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Autonomous vehicle fleets for public transport: scenarios and comparisons

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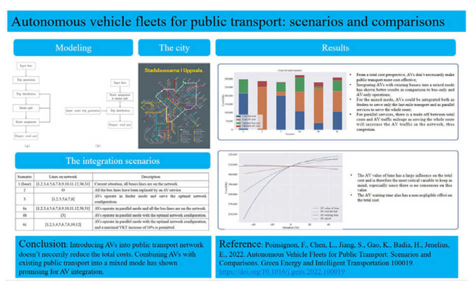
HIGHLIGHTS

- A transport planning model with integration of autonomous vehicles in public transportand impact analysis.
- Simulation study on integration alternatives based on a typical European city withrealistic traffic data.
- Cost estimation and sensitivity analysis of different integration scenarios.
- A mixed-mode with autonomous fleets and buses is better compared with a single mode.
- The value of time of autonomous vehicles has big impact on the overall network costs.

GRAPHICAL ABSTRACT



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ABSTRACT

Autonomous vehicles (AVs) are becoming a reality and may integrate with existing public transport systems to enable the new generation of autonomous public transport. It is vital to understand what are the alternatives for AV integration from different angles such as costs, emissions, and transport performance. With the aim to support AV integration in public transport, this paper takes a typical European city as a case study for analyzing the impacts of different AV integration alternatives. A transport planning model considering AVs is developed and implemented, with a methodology to estimate the costs of the transport network. Traffic simulations are conducted to derive key variables related to AVs. An optimization process is introduced for identifying the optimal network configuration based on a given AV integration strategy, followed by the design of different AV integration scenarios, simulation, and analyses. With the proposed method, a case study is done for the city of Uppsala with presentation of detailed cost results together with key traffic statistics such as mode share. The results show that integrating AVs into public transport does not necessarily improve the overall cost efficiency. Based on the results and considering the long transition period to fully autonomous vehicles, it is recommended that public transport should consider a gradual introduction of AVs with more detailed analysis on different combination and integration alternatives of bus services and AVs.

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1. Introduction

With the rapid advancement of enabling technologies, Autonomous Vehicles (AVs) are reaching the level of commercial introduction. The AV market is expected to grow from 1.64 billion USD in 2021 to 11.03 billion in 2028, despite the effects of the COVID-19 pandemic [1]. Enormous resources have been invested in the area with many test activities globally represented by large private companies including e.g., Uber, Apple, Waymo, and Baidu. On the other hand, governments have been busy working on creating new legal frameworks and investment plans to support the development of the industry. For example, 29 of the 50 USA States have enacted legislation related to AVs [2].

With promises of improving traffic safety and efficiency, reducing emissions, and improving travel comfort, AVs have great potential for future passenger mobility and city design [3]. When integrated with public transport, the sustainability benefits could be magnified due to shared mobility. According to the International Association of Public Transport (UITP), autonomous vehicles can help to meet public policy goals when operated as shared fleets [4]. They could be implemented as a swarm of "robo-taxis" or as feeders to a traditional line-based service. Based on the nature of being e.g. shared and demand-responsive, they may decrease the number of parked cars on the streets and offer better accessibility and mobility.

While the potential to introduce AVs in public transport is large, it remains to understand how to integrate them and what the costs will look like. For example, what will be the first choice to integrate AVs in a well-functioning public transport network with no or very little changes on the infrastructure and what will be the cost and benefits quantitatively? This paper takes a typical European city, the city of Uppsala in Sweden, as an example to explore different alternatives for integrating shared fleets of autonomous vehicles in the public transport network for improving the performance and cost-effectiveness. This paper focuses on investigating different integration alternatives of AVs in an existing public transport network from a cost perspective. For this purpose, a transport forecasting model is built based on adaptations of the commonly used "four-step" model. The results of the forecast are used to calculate an estimation of the total cost of the network during the morning peak hour, both from the operator's and the user's perspectives. Integrating AVs as both feeder services and additional parallel services are considered for comparison.

2. Literature review

2.1. Autonomous vehicles for demand responsive transit

Different modes have been considered for AVs as part of the future urban mobility system. Two operation modes are generally considered and compared, namely private and shared. Meyer et al. [5] compared both modes and comes to the conclusion that AVs would increase significantly accessibility and might foster urban sprawl as a result. Other authors such as Bösch et al. [6] have studied AVs from a cost perspective, showing that AV fleets are cost-effective only in areas with a relatively low density, compared with traditional public transport. In particular, private AVs, though more expensive for the user, would still be an option as it offers a wide range of benefits such as the possibility to work during the trip. In [7], the authors studied the total cost of ownership and use for different AV usage alternatives including private own and different on-demand services and identified different factors that affected the costs.

AVs have mostly been considered to enable demand-responsive mobility services due to the flexibility, where users would request the rides and the system would then schedule the trips accordingly. This differs from the fixed-schedule public transport service, where vehicles serve fixed stops, following fixed routes according to a fixed timetable. Demand Responsive Transit (DRT) has been extensively studied in the past. In [8], Mageean et al. reviewed the current landscape of DRT service in Europe with conventional vehicles. While in [9], Papanikolaou et al. designed a methodological framework for assessing the viability of DRT systems. Both authors agreed that this type of offer was relatively niche, partly due to high costs per passenger, but the authors in [9] argued that DRT could potentially be used for low-frequency bus services.

A large part of the research about DRT systems concerns the Dial-A-Ride Problem (DARP). This theoretical problem, which can be formulated in abstract mathematical terms, constitutes the central problem of all DRT service providers. In [10], Cordeau et al. provided an advanced overview of this problem. The main takeaways are that excellent heuristics are now available for the static case (all requests are known from the beginning), while the resolution of the dynamic case (requests are being revealed throughout the time period) is more realistic but also much more difficult. Bruni et al. [11] provided a good example of such a powerful heuristic for the static case while the algorithm was also able to process some dynamic elements. Dagonzo et al. [12] provided an analytical model for the DARP problem, which achieved closed-form solutions for some specific and important cases. This model was further improved in [13] with an additional feature that constrains the maximum detour a vehicle can do.

In this study, the DARP is managed by the SUMO simulation software. It uses an exhaustive search algorithm and allows dynamic rerouting with a timeout on the calculation time for each request. This gives accurate solutions if the timeout is not reached but has the disadvantage of being slow, especially with a large maximal search time.

2.2. Autonomous vehicles in public transport

Integrating AV fleets directly with public transport (PT) has attracted research in recent years. Trubia et al. [14], and Hatzenbühler et al. [15] studied fixed-line autonomous cars and autonomous bus services, respectively, and showed the potential positive effect. Fielbaum [16] studied a feeder system served by AVs where cost could be saved by a third.

In contrast, DRT (non-fixed lines) has also been considered one integration alternative. Lam et al. [17] studied a public transport network served exclusively by AV fleets with ride-sharing. It was shown that the operational cost could be decreased, implying that the implementation of AVs could indeed lower the cost. In addition to exclusive AV services, AVs have been considered as a feeder service in existing public transport systems. Shen et al. [18] developed an agent-based simulation to study the integration of AVs with the bus network in Singapore, where the risks of congestion due to increased road usage were also considered. Badia and Jenelius [19] developed a model to study the integration of autonomous vehicles as feeders to an existing public transport network. These studies show that under a set of conditions, such as a limited demand, AV fleets can potentially offer better performance than traditional public transport. Agent-based simulation has also been used in [20] to consider different groups of people when integrating AVs for mobility services.

Hamadneh et al. [21] took another approach and studied the value of time in AVs and traditional public transport, showing the importance of onboard activities on user perception [21]. Results showed that traditional public transport was favored by the user on this criterion. This can be linked to another study by Rashidi et al. [22] which challenged the statement that AVs could potentially decrease the value of time for users compared to traditional cars.

Despite the above-mentioned research on different aspects of AVs in public transport, there lacks an understanding of the impacts of different integration alternatives on an existing public transport network. Taking the results from the those research, this paper fills the gap to consider different integration scenarios based on an existing public transport network and its operational statistics. Being focusing on the integration and Without changes on the locations of bus stops, the study provides insights on viable integration alternatives of AVs in public transport in the near future.

3. Methodology

3.1. Transport forecast and planning model with AV fleets

The general framework of transport forecasting has been established in the 1950s with the *Four-Step Model* or *Classic Transport Model* [23], and has been widely used. As shown in Fig. 1(a), the first step is the trip generation, where the model takes input data and determines the number of trips departing and arriving in every zone. Following this, in the second step of trip distribution, the origin-destination (OD) pairs are linked with a number of trips. Modal split is then determined as the third step based on the choices of travelers among the travel modes, and as a final step, route assignment is done to assign the optimal route(s) on the network to each origin-destination pair. There are feedback loops from route assignment to modal split and trip distribution. This is due to the fact that crowding and congestion may affect the level of services on the network. For our research purpose, we extend the traditional model to accommodate new features of AV fleets for public transport. Several adjusted modeling process are added based on the traditional four-step model to extend the modeling framework (Fig. 1(a)), which are elaborated in following paragraphs.

