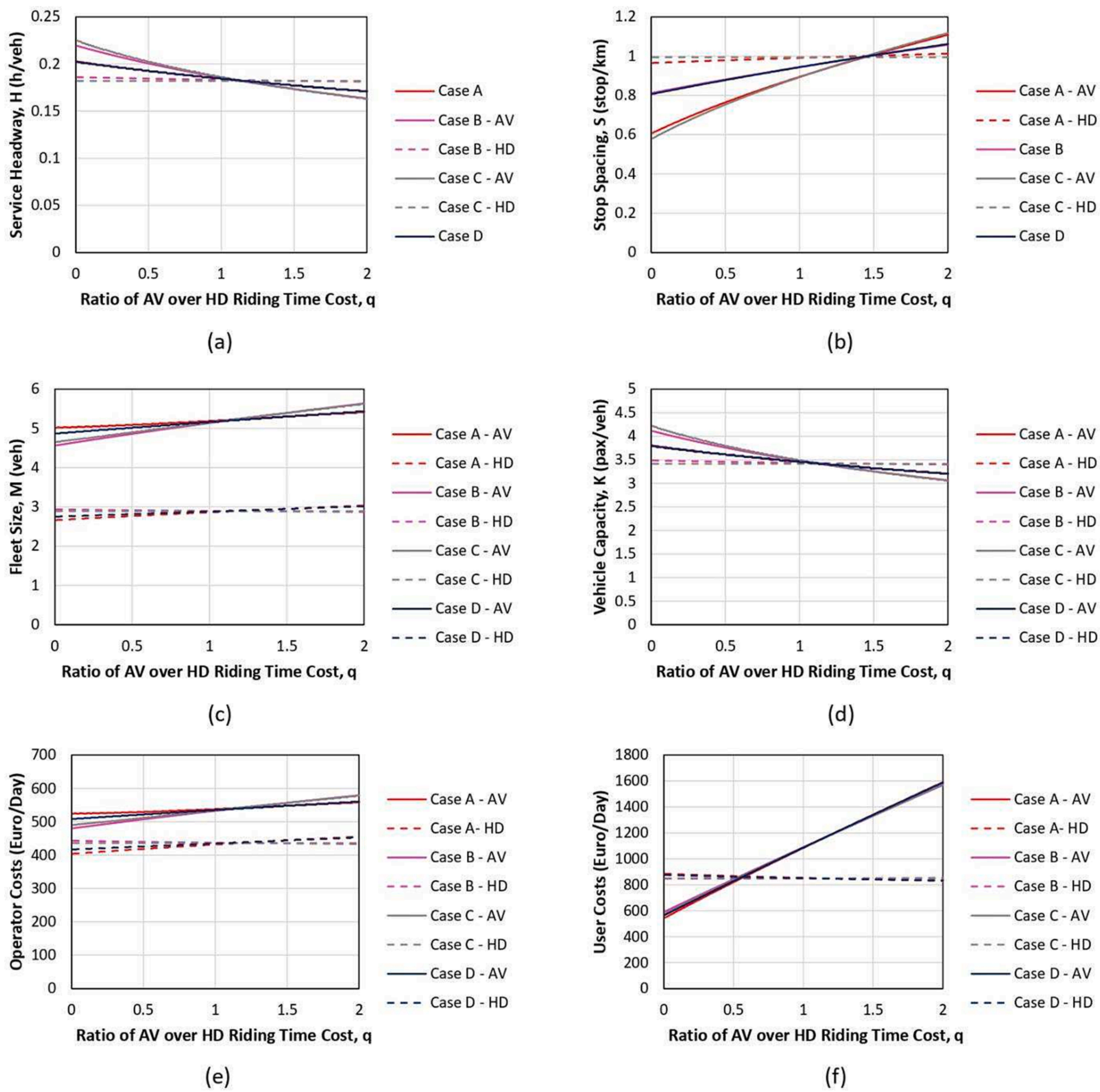

Fig. 5. Effect of AV over HDV riding time cost, q, on a) optimal service headway, b) optimal stop spacing, c) required fleet size, d) required vehicle capacity, e) operator costs, and f) user costs.

capacity. Fig. 4e and Fig. 4f present the operator and user costs respectively, which drop significantly for AVs as r tends to 1.

