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EVALUATION OF THE IMPACTS OF AUTONOMOUS VEHICLES ON THE MOBILITY OF USER GROUPS BY USING AGENT-BASED SIMULATION

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Abstract. An agent-based transport simulation model is used to examine the impacts of Autonomous Vehicles (AVs) on the mobility of certain groups of people. In the state of the art, it has been found that the researchers primarily have simulation studies focusing on the impacts of AVs on people regardless of certain groups. However, this study focuses on assessing the impacts of AVs on different groups of users, where each group is affected variously by the introduction of different penetration levels of AVs into the market. The Multi-Agent Transport Simulation (*MATSim*) software, which applies the co-evolutionary algorithm and provides a framework to carry out large-scale agent-based transport simulations, is used as a tool for conducting the simulations. In addition to the simulation of all travellers, 3 groups of users are selected as potential users of AVs, as follow: (1) long commuters with high-income, (2) elderly people who are retired, and (3) part-time workers. Budapest (Hungary) is examined in a case study, where the daily activity plans of the households are provided. Initially, the existing daily activity plans (i.e., the existing condition) of each group are simulated and assessed before the introduction of AVs into the market. After that, the AVs are inserted into the road network, where different fleet sizes of AVs are applied based on the demand of each group. The marginal utility of the travel time spent in case of a transport mode, the AV fleet size, and the cost of the travel are the key variables that determine the use of a transport mode. The key variables are set based on the characteristics of the case study (i.e., demand) and the AVs. The results of the simulations suggest that the AVs have different degrees of influences on certain groups as demonstrated in the occurred changes on the modal share. The value of changes depends on the Value of Travel Time (VOT) of people and the used fleet size of AVs. Moreover, the influence of the traveller's characteristics on the AVs is manifested, such as different values of fleet utilization. Furthermore, the study demonstrates that an increase in the fleet size of AVs beyond 10% of the demand does not significantly raise the modal share of AVs. The outcome of this paper might be used by decision-makers to define the shape of the AVs' use and those groups who are interested in using AVs.

Keywords: agent-based modelling, autonomous vehicle, *MATSim*, activity chains, utility function.

Notations

AV – autonomous vehicle;
BKK – Budapest Transportation Centre (in Hungarian: *Budapesti Közlekedési Központ*);
DVRP – dynamic vehicle routing problem;
GA – genetic algorithm;
GTFS – general transit feed specification;
HCB – Hungarian Census Bureau;
MATSim – multi-agent transport simulation;
ML – multinomial logit;
MobSim – mobility simulator;
POI – points of interest;
QSim – queue simulator;
RUM – random utility maximization;
SAV – shared autonomous vehicle;
SP – stated preference;
VMT – vehicle miles travelled;
VOT – value of travel time.

Introduction

The traditional daily mobility patterns of travellers might change when AVs become available on the market. The benefits of AVs, such as minimizing the travel time (Hamadneh, Esztergár-Kiss 2019), removing the parking

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process time (Bischoff *et al.* 2019a), conducting on-board activities (Pudāne *et al.* 2018), and utilizing the parking spaces generated from the decrease in parking demand (Greenblatt 2016; Nourinejad *et al.* 2018), have already been introduced in several papers.