Shown in Fig. 1(b), the study takes firstly a *network configuration* as an input, which is a subset of the current public transport network with corresponding parameters. The method proceeds directly to route assignment where the optimal path between every OD pair on the network is found. The exact meaning of "optimal" varies and is explained below. To take account of scenarios where trips are distributed between AVs and buses, a modal split step may be used at this stage. Since the modal split between public transport and AVs is the focus of the study, the mode choice has been put at the bottom level, assuming travelers choose mode first then destination. The optimal routes and travel times are then used as input parameters for the trip distribution step.

Trip generation and trip distribution follow after the modal split. Trip generation is based on boarding data provided by the public transport operator UL for the year 2019, which represents fixed travel demand though variations exist over time of the day. As will be explained below, trip distribution is performed with a doubly-constrained gravity model and uses a friction factor that takes travel time into account. This is why the route assignment is done beforehand. Since there is no iteration between network assignment and trip generation/distribution, the impacts of trip distribution on route assignment, e.g. traffic congestion, are not considered. This should have little impact on the analysis results considering that congestion is mostly caused by and affects private cars, while public transport benefits from dedicated bus lanes and priority traffic signals.

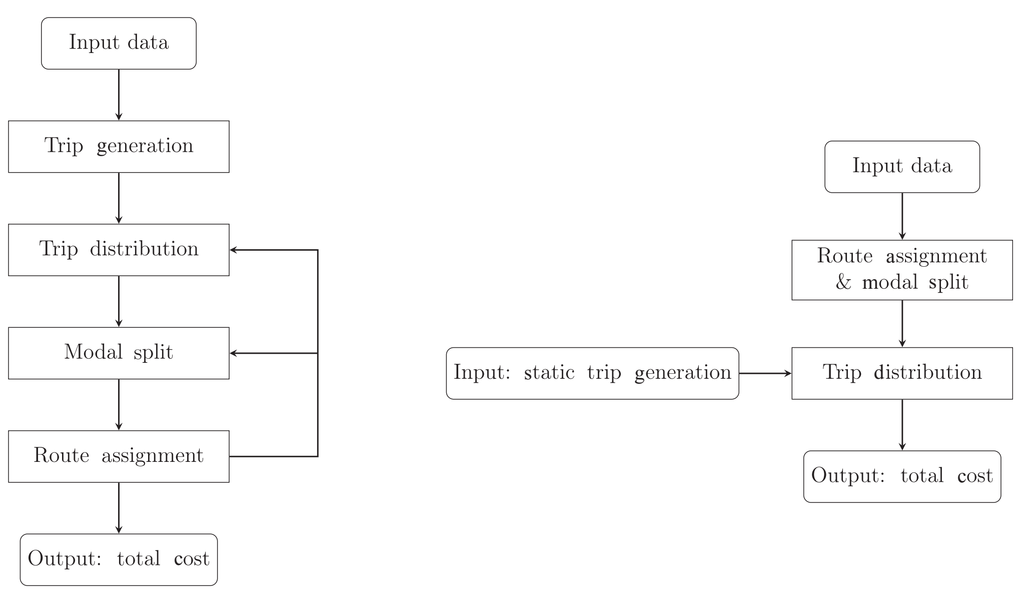
After trip distribution, the total cost of the network is ready to be calculated. The study divides the cost into user costs, representing costs for travelers, and operator costs, corresponding to the costs to run all the vehicles on the network. In the following part, a detailed description of each step is presented with statistics on the public transport network investigated. A case study based on a typical European city is then presented Afterwards.

3.2. Mode inputs and key parameter settings

The model takes as main input a *network configuration* representing a subset of the bus lines in the current bus network, together with related parameters. The lines that are not part of the subset are discarded and the stops on those lines will be served by shared AV fleets as Pick-up Drop-off (PUDO) locations.

Denoting the set of stops by $\mathcal{N}$ and the number of stops by N, all the origin-destination (OD) pairs $(i,j), i,j \in \mathcal{N}$ form a large $N \times N$ graph. Each arc in the graph represents the OD pair (i, j) and is associated with parameters representing the distance between each stop d_{ij}, the travel time t_{ij} and trip volume $Trip_{ij}$. Distances for each OD pair were obtained with HERE MAPS Application Programming Interface (API),[1] while the travel time and trip volume are the output of route assignment and trip distribution, respectively, which are discussed in the following section.

With the chosen public transport network, a set of parameters are chosen based on literature studies. The parameter values associated with buses and AVs are summarized in Table 1 and are explained as follows. The Swedish currency SEK is used for analysis.



(a) (b)

Fig. 1. Transport planning models. (a) Traditional four-step model. (b) Revised planning model.

[1] https://developer.here.com/.

Table 1
Model parameters.

Name		Symbol	Value	Source
Bus	Value of time (SEK·h^{-1})	$\sigma_{\mathrm{h}}^{\mathrm{Bus}}$	71.5	[19]
	Cost per hour (SEK·h^{-1})	$c_{\mathrm{h}}^{\mathrm{Bus}}$	493	[19]
	Cost per km (SEK·km^{-1})	$c_{\mathrm{km}}^{\mathrm{Bus}}$	7.31	[24]
AV	Value of time (SEK·h^{-1})	$\sigma_{\mathrm{h}}^{\mathrm{AV}}$	82.0	[22]
	Cost per hour (SEK·h^{-1})	$c_{\mathrm{h}}^{\mathrm{AV}}$	8.33	[6]
	Cost per km (SEK·km^{-1})	$c_{\mathrm{km}}^{\mathrm{AV}}$	4.80	[6]
	Maximum speed (km·h^{-1})	$v_{\mathrm{max}}^{\mathrm{AV}}$	25.0	[19]
	Feeder distance (km)	r^{AV}	1.61	/

The value of time for AV has not reached a consensus in the literature [22], and the one provided in [25] is used in this study. It is worth noting that the value of time for AV is set to be higher than for buses. This is due to the fact that values of time for private cars are generally accepted to be higher than those for public transport mostly due to the attention required to drive [26]. Though such values decrease following a shift to an autonomous vehicle as time can be disposed more freely, it remains above the level of public transport.

The costs per hour are the costs to run a single vehicle for the chosen mode in 1 h. As shown, it is significantly higher for buses than for AVs. This is mostly due to the high costs associated with drivers. The costs per km represent the operational costs to run a single vehicle for the chosen mode for a kilometer. It includes acquisition costs, fuel costs, maintenance costs and depreciation costs for the vehicle. We refer to [6,19,24] for the detailed cost structure for both buses and AVs. For the buses, the value chosen is for an average-sized bus with a capacity of 100 people. For AVs, the value is chosen for an electric car with 4 seats. In addition to the common parameters, specific parameters are chosen for AVs. Considering the reality of operating AVs in urban areas, a maximum speed of 25 km/h is used. When using AVs as a feeder for last-mile services, the feeder radius, that is the maximum distance AVs can travel as a feeder, has been fixed to 1.61 km (i.e., 1 mile).

3.3. Route assignment

With the given input and following the model process, the first step is the route assignment where the optimal routes between each OD pair are found. Here, optimal is defined as the “fastest on average”. For each OD pair, the optimal path can be served by buses, AVs, or a combination of both. The passengers may need to transfer from one bus to another or between buses and AVs.

The travel time $t_{ij}, i, j \in \mathcal{N}$ between each OD pair (i, j) consists of two components, the waiting time and the transit time. Regarding waiting times, for buses, they are set to be half the headway of the line on average. This is based on the assumption that the flow of passengers arriving at the bus stop is homogeneous over time, i.e., passengers are not checking the bus timetable. For AVs, the waiting time is obtained with the simulation described in Section 5. In addition, all waiting times are weighted by a factor $\alpha_{\mathrm{w}} = 1.5$ to reflect the distaste of passengers for waiting [19].

For transit times of buses, they are obtained from the public transport operator UL. The AV travel times are obtained by dividing the distance between the origin and the destination with the maximum speed of the car $v_{\mathrm{max}}^{\mathrm{AV}}$. This relies on the assumption that the average speed of the car is close enough to the maximum speed of the car. This is reasonable as the maximum speed is quite low and will not be affected by the overall road speed limit. In addition, pooling is allowed where AVs may conduct detours to allow more passengers in the same vehicle. The impacts of pooling are considered by multiplying the AV travel time by a factor α_{p}. This constant is obtained in the simulation.

To integrate AV fleets into public transport, two operation modes are considered, namely feeder and parallel services. In the case of feeder service, AVs only serve stops that are not served by buses and they can only travel up to the feeder distance r^{AV} which is 1.61 km. In the case there is no bus stop found within the feeder distance, AVs can travel to the bus stop with the shortest distance. For parallel service, AVs may travel between any OD pair regardless of distance and users are free to choose between bus and AV for their trip.

With the given travel times and depending on the operational mode, routing is then done following two successive steps. The first step relates to the OD pairs with both ends on the bus network, followed by the OD pairs with at least one end not on the bus network, as discussed as follows.

3.3.1. OD on the bus network with only bus services

This applies for OD pairs with both ends within the bus network and the trip can be serviced by bus services, the optimal route is the one that minimizes 1) the number of transfers and 2) the travel time. To simplify the problem, it is assumed that the bus lines are not synchronized, and a possible transfer time is equal to the waiting time for the line, therefore equal to half of the headway of the line. The routing process is illustrated schematically in a process chart in Fig. 2, and a simple example shown in Fig. 3 is used for discussion.