6.3. *In-vehicle travel cost*

The effects of riding time cost are investigated through considering a ratio, q, of a_r^{AV} over the HDVs' riding time cost, a_r^{HDV}. Values of q considered here vary from 0.01 to 2. According to Fig. 5a, the optimal service headway of AVs for Cases B and C (i.e., the two types of vehicles operate with different headways) are greater than the ones of HDVs until $q \approx 1.15$. For $q > 1.15$ the HDVs require greater optimal service headways than AVs. Regarding stop spacing, Fig. 5b shows that for q lower than approximately 1.45 the HDVs require greater stop spacings than AVs for the operational cases that the two vehicles operate with different stop spacings (i.e., Cases A and C). In terms of required fleet size, AVs requirement is always greater than HDVs', according to Fig. 5c. The fleet size requirements for the four operational cases intersect for each type of vehicles separately shortly after $q = 1$. For q lower than 1, Case A requires the most and Case B requires the least AVs. They also require the least and the most HDVs, respectively. In Fig. 5d, Cases B and C require the greatest passenger capacities for AVs and the lowest for HDVs, while Cases A and D have the same requirements for both AVs and HDVs for all q. The operator costs for all required AVs are always greater than the costs of HDVs for all q values (Fig. 5e). Fig. 5f shows that in all four cases, the two types of vehicles operate with similar user costs, which increase for AVs as q increases. As observed in Sections 6.1 and 6.2, common service headways between the two types of vehicles (i.e., Cases A and D) lead to similar operational characteristics (except for stop spacing) and costs. The same holds for the two cases in which optimal service headway is not common (i.e., Cases B and C).

7. Service and automation in mixed fleets

7.1. *Service flexibility and percentage of passengers served by AVs*

The assumption in this study is that AVs and HDVs offer the same

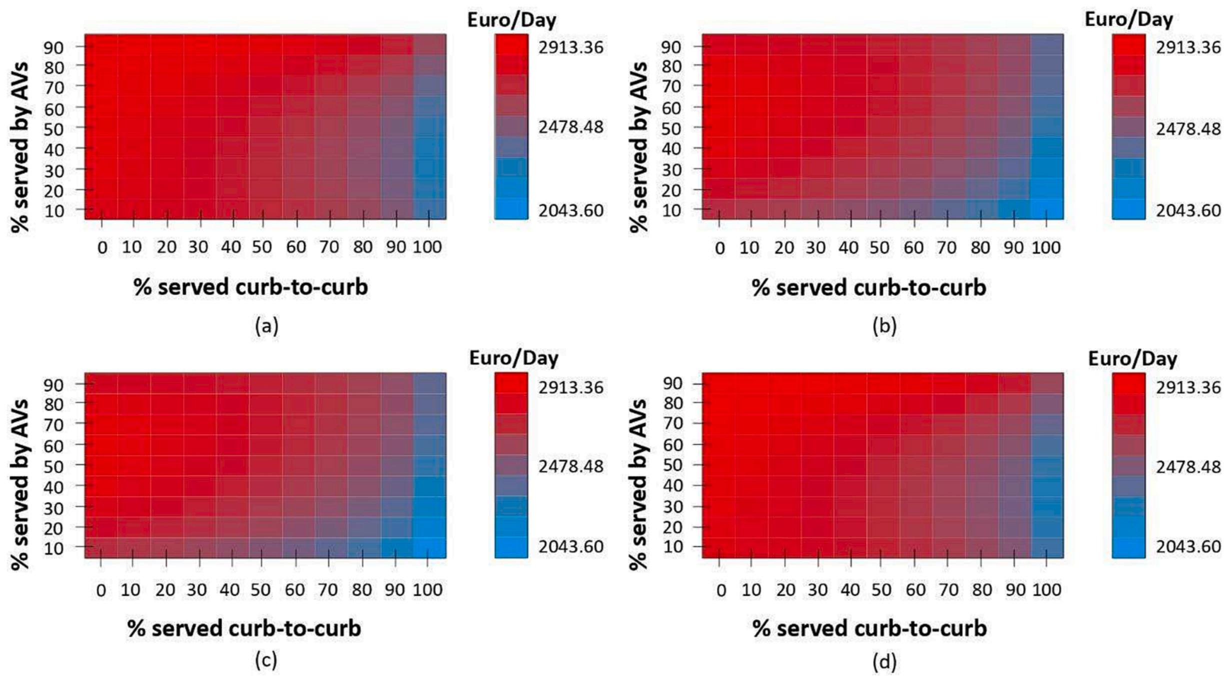

Fig. 6. Total generalized cost of mixed fleets for a) Case A, b) Case B, c) Case C, and d) Case D.