In the AVs era, as a result of the distinct characteristics of the technology, the travellers do not need to consider what happens to the cars after the arrival to the destinations because drivers are converted to passengers as the machine takes the role of driving and goes to the nearest parking space or to pick up a new traveller (Levin, Boyles 2015; Pudāne *et al.* 2018). Litman (2021) explains that the AV is a door-to-door service, which influences the arrival and the departure times of the travellers. For example, a traveller can depart home at 7:30 AM rather than 7:20 AM because there is not a walking time to the bus stop as well as no parking time is needed. In fact, the shift to AVs depends on people's acceptability. Zhong *et al.* (2020) state that the acceptability of AV as a replacement transport mode depends on the VOT of the travellers. Small (2012) concludes that the VOT is not equally valued by every traveller because the travel time valuation is based on various factors and people might pay additional money to reduce the perceived travel time. As a result of introducing AVs into the market, a new modal share (i.e., in the AVs era), which changes the travel behaviour of people, the capacity of the road network, the VMT, and the traffic flow volume, is developed since the people without driving licenses can have an access to AVs, too (Pinjari *et al.* 2013; Zhang *et al.* 2018). An indirect impact of AVs is found in the real estate sector; due to the shift from conventional car to AVs, the number of the required spaces for parking per development (e.g., residential building) is decreased compared to the case where solely conventional transport modes are available (Al-Sahili, Hamadneh 2016; Menon *et al.* 2019). Further research concerning the impact of AVs on the existing transportation system, such as modal share, is needed to understand the travel behaviour of travellers in the era of AVs. Koryagin (2018) says that the AVs will probably facilitate the problems of travel demand management as a benefit of the technology advancement. AVs have already been modelled with a macroscopic tool, and it is found that the easiest way to include AVs in the traffic simulation is by making modifications in the parameters of the passenger car as stated by Török *et al.* (2020).

In fact, the optimization of the daily activity plans of the travellers, in which the utility of the travellers is maximized, is conducted. The simulations of the daily activity plans of the travellers aim to assess the impact of AVs on different groups of users based on the change in the existing modal share, the travel time, and the travel distance. As stated by Horni *et al.* (2016), the concept of the simulation includes the maximization of the utility of the travellers based on various parameters, such as the travel time, the travel cost, the fleet size of AVs, the available transport modes (i.e., bike, car, taxi, AV, and public transport), and the network capacity.

The contribution of this research is to assess the impacts of AVs on the travel behaviour of certain groups of users through an agent-based transport simulation model by examining Budapest (Hungary). The potential changes on the travel behaviour are assessed based on the changes on several variables, such as the modal share, the travel time, the fleet utilization, and the travel distance. The study reveals the differences between the impact of AVs on certain groups of people, for instance, the percentage of those travellers who shift to AVs, the travel time reduction, and the additional driven VMT. Moreover, the changes in the modal share of each group are presented and discussed concerning two penetrations of AVs. Previous studies mentioned some potential users of AVs based mainly on SPs surveys' results (Choi, Ji 2015; Das *et al.* 2017; Etzioni *et al.* 2020; Hao, Yamamoto 2017; Krueger *et al.* 2016); however, scarcely can be found studies that simulate certain groups of people based on the results of the SPs. Three groups of users are selected based on the literature, and later, they are called scenarios. The scenarios consist of Scenario 1, which includes the simulation of all travellers, Scenario 2, which includes the group of long commuters with high-income, Scenario 3, which includes elderly people who are retired, and Scenario 4, which includes part-time workers. Thus, the research includes four scenarios, where the existing condition (i.e., no changes on the daily activity plans of the travellers) in each scenario is simulated and compared with the two proposed penetration levels in the AVs era.

1. Literature review

The advancement of the automotive industry created a new technology known as autonomous vehicle, driverless car, vehicle without a driver, or automated vehicle. The availability of this technology on the market might impact the travel behaviour of people. Understanding these impacts of AVs are realized through simulations, pilot tests, and SPs. Hao and Yamamoto (2017) said that the attractiveness of AVs depends on the riders' trust and the sustainability of AVs, which have not been proven yet due to the lack of sufficient empirical experience. The authors studied the intention of people to use AVs and presented some factors that affect the use of AVs, such as the cost and the travel time. The results of the SP survey demonstrated that around 20…30% of the trips by conventional transport modes can be switched to AVs; furthermore, it was demonstrated that those people who work part-time were more likely to use AVs. A study conducted by Krueger *et al.* (2016) concluded that the potential user groups of AVs could be elderly people, people without driving licenses, and pensioners. The authors mentioned that elderly people tend to use AVs to simplify their travel and eliminate the negative impacts of using other transport modes, such as congestion, the possible unavailability of seats, stairs, driving, weather, and waiting outside. Another study conducted by Das *et al.* (2017) showed that the long commute drivers, the long transit commuters, and the elderly are potential group of people who might benefit most from using AVs. Furthermore, Yap *et al.* (2016) said that the first-class riders of train would prefer to use AVs when they need to egress from the train to reach their last destination (i.e., last destination is any activity except for home). The authors concluded that AVs will add a positive value to encouraging multimodal trips that combine train plus AVs because based on the study, travellers who will use an AV plus a train get more benefit than those who parked their vehicle close to or at a train station. Laidlaw (2017) finds that travellers with flexible work schedules are more likely to use AVs, such as part-time workers.