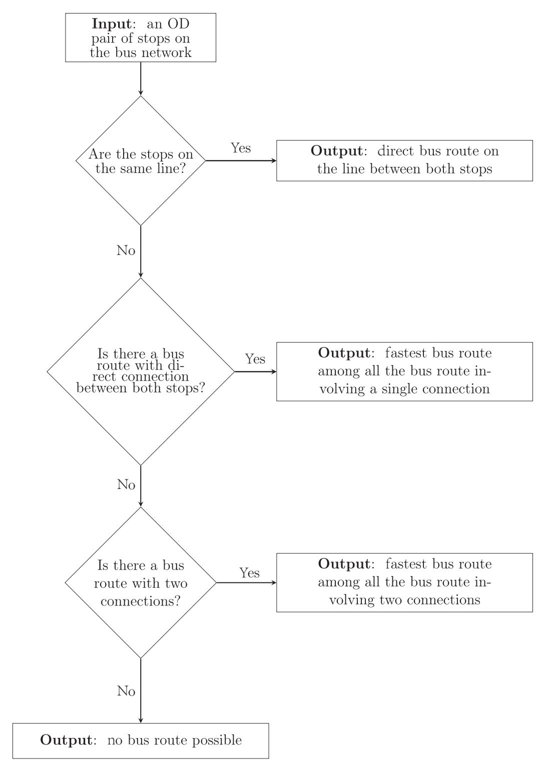


Fig. 2. Bus routing algorithm.

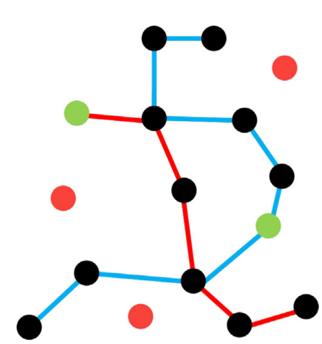


Fig. 3. Example of a bus route assignment problem. The network has two bus lines (blue and red) and red stops that are not connected to the network. The green dots are the origin and destination stops.

Following the search process, the first routes to be searched are the routes connecting two stops on the bus network configuration, i.e. the subset of the bus lines chosen as an input. The assignment algorithm prioritizes routes with the smallest number of transfers possible. It first checks if the two stops can be served by a single bus line. In such a case, the optimal route consists in simply traveling on the line in question, where the travel time is equal to the weighted waiting time plus the transit time, obtained with the timetable of the line. If no direct route exists, the algorithm checks if the origin-destination pair is connected by routes involving two bus lines and a single transfer. All such routes are identified and the route with the lowest total travel time is kept. In this situation, the travel time includes the waiting time, the transit time, as well as the transfer time (equal to the waiting time for the line concerned). If those two cases cannot be satisfied, a final case where three bus lines with two transfers will be checked for the route with the lowest travel time. For the situations outside the three cases, it is assumed that a route involving only buses is not optimal and is thus discarded. Fig. 4 illustrates possible solutions for the routing problem in Fig. 3.

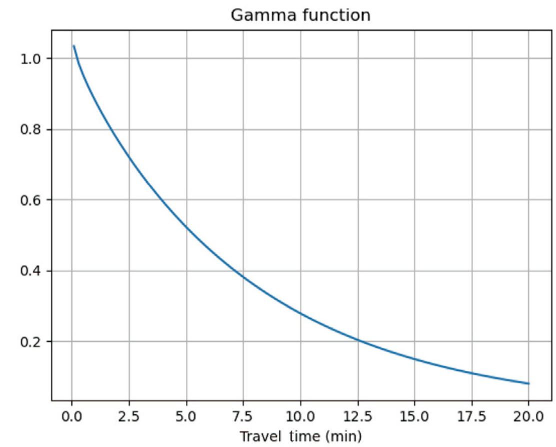


Fig. 5. Gamma function to weight travel time.

Fig. 4. Two possible route solutions (in green) for the bus routing.

3.3.2. *OD on the bus network with parallel AV services*

For OD pairs having both ends within the bus network and considering AVs as a parallel service, the passenger flow will be shared. Firstly, the ratios of the total flow for AVs f_{ij}^{AV} and Buses f_{ij}^{Bus} are calculated by Eqs. (1) and (2), respectively.

$$f_{ij}^{\mathrm{AV}} = \frac{\Gamma\left(t_{ij}^{\mathrm{AV}}\right)}{\Gamma\left(t_{ij}^{\mathrm{Bus}}\right) + \Gamma\left(t_{ij}^{\mathrm{AV}}\right)} \tag{1}$$

$$f_{ij}^{\mathrm{Bus}} = \frac{\Gamma\left(t_{ij}^{\mathrm{Bus}}\right)}{\Gamma\left(t_{ij}^{\mathrm{Bus}}\right) + \Gamma\left(t_{ij}^{\mathrm{AV}}\right)} \tag{2}$$

where

$$\Gamma(t) = t^{-\alpha} e^{-\beta t} \tag{3}$$

The Γ function models the variation of the flow relative to the travel time t and is illustrated with the plot in Fig. 5. To the authors' knowledge, such data does not exist in the Swedish context. Therefore, the general recommendations from [27] are used to model the impact of travel time on trip distribution. More specifically, the parameters chosen are $\alpha = 0.02$ and $\beta = 0.123$ (for a time unit in minutes), and are valid for home-based work (HBW) trips. The assumption is made that the majority of the trips are HBW trips during the morning peak hour.

With this modal split, the travel time for the route is calculated as the weighted sum shown in Eq. (4).

$$t_{ij} = f_{ij}^{\mathrm{AV}} t_{ij}^{\mathrm{AV}} + f_{ij}^{\mathrm{Bus}} t_{ij}^{\mathrm{Bus}} \tag{4}$$

3.3.3. *OD outside the bus network*

For OD pairs having one end or both ends not on the bus network such as shown in Fig. 6, AVs will be needed, and they could serve as a feeder for the first and last-mile transport, or run as parallel services to cover the whole trip (see Fig. 7).

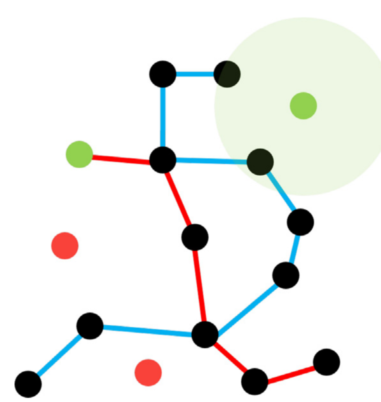


Fig. 6. Example of a AV-bus route assignment problem.The green dots are the origin and destination stops. The green circle represents the feeder radius distance in the case of a feeder operation mode.

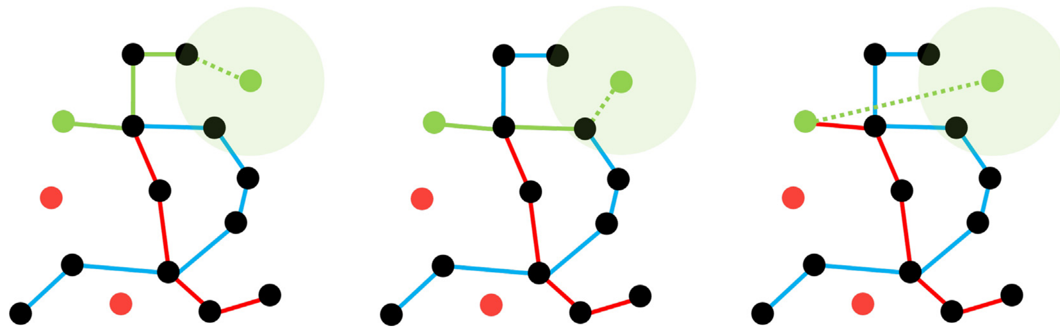


Fig. 7. Three possible route solutions (in green) for the AV-Bus routing. The dashed line represents an AV connection. The third option is only available in parallel service.

For AVs serving as feeder services, route assignment generates a mixed-mode route combining bus services covering the bus network segment and AV services covering the first and last-mile segment. The algorithm firstly identifies AV segments to reach the bus network from the end stops. These segments correspond to the fastest route between the end stops and any stop on the bus network within a radius of r^{AV}. If no bus stop is located within this radius, the selected stop on the bus network is the closest stop. Once the stops within the bus network are chosen, a bus-only route between the intermediate stops is then chosen.

In the case that AVs run also in parallel services, direct route between the OD pair is possible, and trips will be shared between the direct AV route and the mixed-mode route. The modal split follows the same principle illustrated in Eqs. (1) and (2), where in this case Eq. (1) is for the mixed-mode route instead of only for the bus route.

The route assignment will generate the optimal travel time matrix $\boldsymbol{t}_{ij}$, $i, j \in \mathcal{N}$ that contains the optimal travel times between every pair of stops, and a path matrix $\boldsymbol{P}_{ij}$, $i, j \in \mathcal{N}$ that contains path information on the route between every pair of stops (bus or AV, bus line, etc.)