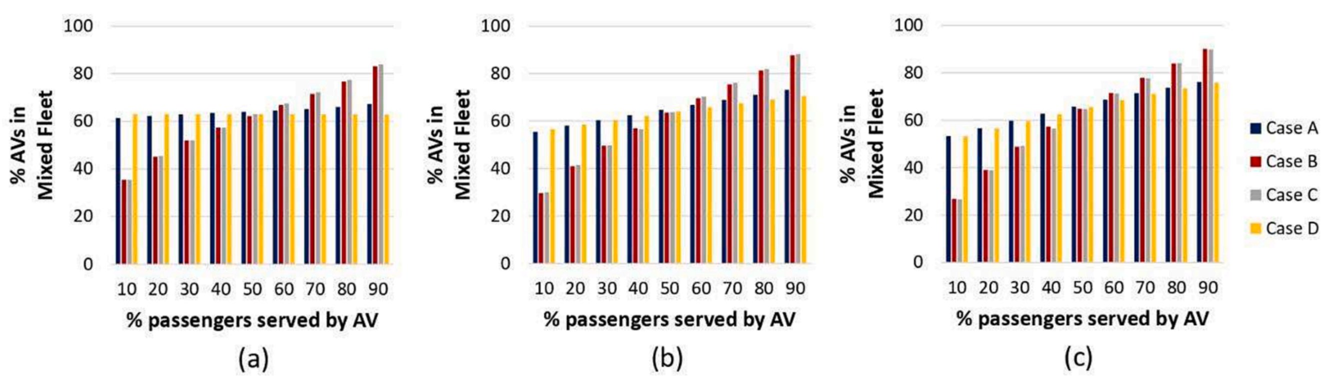

Fig. 7. Percentage of AVs in mixed fleets for a) $a = 0\%$, b) $a = 50\%$, and c).$a = 100\%$

type of flexible route deviation services that HDVs offered before the AVs' introduction. The aim of this Section is to investigate the relationship between the percentage of passengers served by the AVs, p^{AV}, and the level of flexibility that the mixed fleet offers, a, under the four operational cases considered here. Analyzing the strategy of operating each type of vehicles with a different type of service (i.e., fixed route, flexible, on-demand) lies beyond the scope of this study. It is noted that the percentage of passengers served curb-to-curb might depend on the existence of people with disabilities or elderly people in the service area that need to be served in a flexible way. Thus, depending on the transit agency's policy, it might be a parameter that cannot change after the AVs introduction.

Fig. 6 presents colormaps with total generalized costs for the input values included in Table 1. Values of p^{AV} range from 0.10 to 0.90, to focus only on mixed fleets. According to this figure, the four operational cases result in similar magnitudes of total generalized costs per day. In all four cases, the lower the percentage of passengers served by AVs, p^{AV}, the lower the total generalized costs. For Cases A and D, the lowest total generalized cost is met when $p^{AV} = 0.30$ and $a = 1$, while for Cases B and C when $p^{AV} = 0.10$ and $a = 1$.

The relationship between a and p^{AV} in terms of required fleet size for both types of vehicles is investigated in Fig. 7. More specifically, the

Table 5
Operational characteristics of optimal service headway, H^* (h/veh), optimal stop spacing, S^* (km/stop), optimal passenger capacity, K^* (pax/veh), required fleet size, M^* (veh), and cycle time, C^* (h) for mixed fleet with no driver costs for AVs.

Case	AV					HDV				
	H^*	S^*	K^*	M	C	H^*	S^*	K^*	M	C
A	0.15	0.66	2.81	6.35	0.95	0.15	1.05	2.81	3.36	0.50
B	0.11	0.86	2.00	8.25	0.88	0.18	0.86	3.46	2.93	0.54
C	0.11	0.69	2.06	8.23	0.91	0.18	1.00	3.38	2.92	0.52
D	0.15	0.88	2.81	6.15	0.92	0.15	0.88	2.81	3.46	0.52

percentage of AVs within the mixed fleet is shown for three levels of flexibility, namely $a = 0$ (i.e., fixed route service), $a = 0.50$, and $a = 1$ (i.e., full flexible route deviation). For $p_{AV} \leq 0.30$, the increase of flexibility decreases the percentage of AVs in the mixed fleet. For $p^{AV} = 0.40$, the percentage of AVs within mixed fleets does not change significantly as flexibility increases. For $p^{AV} > 0.40$, increased flexibility leads to increase of AVs in the mixed fleet. These observations hold for all four cases. It is also noteworthy that Cases A and D have greater number of AVs than HDVs in the respective mixed fleets for $p^{AV} \leq 0.50$. After $p^{AV} = 0.50$, the Cases B and C have the greater percentage. This observation is not affected by the level of flexibility incorporated in the services.