The VOT is another factor, which is presented in the literature and helps to understand why people choose a particular mode over others. The VOT depends on variables pertaining to sociodemographic and travel characteristics, such as income, age, job, and trip purpose. The value of VOT differs from one traveller to another (Zhong *et al.* 2020). Steck *et al.* (2018) concluded that AVs whether it is shared or unshared will reduce the value of travel time saving for people who make commuting trips. The reduction comes from the potential for conducting more activities on the board of AVs than conventional cars'. Furthermore, the study showed that the VOT for high-income people is higher than for low-income people in case of all transportation modes including future technologies, such as AVs. Sadat Lavasani Bozorg (2016) mentioned in their review study that the VOT of high-income people will decrease by 35% when AVs are used. It was concluded that high-income people are more willing to pay for saving commuting time. Steck *et al.* (2018) realized that the VOT of the unshared AV is less than that of the SAV, and the VOT of SAV is less than a conventional car's. Litman (2009) said that the VOT increases with the rise of income since time-saving is more precious for employed people than for others.

Based on their study in Berlin, Bischoff and Maciejewski (2016) showed that one SAV might replace ten conventional cars, and one AV could replace six conventional cars. A simulation study conducted in Budapest showed that one SAV can replace up to eight conventional cars with an acceptable waiting time, i.e., 10…15 min (Hamadneh, Esztergár-Kiss 2019). A simulation of workers and shoppers concerning the park-and-ride system and the AVs in Budapest showed that one AV can replace four conventional cars (Ortega *et al.* 2020). One SAV replaced 9.3 conventional cars in a study conducted in Austin city by Fagnant *et al.* (2016). They used solely the SAV as a transport mode, and they divided the city into blocks with a certain number of SAVs. The SAVs assigned to a block give priority to pick up the demand in that particular block, and in the case of no demand in that block, they can serve the supply in the adjacent blocks. The methodology of Fagnant *et al.* (2016) participated in reducing the VMT and the waiting time per traveller. In the simulation of AVs and SAVs, the travellers can accept waiting time between 5…15 min based on a study conducted by Hörl *et al.* (2016). The scholars said that the acceptable waiting time is affected by the time of the day, for example at peak periods, travellers can wait 10…15 min. It is worth mentioning that the acceptable waiting time in case of an AV can be compared with the waiting time at a public transport stop and with the walking time to reach the stop location, as illustrated in a study by Hörl *et al.* (2016). The acceptable waiting time has a crucial impact on the determination of the fleet size of AVs, for example, a waiting time of 10 min can cause a reduction in the fleet size by up to 90% (Boesch *et al.* 2016). Regarding the travel time, 20…40 min of traveling tend to be acceptable, but over 90 min, it often causes frustration for the travellers. The reduction in congestion and the increase in the speed might generate more trips rather than saving time, which leads to more VMT and travel time, as mentioned by Litman (2009).

Connected to the behaviour analysis, AVs can attract travellers based on the preferences in travel time, travel cost, waiting time, and ride-sharing that form the main determinants of using AVs (Acheampong, Cugurullo 2019; Krueger *et al.* 2016; Zmud *et al.* 2016). Godoy *et al.* (2015) showed that AVs may improve safety and alleviate congestion since the machine drives with higher precision than human drivers. A study by Fagnant and Kockelman (2015) presented some benefits of AVs, such as travel time reduction, increased safety, and reduction in the necessary parking spaces. They addressed some obstacles of AVs implementation, such as the cost, the liability, the certification, the security, the privacy, and the insurance. Based on previous studies and the potential benefits of AVs on the travellers' mobility, this study adds a new contribution to show the impact of AVs on the travel behaviour of certain groups of people concerning the VOT of the travellers, the travel cost, and the travel time.