3.4. Trip generation

Trip generation is based on realistic data provided by the public transport operator UL in the city of Uppsala, which contains static and aggregated boarding information. The dataset provides the average number of people boarding at every bus stop for every interval of 15 min, and the data have been aggregated for the peak hour per stop. HBW is considered where the majority of commuters travel from their home to work in the morning and travel back with the same route from work to home. Based on this, it is reasonable to assume that the boarding data B_j^{pm} in the afternoon at stop j is comparable to the alighting data A_j^{am} in the morning at the same bus stop j. In such a case, the boarding data B_j^{pm} in the afternoon at stop j is used to calculate the alighting data A_j^{am} in the morning. Since the afternoon peak is more widespread than the morning peak, the B_j^{pm} may not be exactly the same as A_j^{am}. For dealing with this, a factor ρ is introduced for calibrating such effect, as calculated as follows.

$$\rho = \frac{B^{am}}{B^{pm}} \tag{5}$$

where B^{am} is the total number of people boarding in the morning peak hour between 7 AM and 8 AM (for every stop) and B^{pm} is the total number of people boarding in the afternoon peak hours between 4 PM and 6 PM.

With ρ, the number of people alighting at stop j in the morning peak hour between 7 AM and 8 AM is calculated as follows

$$A_j^{am} = \rho B_j^{pm} \tag{6}$$

where B_j^{pm} is the number of people boarding in the afternoon peak hours (4 PM $\sim$ 6 PM) at stop j.

3.5. Trip distribution

Trip distribution applies the widely used double-constrained gravity model [28] to calculate the traffic volumes for each link $i, j \in \mathcal{N}$. The model assumes that the flow of people commuting from stop i to stop j is directly proportional to the total number of people departing in i and the total number of people arriving in j. Based on the model, and can be calculated with Eq. (7)

$$Trip_{ij} = \zeta_i B_i^{am} \eta_j A_j^{am} \lambda_{ij} \tag{7}$$

where ζ_i, η_j and λ_{ij} are balancing factors, and are calculated iteratively with the following formulas.

$$\zeta_i^m = \frac{1}{\sum_j \eta_j^m A_j^{am} \lambda_{ij}} \quad \text{and} \quad \eta_j^m = \frac{1}{\sum_i \zeta_i^m B_i^{am} \lambda_{ij}} \tag{8}$$

The superscript m denotes the iteration step. The iteration stops until the values converge after m^* steps as shown below,

$$|\zeta_i^{m^*} - \zeta_i^{m^*-1}| < \varepsilon \quad \text{and} \quad |\eta_i^{m^*} - \eta_i^{m^*-1}| < \varepsilon \tag{9}$$

where ε is an arbitrarily small value. The final values $\zeta_i = \zeta_i^{m^*}$ and $\eta_i = \eta_i^{m^*}$ are then derived and used throughout the model.

The factor λ_{ij} is a function of the travel time and reflects the dependency of traffic flow on the travel time. It applies the same function used for the modal split in the route assignment step, as follows.

$$\lambda_{ij} = \Gamma(t_{ij}) = t_{ij}^{-\beta} e^{-\alpha t_{ij}} \tag{10}$$

3.6. Cost estimation

In this section, details on the costs and calculations are explained. The complete cost structure is summarized in Fig. 8. As shown, the total cost C_{tot} is divided into two parts, the user cost C_u and the operator cost C_o,

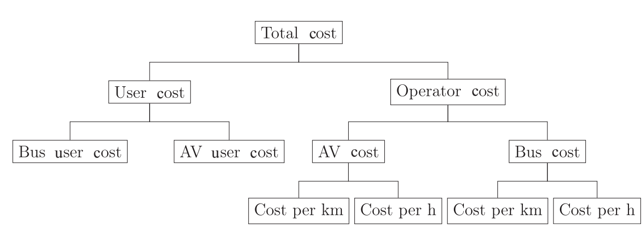


Fig. 8. Cost structure.

$$C_{tot} = C_u + C_o \tag{11}$$

3.6.1. User cost

The user cost C_u is equal to the total time spent on the network by all passengers (which comprises the weighted waiting time and the travel time) multiplied by the corresponding value of time (σ_h^{AV} for AV trips and σ_h^{Bus} for bus trips. For a given OD pair (i, j), this time equals the flow of passengers $Trip_{ij}'$ multiplied by the travel times for each segment of the trip.

3.6.2. Operator cost

The operator cost C_o is the cost of running the network consisting of both bus costs C_o^{Bus} and AV costs C_o^{AV}. This includes distance and time-related costs for both buses and AVs. It should be noted that acquisition costs are considered in the cost per km as discussed in Section 3.2. The distance-related cost is obtained by multiplying the total AV distance by the cost per km, while the time-related cost is obtained by multiplying the cost per hour by the fleet size. Considering 1 h operation, they are calculated as follows:

$$C_o^{AV} = c_h^{AV} Num^{AV} + c_{km}^{AV} d_{tot}^{AV} \quad \text{and} \quad C_o^{Bus} = c_h^{Bus} Num^{Bus} + c_{km}^{Bus} d_{tot}^{Bus} \tag{12}$$

The number of buses on the network Num^{Bus} is obtained by considering each line separately. For a bus line $k \in \mathcal{L}$, Num_k^{Bus} is obtained by first dividing the total duration needed to drive on the line t_k^{tot} by the headway on the line h_k and then rounding up and multiplying by two to consider both directions, as shown by the following equation.

$$Num_k^{Bus} = 2\left\lceil \frac{t_k^{tot}}{h_k} \right\rceil \tag{13}$$

where $\lceil \cdot \rceil$ represents the function that links a floating value to the nearest larger integer.

The total number of buses is then obtained by summing the number of buses for each line $k \in \mathcal{L}$:

$$Num^{Bus} = \sum_{k \in \mathcal{L}} Num_k^{Bus} \tag{14}$$

The distance run by each bus (in 1 h) on a line is calculated by dividing the total length of the line d_k^{tot} by the total line duration t_k^{tot}. To get the total distance for all bus lines, this number is multiplied by the number of buses on the line Num_k^{Bus}:

$$d_k^{Bus} = Num_k^{Bus} \frac{d_k^{tot}}{t_k^{tot}} \tag{15}$$

This number is then summed over all lines to get the total distance run by buses d_{tot}^{Bus}:

$$d_{tot}^{Bus} = \sum_{k \in \mathcal{L}} d_k^{Bus} \tag{16}$$

The process to calculate the total cost for AVs is similar but the total number of AVs Num^{AV}, the distance run by AVs d_{tot}^{AV} and the time spent by customers on AVs t_{tot}^{AV} were obtained with the simulation, as discussed earlier.

3.6.3. CO_2 emission

CO_2 emissions for the public transport network are calculated based on the fact that buses are not yet fully electrified. The AVs are electrified, and other CO_2 emission sources are considered to be negligible. The total CO_2 emissions of buses e^{Bus} are modeled to be proportional to the total bus mileage d_{tot}^{Bus}:

$$e^{Bus} = e_{km}^{Bus} d_{tot}^{Bus} \tag{17}$$

where e_{km}^{Bus} is the CO_2 emission of a bus per km. This value is not known and varies from one bus model to another. It is not estimated here, only relative changes are calculated.

4. Case study scenario and data

The study is conducted for the city of Uppsala. The city of Uppsala has a size of approximately 50 km^2 and a population of 168,000 inhabitants in 2017 [29]. According to the data provided by the public transport operator UL, during the morning peak hour, about 10,000 rides are registered on the network. Currently, the Uppsala public transport network consists of traditional bus lines with predefined timetables.

4.1. The public transport network and traffic data

The chosen public transport network in Uppsala consists of 14 bus lines (numbered 1 to 12, plus lines 30 and 31) and 264 bus stops, illustrated in Fig. 9. The set of bus lines is denoted by $\mathcal{L}$. These 264 bus stops represent the origin and destinations for a trip, which is designated as an OD pair.

The morning peak hour traffic, that is traffic between 7 AM and 8 AM, in a typical weekday is considered. This corresponds to the time of the day with the highest load on the network, therefore the most critical. Supported by the Uppsala public transport operator UL, boarding data is provided for the period between 01/09/2019 and 30/11/2019, which was before the COVID-19 pandemic. The data shows a stable total demand, implying that shorter travel times will not increase the total demand. However, travel times do affect the distribution of passenger flows in the area.

In addition to the dataset, the UL API provides information on the Uppsala bus lines including stops and real-time traffic information. The API has been used in the study to collect information on the names and number of the stops for each line, as well as their precise locations (latitude, longitude). The location of the stations was used to calculate inter-station distances through another API provided by HERE Maps.

4.2. AV assumptions

The study assumes that AVs have the same size as conventional cars with a capacity of four people. They are also assumed to be electric, though the charge of the vehicles is not modeled. It is however expected that vehicles would not need to charge during the peak hour which has a very limited duration. AVs serve passengers at a set of PUDO locations, which correspond to the existing bus stop locations (no door-to-door service). Fixed PUDO locations reduce the risk of congestion as the vehicles will stop in areas already designed for short stops. This also simplifies the simulation step as well as the trip generation and distribution in the model, as AV customers start and end their trip in a fixed and limited number of locations. The AVs may use pooling which may result in a longer trip than a direct trip from origin to destination. Such impacts are considered in the model. No changes to the design of the bus network are made, besides the replacement of bus lines by AV service. The routes and timetables of the lines are not altered.