7.2. Service transition from human-driven to automated vehicles

The focus of this analysis is on the early stages of introducing AVs in public transit fleets and thus the assumption here is that driver costs for AVs are not fully saved due to automation. According to Tirachini and Antoniou (2020), for the case study of Munich (Germany) the operational cost coefficient for AVs when driver costs are fully saved is approximately one third of the cost coefficient when 50% of driver costs are saved (i.e., $c_0^{AV} = 11.24$€/veh-h for the former and $c_0^{AV} = 3.56$ €/veh-h for the latter). The marginal cost coefficient, c_1^{AV}, is the same for both levels of human intervention (i.e., $c_1^{AV} = 0.28$€/veh-h-pax). Table 5 shows the effect of driver costs on required operational and vehicular characteristics, for c_0^{AV} equal to 3.56 €/veh-h and c_1^{AV} equal to 0.28 €/veh-h-pax. The comparison between Table 5 (i.e., no driver costs) and Table 2 (i.e., half driver costs) gives interesting insights on the effects of c_0^{AV} on optimal operational characteristics and required vehicular characteristics. The lower value of c_0^{AV} in Table 5 leads to lower values of optimal service headway for AVs in all cases and lower optimal service headway for HDVs when it is common with AVs (i.e., Cases A and D). Unlike Table 2, the AVs operate with lower service headways than HDVs when the driver costs are fully eliminated in Cases B and C. Regarding optimal stop spacing, when there are no driver costs it is lower for AVs, while HDVs' stop spacing is less affected by c_0^{AV}. Comparing Table 5 with Table 2 in terms of vehicular characteristics shows that AVs without driver costs lead to greater requirements for AV fleet size for all four cases. The greatest increase is met for Case B and the lowest for Case D. Regarding the required fleet size for HDVs, driverless AVs increase requirements in Cases A and D, but not in Cases B and C. Vehicle capacity is decreased for both AVs and HDVs when AVs are driverless. Regarding HDVs' capacity requirements, Cases B and C are not affected by the AV driver costs. Cycle time for AVs is lower when there are no driver costs for all cases, while for HDVs it is lower for cases A and D and the same for Cases B and C. The differences in the mixed fleet's vehicular requirements under the four operational cases studied here are more apparent for AVs with no driver costs (i.e., Table 5) compared to AVs with 50% driver costs (i.e., Table 2).

The transition from a public transit fleet with HDVs only to a fleet of AVs only is expected to be gradual and with uncertain duration. The intermediate phase of this transition includes mixed fleets of both HDVs and AVs. According to Table 6, both the operator and user costs of HDVs only are lower than the respective costs of the mixed fleet in all four operational cases considered here. This Table also includes four scenarios of operating AVs only, also considered in Tirachini and Antoniou (2020):

- Scenario 1: AVs operate with 50% of HDVs' speed and with 50% of driver costs.
- Scenario 2: AVs operate with the same speed as HDVs and with 50% of driver costs.
- Scenario 3: AVs operate with 50% of HDVs' speed and without driver costs.
- Scenario 4: AVs operate with the same speed as HDVs and without driver costs.

The fourth scenario has the lowest costs among the four scenarios for AVs' operation and also among all the three phases of the transition analyzed here (i.e., HDVs only, mixed fleets, and AVs only). In order to better understand the role of AVs in the mixed fleet during the transitioning period, it is important to highlight that the assumption of low speed for AVs leads to greater cycle times which result in greater fleet size requirements and greater riding times, among others. According to Table 2, AVs require greater service headways than HDVs which also leads to greater passenger capacity requirements, since demand density per direction and the percentage of passengers served by each type of vehicles are the same between AVs and HDVs in this analysis. Although the difference in passenger capacity between the two types of vehicles is not significant in this numerical analysis, a greater passenger capacity still leads to greater operational costs, since the cost function considered in this study accounts for this parameter and uses a greater respective cost coefficient for AVs (i.e., 0.28 for AVs and 0.25 for HDVs). As shown in Table 6, the intermediate phase of mixed fleets is the one associated with the greatest costs which are almost equal in the four operational cases studied here, at least for the input values and the assumptions made in this analysis. Both the operator and user costs of the first scenario of operating AVs only are very close to the ones of the mixed fleet, but they become significantly lower when the AVs' speed becomes equal to HDVs' speed and the AVs are driverless (i.e., scenario four). These observations are based on the assumption that all other parameters remain constant during the transitioning period and highlight the potential benefits and challenges that AV technology may bring to public transit fleets for both operators and users.