2. Methodology

In this section, the implemented methodology including demand preparation, mobility simulation, scoring, and re-planning (i.e., innovation is made on the initial demand by using a GA) are explained (Horni *et al.* 2016). The implementation of the methodology was conducted by *MATSim*, which is an open-source, activity-based microsimulation software that applies the concept of a co-evolutionary algorithm (i.e., the aggregation of findings is obtained from the interactions of all agents/travellers to make selection decisions) based on flexible functions (Popovici *et al.* 2012; Maciejewski, Nagel 2013). The mobility simulation, the scoring, and the re-planning form an iterative loop called *MATSim* loop (Horni *et al.* 2016). The *MATSim* loop is used to solve the traffic assignment problem and to maximize the utility of the travellers.

Figure 1 shows the four scenarios. The scenarios are filtered based on the characteristics of every scenario, where the dataset that are used includes information about the trip time of each traveller, the age of each traveller, and the type of work of each traveller. The scenarios are selected based on the literature (Choi, Ji 2015; Etzioni *et al.* 2020;

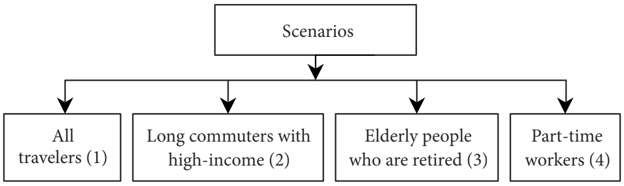

Figure 1. The proposed travellers' behaviour simulation scenarios

Hao, Yamamoto 2017; Krueger *et al.* 2016; Litman 2021), and the availability of data (i.e., daily activity plans of travellers) as mentioned in the introduction section. The characteristics of each scenario are described in the data description subsection, while the implementation of the simulation is presented in the simulation setting subsection. The Scenario 1 represents all travellers. The (Scenario 2 includes the long commuters with high-income, where those travellers who belong to the high-income class and travel more than 40 min in any daily trip are selected. Scenario 3 consists of the elderly people who are retired. For this scenario, those travellers who are more than 65 years old and retired are selected. Finally, Scenario 4 includes part-time workers, where the selected travellers work on a part-time basis. In this paper, first, the simulations were carried out without any changes on the daily activity plans of the travellers (i.e., existing condition) for the four scenarios to be compared with the changes in the travel behaviour when AVs are on the market.

The following subsection describes how the simulation was implemented starting from the initial demand through the travellers' utility maximization to the simulation results, as shown in Figures 2 and 3.

2.1. Initial demand

To prepare the initial demand for the simulation, the necessary data are depicted in Figure 2. Firstly, the daily activity plans contain information about the locations of the activities, the departure time and the arrival time, the duration of the travel, and the used transport modes in each trip, such as conventional car, public transport (i.e., transit), walking, and cycling. Secondly, the facilities (i.e., the POIs) for the travellers, which were taken from *OpenStreetMap* contain the locations (i.e., coordinates), the type, and the active time (i.e., the opening hours) of each facility to be used as alternative facilities for the travellers in the re-planning process (OSM 2021). Thirdly, the road network components of Budapest were extracted from *OpenStreetMap* with the support of JOSP *MATSim* plugin (JOSM 2021), while public transport (i.e., transit) data were received as GTFS files from the Budapest Transportation Centre, called BKK (Transitfeeds.com 2018). Consequently, a specific contribution in *MATSim* (i.e., *Java* code) was used to convert GTFS to transit schedule file format (XML) based on a pre-developed code in *Java* programming language (Poletti *et al.* 2017). Technically, the daily activity plans of each user were reformulated to match the requirements of *MATSim* inputs, for example, the coordinate, the departure and the arrival time of each activity as well as the trip mode and the trip time. Finally, the configuration file is used as a control file of the simulation, in which all simulation parameters are set. Figure 2 depicts how the data were formulated, structured, and organized to create the initial demand of the simulation. In the end, the population for *MATSim* is created, but it is not distributed over the network (i.e., the initial demand). The initial demand is loaded on the road network by using *MobSim*, as explained in the following subsection.