5. Model implementation and simulation

5.1. Simulation setup

For traffic simulation, Eclipse SUMO [30] was used. SUMO implements a script "drtOnline.py" for demand-responsive transport simulation. The module takes as inputs the network graphs containing nodes and edges, a list of vehicles and their departure location, a list of travelers and trips containing the origins and destinations and the request time. The script was used for simulating AV services.

As the entire study is based on the morning peak hour, simulation was conducted for 1 h. A* algorithm was selected as the routing algorithm, and DARP is managed by SUMO with an exhaustive search with a time limit of 5 s. That is, the DARP solver tries all possible solutions before timeout. The maximum waiting time for customers was set to be 10 min as a trade-off between service quality and responsiveness of the system. Vehicles were randomly distributed during initialization.

Fig. 9. Current uppsala bus network. Source: Ul, 2021.

5.1.1. *OD matrix setting*

The demand considered is an OD matrix obtained as a result of the trip distribution. The matrix contains decimal (or floating) numbers that need to be transformed into integers to facilitate the simulation. When the flow for a trip is greater or equal to 1 (more than 1 person commuting on average), the flow for this trip is rounded to the closest integer, shown as follows:

$$\forall\, i,j \in \mathcal{N} \mid Trip_{ij} \geq 1, \quad Trip'_{ij} = round(Trip_{ij}) \tag{18}$$

where $round(\cdot)$ is the function that links a floating value to the closest integer.

For all trips that have a flow of less than 1 (uncommon trips), another transformation is carried out. First, all trips with a flow that is less than 1 are collected into a set Ω as below:

$$\Omega = \left\{(i,j), i,j \in \mathcal{N} \,\middle|\, Trip_{ij} < 1\right\} \tag{19}$$

and the total flow over all those trips is calculated as below:

$$Trip_{<1} = \sum_{(i,j)\in\Omega} Trip_{ij} \tag{20}$$

Then the proportion of each individual flow over the total flow can be represented by

$$\forall\,(i,j) \in \Omega,\ p_{ij} = \frac{Trip_{ij}}{Trip_{<1}}, \quad \sum_{(i,j)\in\Omega} p_{ij} = 1 \tag{21}$$

Following the above definition, the floating number $Trip_{<1}$ is rounded into an integer number $round(Trip_{<1})$ representing the total number of people commuting on such uncommon trips. Those people are then allocated to each of the arcs according to the probabilities p_{ij}. When a person is attributed to the trip (i, j), the flow for this trip increases by one. This process thus fills the matrix $(Trip'_{ij})$ with integers. In practice, the total demand is approximately preserved, that is to say, $\sum_{ij} Trip'_{ij} \approx \sum_{ij} Trip_{ij}$.

5.2. Optimal network configuration

To integrate AVs into the current bus network with 14 bus lines by replacing some of them, the number of potential network configurations is huge. An optimization algorithm based on integer programming is used to find the best configurations without the need for an exhaustive calculation. *Tabu search*, a widely used heuristic for integer optimization [31], was used for solving the problem and is described as follows.

Denoting the status by a boolean variable $s_k, k \in \mathcal{L}$ to represent the presence or not of each of the 14 bus lines, the optimization algorithm finds the optimal configuration of $s_k, k \in \mathcal{L}$ that minimizes the total network cost while satisfying the traffic demand under a given AV operating mode.

A tabu search algorithm maintains a tabu list that contains solutions that have been visited and are not allowed to be visited again. A size of 5 is used for the tabu list which means there are maximal 5 configurations kept in the tabu list, and once a solution is removed from the tabu list, it is allowed to be visited again. A tabu search algorithm can be stopped by either time or number of iterations. A maximal number of 30 iterations was used.

Tabu search starts with the network configuration where all bus lines are present, i.e., $s_k = 1, k \in \mathcal{L}$ and the cost is recorded as the optimal cost. It then iterates by changing the status of each of the variables s_k between 0 and 1. For each iteration, the algorithm evaluates in each step by changing the status of the bus line s_k between 1 and 0. As can be interpreted, a total of 14 steps are needed. Then the configuration with the lowest cost is considered as a local optimal and the configuration is put into the tabu list. If this local optimal cost is lower than the global optimal cost, the global optimal cost will be updated and the global optimal configuration will be recorded, and it will be the start configuration for the next iteration, and the algorithm continues.

Tabu search is very efficient in practice and in this study, the optimal solution can be found with less than 20 iterations. As said, the optimal network configuration represents a subset of the total bus lines.

6. Cost analysis

In total, six scenarios have been designed to study the different integration alternatives of AVs in existing public transport and they are shown in Table 2. The optimal network configurations for Scenarios 3, 4b and 4c are calculated based on the methods discussed in Section 5.2.

Table 2
Network configuration for each scenario.

Scenario	Lines on network	Description
1 (base)	[1–12,30, 31]	Current situation, all buses lines are on the network.
2	Ø	All the bus lines have been replaced by an AV service.
3	[1–3,5–8]	AVs operate in feeder mode and serve the optimal network configuration.
4a	[1–12,30, 31]	AVs operate in parallel mode and all the bus lines are on the network.
4b	[3]	AVs operate in parallel mode with the optimal network configuration.
4c	[1–8,10,12]	AVs operate in parallel mode with the optimal network configuration, and a maximal VKT increase of 10% is permitted.

6.1. Cost results

With the above designed scenario, total cost and cost segments were calculated. The results are summarized in Table 3 and illustrated in Fig. 10.

Table 3
Cost for all scenarios.

Sc.	Total cost (kSEK)	User cost (kSEK)	Bus user cost (kSEK)	AV user cost (kSEK)	op. cost (kSEK)	Bus op. cost (kSEK)	AV op. cost (kSEK)
1	298	216	216	0	82	82	0
2	286	251	0	251	35	0	35
3	283	225	203	22	58	55	3
4a	323	225	111	115	98	81	17
4b	281	244	40	204	37	10	204
4c	309	227	107	120	81	64	17

A first observation that can be made is that there is no scenario with significantly lower or higher costs than the others, though the distribution of the cost varies a lot among the scenarios. This implies that integrating AVs in public transport, whichever implementation mode is chosen, does not significantly improve the overall costs. However, this conclusion is only valid with the setting of hypothetical variables that characterize the AV service, such as AV speed, value of time, etc. A sensitivity analysis is thus conducted for further conclusions.

Shown in Table 3, operator costs vary substantially depending on the scenarios. The scenario with only AVs is the cheapest, with an operator cost reduced by 55% compared to the base scenario. AVs are generally cheaper to operate due to their negligible cost per hour (a consequence of the absence of drivers) and very low cost per km (a consequence of electrification). If the prime focus is to reduce operator costs, AVs seem to be an obvious solution.

User costs also differ among the scenarios, but to a lesser extent than the operator costs. The base scenario with current public transport has the lowest user costs, and AVs tend to be more costly for the user, due to pooling and a slightly higher value of time. The scenario with only AVs shows a 16% increase in user costs over the base scenario.

Regarding the overall cost, the scenario with the lowest overall cost is Scenario 4b (Bus and AV in parallel, with only a single bus line), but Scenario 3 (AVs as feeders only for last-mile service) is very competitive as well, with a cost only slightly higher. This shows that these two modes of AV operation, though very different, both lead to a decreased overall cost compared to the base scenario. It also implies that scenarios that implement buses and AVs in a mixed fashion perform better than scenarios with AVs only. It turns out these two scenarios also outperform other scenarios in many aspects with e.g., the highest and second-highest emission reduction. A closer look into the results of those two scenarios is given later in this section.

6.2. Traffic statistics

In addition to cost analysis, traffic statistics related to buses and AVs are calculated. Bus loads and key indicators related to AVs are summarized in Table 4, while mode share and emission statistics are summarized in Table 5.

Busloads increase in Scenarios 3 and 4b. For Scenario 3, this can be explained by reduced bus lines and that AVs only serve last-mile transport. Due to this, bus services still dominate the mode share with 87.2%, followed by the mixed-mode with 12.4% share, and AV services have only a small share of the mode (less than 1%). Therefore, this scenario

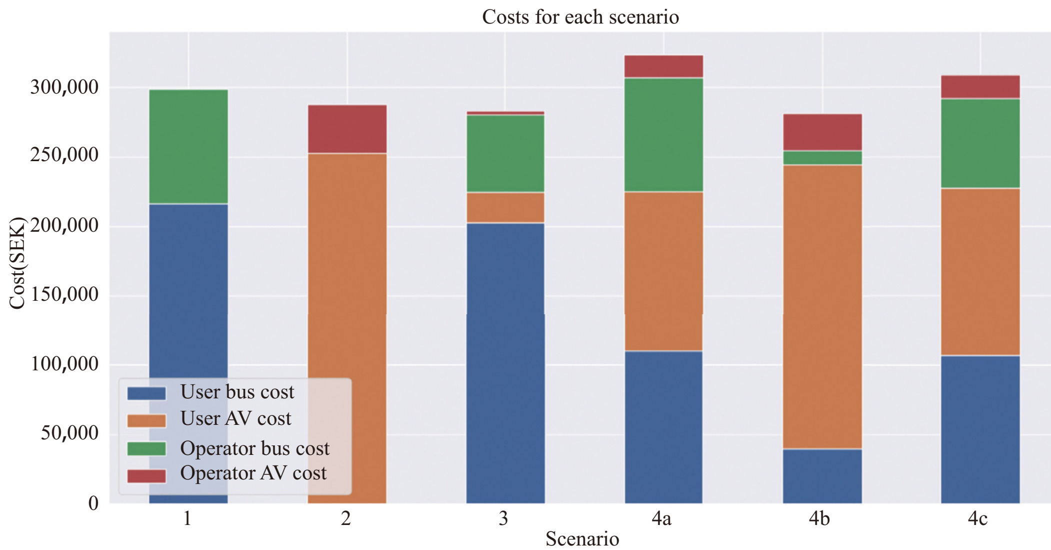


Fig. 10. Cost distribution for all scenarios.