8. Discussion and conclusions

8.1. Summary of results and comparison to previous studies

The mixed fleet of transit vehicles is expected be met in several transit agencies in the future, as AVs will start gradually being introduced into public transit fleets. It is thus important to investigate the optimal operation of both types of vehicles in the same transit fleet. The operation of the mixed fleet in a low demand density area and within a service line is optimized here. Low density areas with flexible services are chosen, since the introduction of AVs is expected to be smoother there. Analytical models for optimal service headway and stop spacing are the main outputs of this study, along with insights on the vehicle-related requirements and the overall operation of the mixed fleet under different operational strategies. It is important to investigate the operation of the mixed fleet under different operational strategies, in which the two vehicle types operate either jointly (i.e., Cases A, B, and D) or independently (i.e., Case C), in order to have a full view of their potential co-existence and performance within a transit fleet. The numerical analysis is based on realistic input values taken from existing literature on flexible route deviation

Table 6
Total operator costs (O.C.), user costs (U.C.), and generalized costs (G.C.) (€) for the transition from HDVs to AVs only.

Cost	HDV	Mixed Fleet (HDV + AV)				AV			
		Case A	Case B	Case C	Case D	Sc. 1	Sc. 2	Sc. 3	Sc. 4
O.C.	717.76	922.78	935.85	939.36	923.48	858.99	548.37	462.13	295.04
U.C.	1540.79	1771.46	1760.18	1754.30	1772.94	1639.41	1232.44	1403.06	1067.06
G.C.	2258.56	2694.24	2696.03	2693.65	2696.42	2498.40	1780.81	1865.20	1362.10

services and pilot studies implemented to test the performance of AVs. The four operational cases considered here are shown to perform similarly in terms of costs, but are associated with different operational characteristics for the mixed fleet. The performed sensitivity analyses showed that the numerical results are sensitive to important input values, such as the percentage of passengers served by AVs, the AV speed and the user perception towards in-vehicle travel time when using AVs. They also indicated that the influence of stop spacings on the operations and costs in this study is low. Cases with common service headway for the two types of vehicles are not recommended when the percentage of passengers served by a type of vehicle approaches zero, since they still lead to high fleet size requirements for the respective type of vehicles and thus to high operating costs.

The numerical results obtained in this study are highly associated with the input values, as well as with the unique characteristics of the mixed fleet's operation (e.g., both types of vehicles serve the same line and offer flexible services while most of the literature studies either fixed route or on-demand services). There are still, however, interesting comparisons with results existing in literature in this field. Regarding service headway, according to Tirachini and Antoniou (2020), PT users should expect benefits from AVs through a reduction of waiting times. Considering that waiting is strongly determined by service headway, it is observed in our numerical analysis that the two types of vehicles have almost equal service headways, even when they are not planned to operate with the same. The difference refers to 0.01 hr/veh, with AVs having greater headways than HDVs, hence, implying slightly greater waiting times for the AV users. Sensitivity analysis performed here showed that this result is sensitive to input values, namely the percentage of users served by AVs, the speed of AVs compared to the speed of HDVs and the AV users' perception of in-vehicle travel time. In all three sensitivity analyses it is shown that there is a critical point after which HDVs' service headway becomes greater than AVs' (i.e., Fig. 3.a, 4.a, and 5.a), hence leading to lower waiting times for AV users. Moreover, as shown in Table 5, when driving costs are not considered at all in AVs' operating costs, then AVs are associated with much lower headways than HDVs and thus with much lower waiting times for AV users. Automated vehicles within the mixed fleet also operate optimally with more fixed stop locations. Studies with optimal stop spacing insights for AVs were not identified in existing literature in order to perform a comparison. Greater fleet sizes for AVs result from the proposed optimization process, which is aligned with existing studies which support that AVs favor larger fleets of smaller vehicles (e.g., Fielbaum (2019)). Regarding vehicle sizes, they are found to be similar for both types of vehicles in this study. However, if for example, the two types of vehicles operated with similar speeds, then AVs would have smaller required size.