2.2. *MobSim*

The *MobSim* is the transport simulation module, which is incorporated into *MATSim* and used to load the activity plans into the network by implementing a queue-based model (Bösch, Ciari 2017). *MobSim* uses the *QSim* engine to load the plans into the road network. At the initial

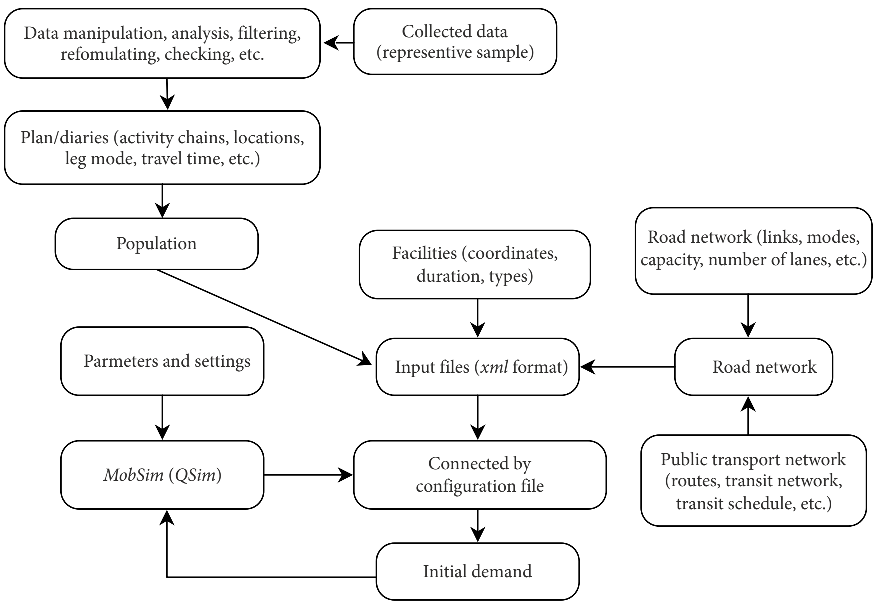

Figure 2. Initial demand preparation mobility simulation

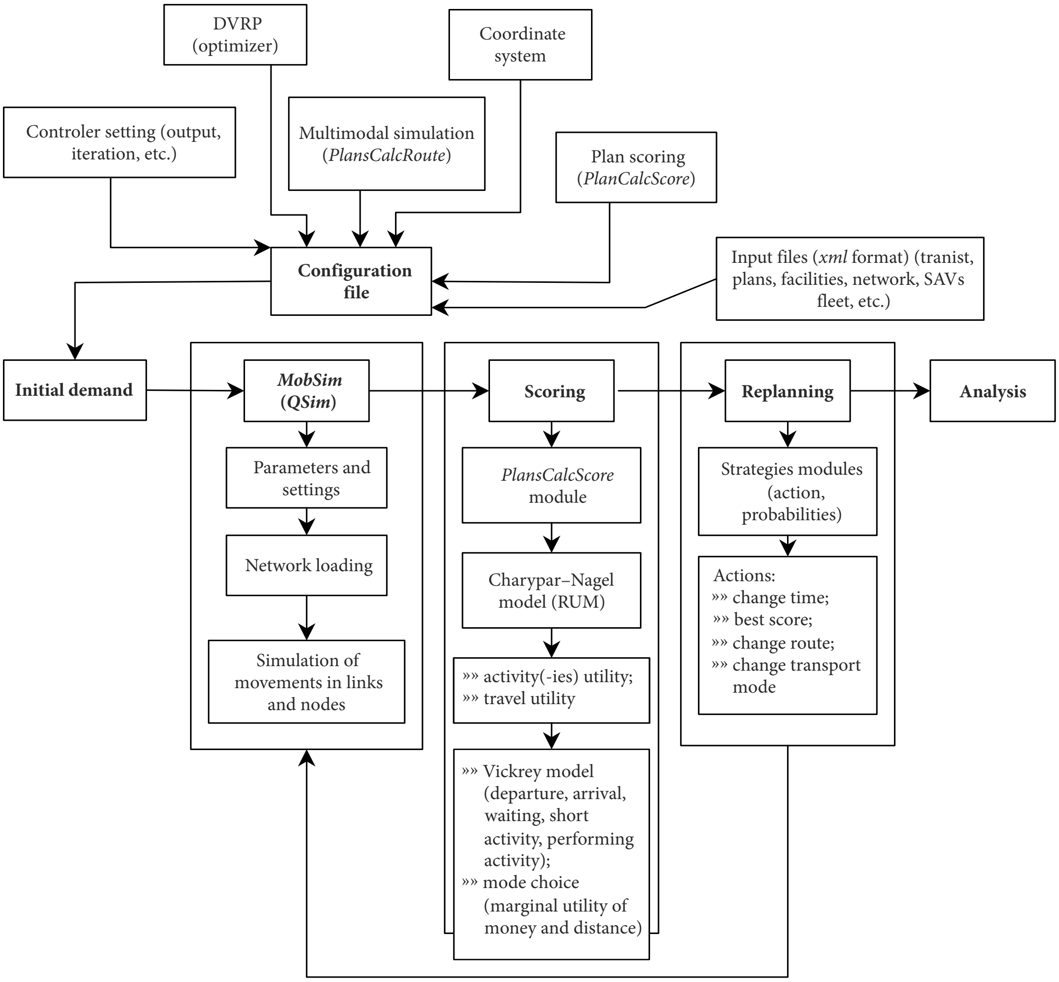

Figure 3. Data analysis flow chart

point, the travelers were located in the network by using the coordinates of activities. A specific algorithm was used to assign the best route to a trip based on the selected transport mode and the departure time (stochastic user equilibrium). The Dijkstra routing algorithm is used to find the shortest path algorithm. It is worth mentioning that the *MATSim*'s default transport mode is car mode, while other modes (i.e., walking, bike, AVs, and public transport) were defined based on the modifications of the car mode parameters in a process called as "teleportation process" (Horni *et al.* 2016). A "teleportation process" enables the *QSim* to simulate all transport modes based on the travel time, the distance, and the speed factors (Horni *et al.* 2016). For example, the speed of the car is faster than that of the public transport, the bicycle, or walking (Hamadneh, Esztergár-Kiss 2021).

2.3. Scoring (utility function)

Scoring is the process during which the daily activity plans are evaluated based on the utility function in each iteration, where the first iteration is taken by simulating the initial demand. The scoring step is followed by the replanning, which makes changes in the daily activity plans, and afterward, calls for *MobSim* to simulate the generated new daily activity plans to be followed by the scoring step again. A utility function that combines both activity and travel