Table 4
Results related to Bus and AV, respectively.

Scenario	BUS		AV		
	average bus load (%)	Average max. bus load (%)	fleet size	VKT (km)	Traffic increase (%)
1	15	46	0	0	0
2	/	/	328	6,722	+20
3	20	58	31	517	+2
4a	8	27	161	3,236	+9
4b	19	58	251	5,111	+15
4c	9	30	162	3,259	+9

Table 5
Mode share and CO_2 emission changes.

Scenario	Mode share			CO_2 emission variation
	bus (%)	AV (%)	Mixed (%)	compared to base scenario (%)
1	100	0	100	0
2	0	100	0	−100
3	87.2	0.43	12.4	−35
4a	53.4	46.6	0	0
4b	15.8	70.5	13.7	−89
4c	50.2	46.8	3.00	−22

has a very low VKT increase at around 2%. The same reason for bus load increase applies for Scenario 4b since there is only one bus line left. The bus services share rather a small part of the trips with 15.8% with an increased busload. Different from Scenario 3, Scenario 4b has a high mode share of AV-only mode at 70.5% and mixed-mode at 13.7%, which leads to a high increase of VKT at 15%. This is expected as AVs run in parallel mode and only one bus line is left with the optimal configuration. Scenario 4c is thus designed for the purpose to balance the costs and VKT increase by limiting the maximum VKT within 10%.

Scenarios 4a and 4c show very similar results with decreased busloads, rather even distribution of trips between buses and AVs, and VKT increases of 9%. For Scenario 4a, considering the fact that AVs operate in parallel with all bus lines, it is expected the trips are distributed evenly between bus-only and AV-only modes. For Scenario 4c, this is mostly due to the limited VKT increase, which forces that trips are allocated to bus services with 10 lines left. For Scenario 2, due to the AV-only service, the VKT shows a significant increase by 20%, which is a risk factor on congestion.

Regarding CO_2 emissions, Scenario 2 has a 100% emission reduction because of the replacement of all bus lines with AVs. This makes Scenario 2 the best from the emission reduction perspective when electric buses are not considered here. However, as already mentioned, this scenario is less competitive with an increase on the user cost by 16%, and VKT by 20%. Other than that, Scenario 4b has the highest emission reduction at 89% due to the fact that only one bus line is kept. This is followed by Scenario 3 with a 35% reduction where AVs run in feeder mode with 7 bus lines, and Scenario 4c with a 22% reduction where AVs run in parallel mode with 10 bus lines. As emission comes from the buses, the results are expected as more bus lines result in more emission.

6.3. Scenario comparison

As mentioned, Scenarios 3 and 4b are interesting and they represent two different AV integration methods with promising results. The following part takes those two scenarios as examples for a closer look at the results. Figs. 11 and 12 illustrate the cost distribution and mode share for Scenarios 3 and 4b, respectively.

In Scenario 3, AVs are introduced in the optimal network configuration with seven bus lines left and operate in feeder mode, that is to say, AVs only serve the last-mile travel. The total cost found here is slightly lower than that in Scenario 2 with AV-only services, and 5% lower than that in the base scenario with bus-only services. This shows that a mixed operation of buses and AVs works better than the operation of a single mode. Because of the feeder mode of AVs, they only make a small part of the total cost accounting for 10% of the user cost and 5% of the operator cost, respectively.

With AV integrated, mode share appears. As shown in Fig. 11, around 87% and 12% of the trips are served by buses and the mixed-mode, respectively, and AV-only trips account for less than 1%. The buses are more loaded than the base scenario, with a 25% increase on average maximal load due to the reduction of bus lines. Since AVs only serve last-mile, their VKT is quite low, representing only 2% of the Private car value. The effect on congestion is therefore very limited.

In Scenario 4b, AVs and buses operate in parallel with the optimal network configuration having only one bus line left, that is line number 3. This scenario has the lowest cost of all scenarios, which is 6% lower than that for the base scenario. Regarding the mode share, AVs take a significant part with 70% of trips by AV-only services, and 16% by mixed mode. The rest 14% of trips are bus-only trips. It is therefore a high VKT is shown that accounts for about 15% of the private car VKT, which may

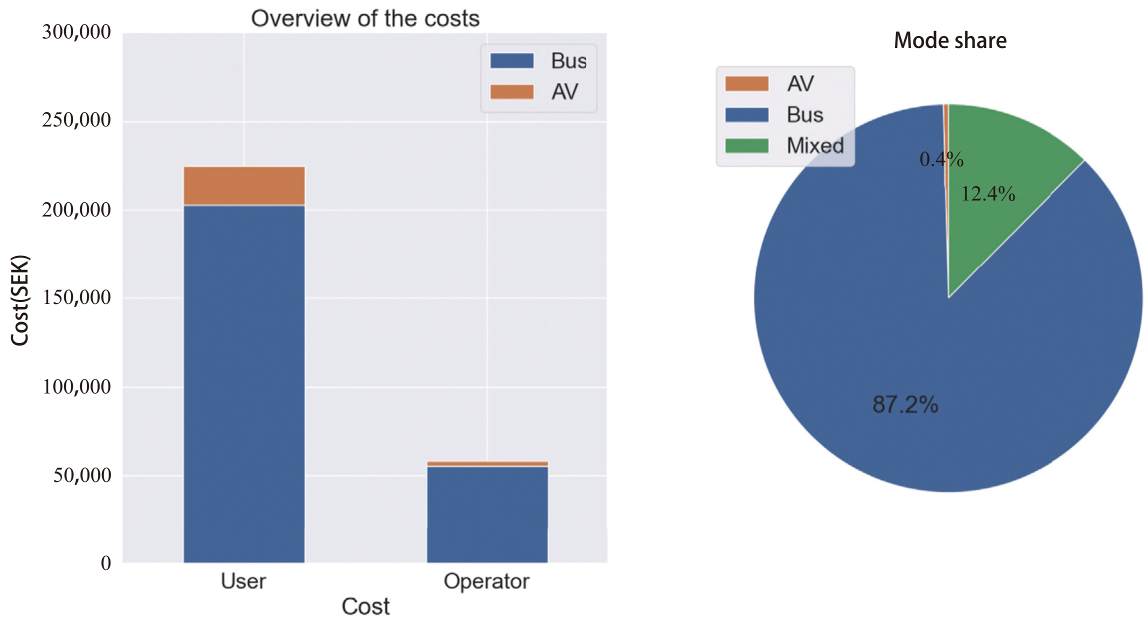


Fig. 11. Scenario 3.

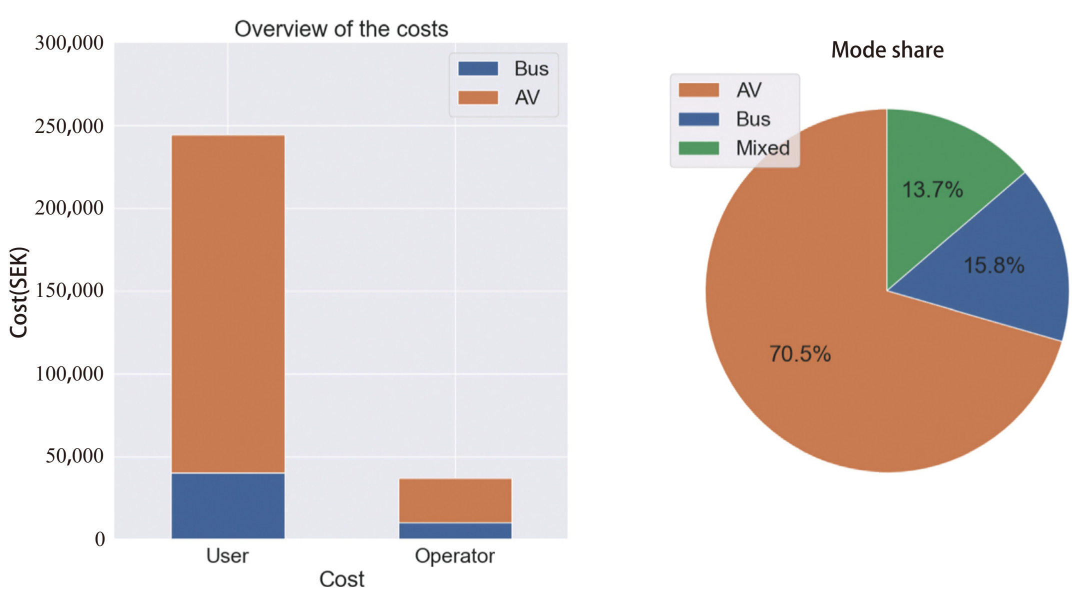


Fig. 12. Scenario 4b.

cause congestion. This problem could be addressed by limiting the maximal VKT increase, such as in Scenario 4c, but the trade-off is a higher overall cost. The load on the bus service increases relative to the base scenario level, by 27%, but remains largely under capacity and even under seated capacity, except at a few specific stops.