Focusing on the transition from public transit fleets of HDVs only to fleets of AVs only, the intermediate phase of mixed fleets is found to be costlier for both operators and users, but AV costs are decreased as AV technology is improved (i.e., in terms of speed and human intervention). Existing literature also highlights the effects of technology development degree on AVs' costs (e.g., Badia and Jenelius (2020)). The lowest costs among all three transitioning phases (i.e., HDV only, mixed fleets, AV only) are met when transit fleets include only AVs, which operate with the same speed as HDVs and without a driver. These observations are aligned with existing studies (e.g., Tian et al. (2021)) that consider driverless AVs with the same travel times as HDVs and their introduction into a fleet can lead to lower costs. Unlike most existing studies that focus on either fixed route or on-demand services and the respective comparison (e.g., Liu and Schonfeld (2020)), this study focuses on a flexible system with elements of both. Its modeling thus allows investigating different levels of flexibility, which was found to be essential in studying the mixed fleet. Results showed that lower total generalized costs can be achieved for greater levels of flexibility and lower levels of demand served by AVs. The relationship between the required AV and HDV fleet size within the mixed fleet depends on the relationship between the level of flexibility and the user acceptance towards AVs.

8.2. Implications for decision-making in practice

An important assumption in the modeling process presented here is that the introduction of AVs within the mixed fleet is unconstrained. In an actual implementation within a specific public transport system, policy-related constraints are always present and decision on fleet change pertains to other aspects – network design, fare design, organizational structure, etc. For example, if a transit agency decides to introduce AVs in their fleets and has no limitations regarding the number of AVs to purchase, these models can be used to identify the required fleet of AVs, as well as the optimal operation of the resulting mixed fleet. On the other hand, if an agency has budget limitations regarding how many vehicles to purchase, then some modifications are required in the modeling approach to account for this constraint or the analysis would have to be done in an iterative manner. Another assumption is that transit agencies know in advance the percentages of passengers that are served by each type of vehicle and they are constant on a daily basis for a given time period. In this time period, transit agencies plan their operations and scheduling accordingly and major changes in these percentages within a day are not expected. In real-life conditions, the daily demand for each type of vehicle is associated with some uncertainty for which the transit agencies need to account while planning their operation. This study assumes that both types of vehicles in the mixed fleet offer the same type of service that the HDVs used to offer before the AVs' introduction. A transit agency, however, might wish to investigate the shift of services to a different type before introducing AVs, depending on its flexibility to do so.

8.3. Future research directions

There are different ways that this study can be extended. As presented in Section 8.2, the modeling process could be modified to account for constraints (e.g., fleet size) and demand variations per day. Also, it is worth investigating if there are different types of service for each type of vehicles that would make the mixed fleet more beneficial for agencies and users, assuming that equity among users is assured and that agencies can plan and design any type of service. Existing literature includes several studies on optimizing analytically the operation of fixed route and on-demand services for AVs and HDVs (e.g., Liu and Schonfeld (2020)) which can be used for comparing the performance of the two types of vehicles under the two types of services (i.e., fixed route and on-demand) but not for the cases that the two types of vehicles operate in a joint way. This study evaluates mixed fleets considering operating and user costs that result from their operation. There are additional metrics that could also be considered while evaluating the transitioning period towards operating AVs only. Since the focus of this study is on feeder line services, the effect of AVs within the transit fleet could also be measured in terms of service accessibility in relation to the terminal station with which the under-study area is connected through these services. More details on feeder bus accessibility can be found in Jiang et al. (2020). User friendliness of the mixed fleet can be expressed not only through the travel times per passenger presented numerically in Section 5, but also through the environmental impacts of the transit services. According to existing literature (e.g., Bergqvist and Åstrand (2017)), AVs are associated with much lower emissions per person and distance traveled. Thus, user friendliness measured through environmental impacts of the mixed fleet could serve as an additional measure for an overall evaluation of its performance, among others.

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CRediT authorship contribution statement

Charalampos Sipetas: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Claudio Roncoli:** Methodology, Writing – review & editing, Supervision. **Miloš Mladenović:** Conceptualization, Writing – review & editing, Supervision.

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

No data are used and we have shared the link to the code in the paper

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