parameters is applied. The activity parameters include the characteristics of each activity, such as the opening time, the typical duration, the minimum duration, and the closing time. The travellers are assigned to different utility units based on their arrival, departure, and staying at the activity's location. Staying more at an activity's location generates high utility, while leaving early generates less utility. The traveling parameters include the cost of using a transport mode per time or per distance. Staying long time in traveling means the travellers lose utility as more money is spent on traveling. The utility of traveling is negative, and it is called (dis)utility. The marginal disutility of the travel for a selected transport mode depends on the time, the distance, and the travel cost, where the travellers pay money for using a transport mode based on their preferences and activity parameters (Horni *et al.* 2016). The utility function of Charypar–Nagel, which combines the activity utility and travel (dis)utility, was used in this part of the research. The score of the activity and the travel is determined by using Equation (1) (Charypar, Nagel 2005). Equation (1) presents the function that can be used to reach the maximum benefit obtainable from conducting activities and minimizing both the time spent on traveling and the incurred cost from the selected transport mode:

$$V_{plan} = \sum_{i=0}^{n} \left(V_{activity,i} + V_{traveling,i,j} \right), \quad (1)$$

where: V_{plan} is the utility of performing a selected plan; $V_{activity,i}$ means the utility of performing the activity i, it is always positive; $V_{traveling,i,j}$ is the (dis)utility derived from the traveling to and from the location of activity i by using the transport mode j, it is always negative because travellers pay money rather than get money in case of traveling.