6.4. Sensitivity analysis

As mentioned, the results in this paper are valid for the parameter settings. To understand more general cases, a sensitivity analysis is performed on the main variables related to the AV service including the AV cost per km $c_{\mathrm{km}}^{\mathrm{AV}}$, the AV value of time $\sigma_{\mathrm{h}}^{\mathrm{AV}}$, the AV waiting time $t_{\mathrm{w}}^{\mathrm{AV}}$, and the AV maximum speed $v_{\mathrm{max}}^{\mathrm{AV}}$.

The analysis takes as reference Scenario 4c as it is a scenario where AVs and buses have a roughly equal mode share. Such a scenario also allows seeing the effect of a modal shift between buses and AVs, which is not possible in a scenario where AVs operate as feeders (Scenario 3). For sensitivity analysis, the variables are modified from −50% to +50% of their original values.

For $c_{\mathrm{km}}^{\mathrm{AV}}$ and $\sigma_{\mathrm{h}}^{\mathrm{AV}}$, new simulations are conducted for each of the new values. The AV value of time is shown to have a significant influence on the total cost. As shown in Fig. 13, a 50% decrease in this value leads to a 17.5% decrease in the total cost. However, an increase in this value has less impact due to a modal shift to buses. If the value is set to be equal to the bus value of time (i.e., equal to 71.5 SEK/hour), a total cost of 302 kSEK is achieved corresponding to a 2.3% decrease, which makes

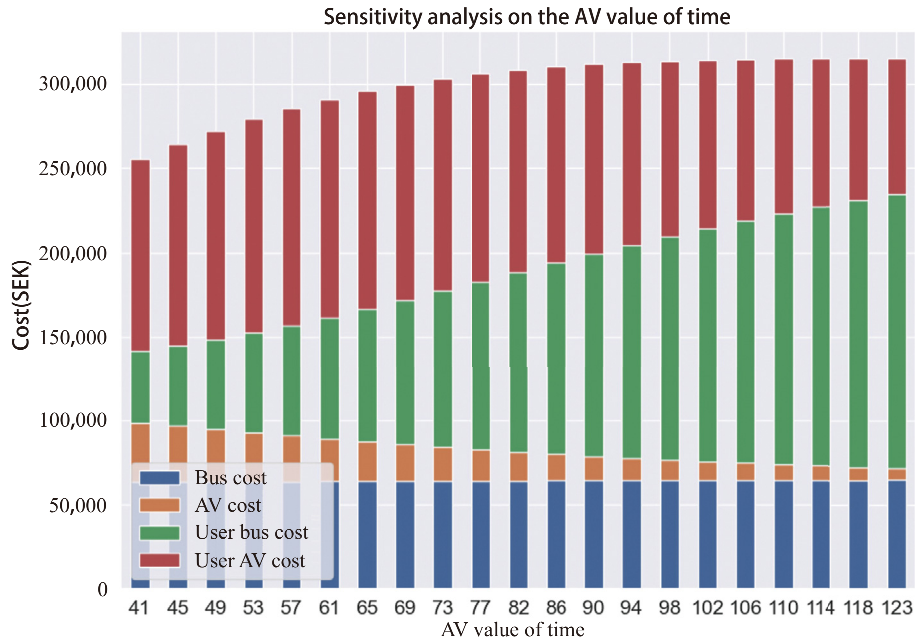


Fig. 13. Sensitivity analysis on the AV value of time.

Scenario 4c more competitive. Since it is still early to have AVs in public transport and the value of time remains unknown, the results give interesting insights.

In comparison, the AV cost per km has relatively little influence on the total cost, as shown in Fig. 14. It only affects the AV operator cost, which is a very small part of the total cost. A 50% increase or decrease of the AV cost per km leads to a mere 2.5% increase and decrease in the total cost, respectively.

For t_w^{AV} and v_{max}^{AV}, the new values are used only for cost calculation without new simulations. It is therefore the validity of these sensitivity analyses is limited for those two variables and some effects might not be considered. For example, an increase in waiting time might allow AVs to perform more direct routes, reducing travel time. It might also reduce the fleet size required. Similarly, an increase in AV speed might reduce the fleet size required and the pooling detour factor. Despite this, the results give insights into their impacts.

AV waiting time is shown to have non-negligible impacts on the total cost, as shown in Fig. 15. A 50% decrease in the AV waiting time leads to

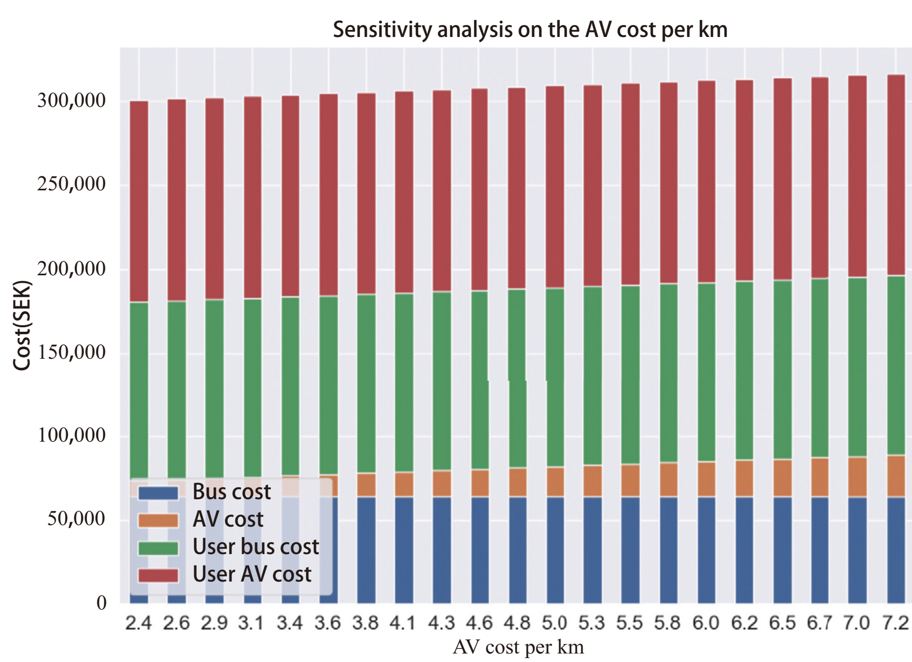


Fig. 14. Sensitivity analysis on the AV cost per km.

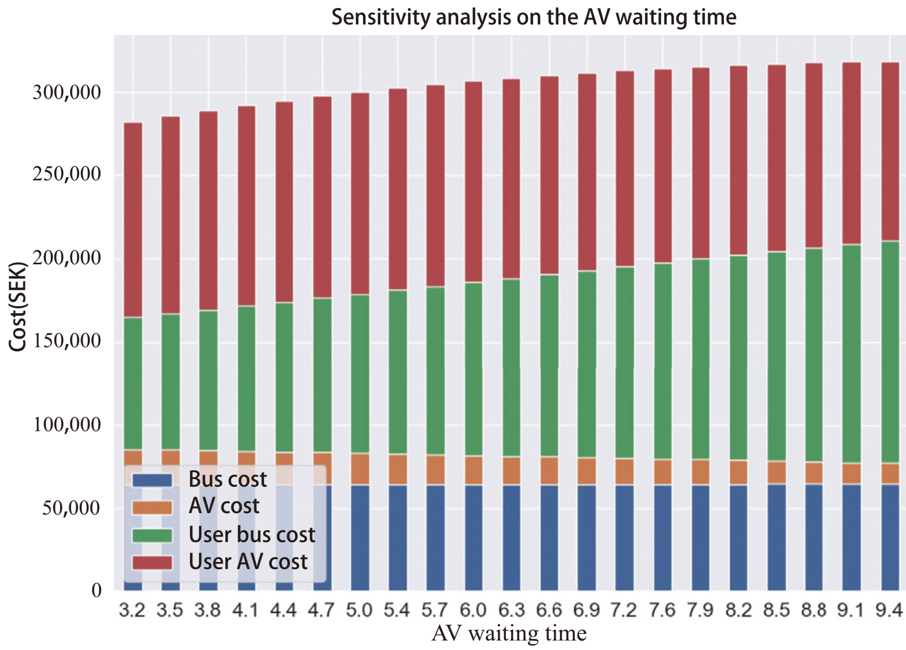


Fig. 15. Sensitivity analysis on the AV waiting time.

a substantial 8.7% decrease in the total cost. This can be explained by the fact that the weighted waiting time has almost the same importance as the transit time in terms of average travel times on the network. On the other hand, an increase in the waiting time has limited effects due to a modal shift to buses.

As for the AV speed, Fig. 16 shows a limited impact on the total cost. This can be explained by the modal shift mechanism. An increased AV speed induces a modal shift to AV, leading to an increased AV total user cost and operator cost, together with a decreased bus user cost. These changes mostly cancel each other out, leading to a negligible change in the total cost.