In the activity utility, Equation (2) is applied:

$$V_q = V_{duration,q} + V_{waiting,q} + V_{late,q} + V_{early,q} + V_{short,q}, \quad (2)$$

where: V_q is the utility of the activity q; $V_{duration,\,q}$ is the utility of performing the activity q; $V_{waiting,\,q}$ is the utility of waiting for the activity q to open; $V_{late,\,q}$ is the utility of arriving late at the location of the activity q; $V_{early,\,q}$ is the utility of leaving the location of the activity q early (not staying enough time at the location of the activity); $V_{short,\,q}$ is the utility of staying a shorter time than required by the activity q (Horni *et al.* 2016).

It is worth mentioning that a logarithmic form of the equation is used to calculate the positive utility, which is shown in Equation (3) (Charypar, Nagel 2005):

$$V_{activity,i}\left(t_{activity,i}\right) = \beta_{activity} \cdot t_{*,i} \cdot \ln\left(\frac{t_{activity,i}}{t_{0,i}}\right), \quad (3)$$

where: $V_{activity,i}\left(t_{activity,i}\right)$ is the utility of performing an activity i; $t_{activity,i}$ is the actual performed duration of the activity i; $\beta_{activity}$ is the marginal utility of performing an activity with its typical duration $\left(t_{*,i}\right)$; $t_{0,i}$ is a scale parameter related to the minimum duration of the activity i and its importance.

In the traveling part, Equation (4) is used for estimating the score of the traveling, where V(travel,i) is the traveling (dis)utility (Horni *et al.* 2016):

$$V_{travel,(M,i)} = C_{(M,i)} + B_{travel,(M,i)} \cdot TT_i + B_{money} \cdot \Delta_{money,i} + \left(B_{d,(M,i)} + B_{money} \cdot \gamma_{d,(M,i)}\right) \cdot D_{travel,i} + B_{transfer} \cdot x_{transfer,i}, \quad (4)$$

where: M refers to the transport mode; i means the activity; d is the travelled distance; $C_{(M,i)}$ is a mode-specific constant; $B_{travel,(M,i)}$ is the marginal utility of the traveling by the transport mode M to reach the activity i; TT_i is the travel time from the location of activity i to the location of activity i + 1; B_{money} is the marginal utility of the money; $\Delta_{money,i}$ is the change rate in the monetary budget caused by the transport fares; $B_{d,(M,i)}$ is the marginal utility of the distance when using the transport mode M while traveling to the activity i; $\gamma_{d,(M,i)}$ is the constant monetary distance rate when using the transport mode M while heading to the activity i; $D_{travel,i}$ is the travelled distance between two successive activities, such as i and i + 1; $B_{transfer}$ is the public transport transfer penalty; $x_{transfer,i}$ indicates if a transfer occurred in the previous or the current plan (0 is no, and 1 is yes); the values of all the previous parameters were derived based on the characteristics of the collected data.

When applying the previous equations, the typical utility values of the Vickrey bottleneck congestion model are used (Horni *et al.* 2016). The applied values in the utility unit [u] are as follow, the marginal utility of the money B_{money}, which is +1 u/monetary unit; the marginal utility of performing $B_{duration}$, which is +6 u/h; the marginal utility of traveling B_{travel}, which is –6 u/h; the marginal utility of waiting $B_{waiting}$, which is 0 u/h; the marginal utility of the short activity B_{short}, which is 0 u/h; the marginal utility of arriving late B_{late}, which is –18 u/h, and the marginal utility of early leave B_{early}, which is 0 u/h. These values were used as a default and those values where no information about the exact parameters of a case study is given. In this study, some of marginal values are changed based on the simulated data.