A summary of sensitivity analysis for all variables is shown in Fig. 17 and exact statistics for variable changes with ±50% are summarized in Table 6. It is quite clear that the AV value of time has a significant impact on the total cost, followed by the AV waiting time, and AV cost per km.

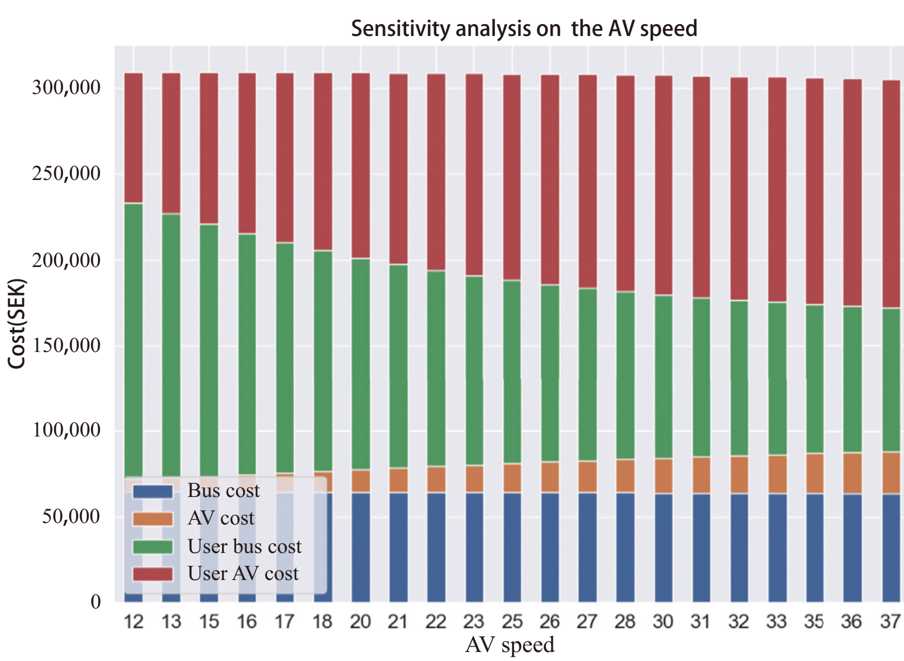


Fig. 16. Sensitivity analysis on the AV speed.

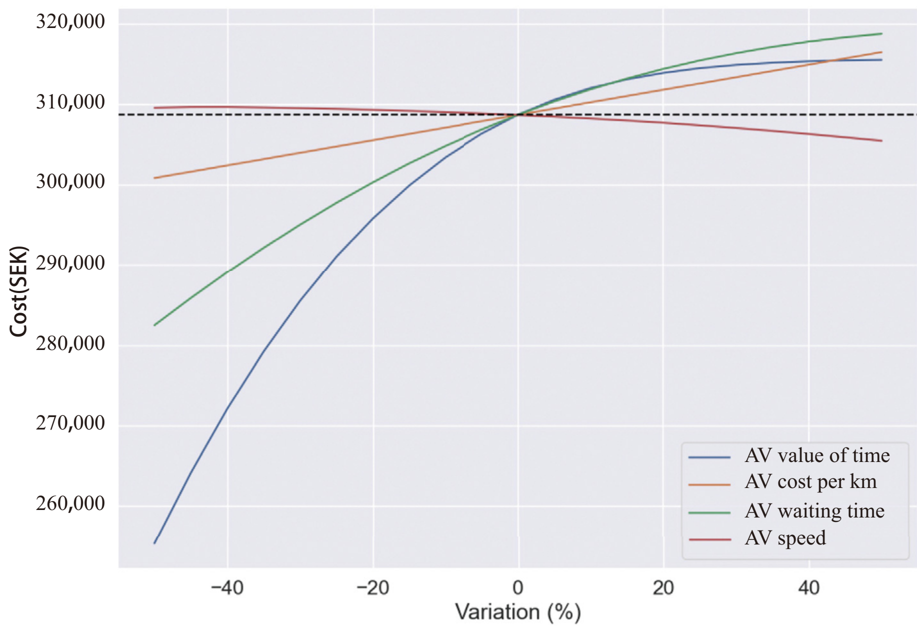


Fig. 17. Comparison of sensitivity analyses.

Table 6
Summary of sensitivity analysis.

Variable	Variable change (−50%)		Variable change (+50%)	
	total cost (kSEK)	Total cost variations (%)	total cost (kSEK)	Total cost variations (%)
V_t^{AV}	255	−17.5	316	+2.5
c_{km}^{AV}	301	−2.5	316	+2.5
t_w^{AV}	282	−8.7	319	+3.2
v^{AV}	309	+0.3	305	−1.0

7. Conclusions and future work

This paper investigates the integration of autonomous vehicles in public transport with a focus on cost analysis. A transport planning model has been formulated and implemented with adaptations of traditional methods. Simulation has been used to estimate variables that are linked to the AV operation and are not known or hard to approximate. A methodology to estimate operator and user costs for the entire network has been developed. To avoid exploring all potential scenarios for evaluation, an optimization procedure has been proposed to find the optimal network configuration for a given AV implementation. Following this, scenarios corresponding to different AV integration strategies have been designed, simulated and analyzed from the cost perspective. In addition, mode share, AV mileage and busload for each scenario have also been reviewed. To make the results more general, a sensitivity analysis has been performed on the main variables linked to AV operation to understand their influence on the total cost.

A general conclusion is that from a total cost perspective, AVs don't necessarily make public transport more cost-effective. Integrating AVs with existing busses into a mixed mode has shown better results in comparison to bus-only and AV-only operations. For the mixed mode, AVs could be integrated both as feeders to serve only the last-mile transport and as parallel services to serve the whole route. For parallel services, there is a trade-off between total costs and AV traffic mileage as serving the whole route will increase the AV traffic in the network, thus congestion. On the other hand, assuming AVs are electric vehicles and considering the fact that buses are not fully electrified, they may help to reduce the overall emission. When scaling the analysis, the AV value of time has a large influence on the total cost and is therefore the most critical variable to keep in mind, especially since there is no consensus on this value. The AV waiting time also has a non-negligible effect on the total cost.

The results in this paper are derived based on assumptions that have certain limitations, which are leading to several directions for future work. Firstly, urban mobility modes such as private cars and taxis were not considered in the model. A shift between these modes and public transport is possible and may change the total demand. In particular, AV operating in parallel mode compete directly against private taxi-like services, a modal shift can happen and increase the demand for AV public transport. This leads to a future study on the entire transport demand of the city, including other modes such as private cars, for considering a modal shift. The modal shift between current carpooling services such as Uber or Bolt could also be studied. Secondly, the study assumed the usage of electric AVs and traditional buses with no discussion on charging, electric buses, and so on. Integrating charging stations into the analysis will introduce one extra layer for both network optimization and cost analysis, for both AVs and buses. In addition, using electric buses will affect the emission calculation significantly. Therefore, integrating connected automated and electric vehicles into public transport form a big research area and is one ongoing research direction. Thirdly, regarding electrification, the generation of electricity has non-negligible impacts on the overall emission, which is not considered in this paper. This requires extensive analysis from the life-cycle perspective at the system level and forms a very interesting research topic. Last but not the least, the effects of congestion on travel times were not modeled. Though the interaction between those two factors is complex, a possible effect is that in scenarios that involve a relatively high AV mileage for public transport, congestion effects might occur, which would increase AV travel times and render buses more competitive, thus affecting the modal split and costs. Furthermore, provided that a mode shift from private car to public transport with AVs happens and due to the sharing nature of public transport, congestion effects could be mitigated through proper optimization. Such an effect is also discussed in [4] and is worthy of further investigation.

Declaration of competing interest

All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version. This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue. The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

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Glossary

(i, j): A path from origin i to destination j
α_p: A weight to represent impacts of pooling
α_w: A weight to reflect disutility of waiting
Γ: A flow variation function for modal split
$\mathcal{L}$: The set of bus lines
σ_h^{AV}: AV value of time
σ_h^{Bus}: Bus value of time
A_j^{am}: Alighting data at stop j in the morning
B^{am}: The total number of people boarding in the morning peak hour
B^{pm}: The total number of people boarding in the afternoon peak hour
B_j^{pm}: Boarding data at stop j in the afternoon
c_h^{AV}: AV cost per hour
c_{km}^{AV}: AV cost per km
c_h^{Bus}: Bus cost per hour
c_{km}^{Bus}: Bus cost per km
C_o: Operator cost
C_u: User cost
C_{tot}: Total costs of the network
d_{ij}: The distance between origin i and destination j
d_{tot}^{AV}: Total distance run by AVs
d_{tot}^{Bus}: Total distance run by buses
e_{km}^{Bus}: Emission of a bus per km
f_{ij}^{AV}: Flow ratio to AVs for OD pair (i, j) during modal split
f_{ij}^{Bus}: Flow ratio to Buses for OD pair (i, j) during modal split
h_k: Headway of bus line k
N: The total number of bus stops
P_{ij}: Routing path from stop i to stop j
r^{AV}: AV feeder distance
t_{ij}: Travel time between stop i and stop j
$Trip'_{ij}$: The rounded trip volume between stop i and j
$Trip_{ij}$: Trip volume between stop i and stop j
v_{max}^{AV}: AV maximum speed
$\mathcal{N}$: The set of all bus stops