2.4. Re-planning

The travellers try to maximize their benefits by selecting the daily activity plans that have the highest score. For example, the traveller can aim to minimize the time and the cost of the travel by selecting the bike instead of the bus with a long headway, which does not affect the arrival time. In the re-planning process, modifications in the daily activity plans are conducted. The re-planning is a learning mechanism in *MATSim*, where the travellers (i.e., agents) can improve their plans in each iteration until a steady-state condition is reached. The improvements are obtained by making modifications in the daily activity plans of the travellers. The GA is used by *MATSim* to generate various activity plans with different score values thus enabling travellers to select the best activity plan with competitive time. During this process, a finite number of options are generated (Charypar, Nagel 2005). An evaluation of the new selected plan is generated based on the mutation and the selection strategies to adopt the next iteration. 3 types of mutation operators were activated: (1) transport mode change, (2) rerouting, and (3) time allocation based on certain probabilities (i.e., not all activity plans are changed). For example, the probability of changing the leg mode was set to 0.1; it means that the 10% of the traveller plans will change the leg mode, and the remaining 90% will use their current transport modes. After generating new daily activity plans, a ML model was used for the selection, and for calculating the probability of using a specific transport mode based on the distribution of the utility function (Simoni *et al.* 2019).

At the end of the process, the selected new daily activity plans are sent to *MobSim* for simulation and then to the scoring step to find the new score. The *MATSim*

Table 1. The sample size and the characteristics of the four scenarios*

Scenario	Description	Sample size	Activity type [%]				
			work	education	shopping	leisure	other
1	All travellers	8500	51.5	16.4	15.4	3.2	13.5
2	Long commuters with high-income	440	74.2	11.2	3.9	1.8	8.9
3	Elderly people who are retired	1020	6.1	0.6	48.5	8.7	36.1
4	Part-time workers	505	51.5	6.5	19.0	3.2	19.8

Note: * home-based activity.

loop continues iteratively until a steady-state condition, where no extra benefit is got from the modification of the daily activity plans of the travellers is reached (Horni *et al.* 2016; Luo *et al.* 2019). Figure 3 demonstrates the flow chart of the analysis to illustrate the implementation of the simulations. In *MATSim*, the setting of the parameters of *MobSim*, the scoring, and the re-planning steps are presented as follows. The re-planning step includes a strategy module, which is used to identify the innovation types (i.e., route change, time allocation, and best score) and the percentage of the travellers to be re-planned (Horni *et al.* 2016). The Charypar–Nagel utility function (i.e., the random utility function) combines the monetary and the time factors for conducting the daily activities of the travellers thus generating a score in every iteration until reaching the maximum score that the travellers can have (GA was applied), as discussed in Equation (1) (Horni *et al.* 2016). Finally, the analysis part compromising the outputs of the simulations is used to evaluate the simulated activity plans, such outputs are the average trip distance, the scoring diagram, the waiting time, the modal share, and the simulation time. In case of the AVs simulation, an additional algorithm called DVRP is used to match those travellers who have the same schedule and to determine the suitable fleet size of AVs, where the daily activity plans and the fleet size of AVs are optimized (Maciejewski, Nagel 2011). The DVRP receives updates on the occurred changes in the fleet of AVs, the daily activity plans, or the traffic situation.

2.5. Data description

Budapest city has around 1.7 million inhabitants, which forms around 18% of the country's population. The study area consists of 23 districts and 1178 zones, where each district is divided into smaller sections called zones. The collected data include the travellers' daily activity chains and their socio-demographic variables. The data include such sociodemographic and travel characteristics variables as activity type, activity location, transport mode, departure time, arrival time, age, gender, family size, vehicle ownership, driving license ownership, public transport type, parking search time, parking fees, and the travellers' job type. The data were collected and aggregated in 2014 by the HCB, which conducts a periodic survey every 10 years (HCSO 2021). The simulated data represents households; thus, each daily activity plan represents a household rather than an individual traveller. 8500 daily activity plans are taken from the HCB, where each activity plan represents a traveller's daily activities for 24 h. The sample size of Scenario 1 includes the entire sample of the 8500 travellers. While the sample sizes of Scenario 2, Scenario 3, and Scenario 4 were taken from Scenario 1 based on the characteristics of each scenario. For example, those travellers who recorded high-income and one of their trip time was higher than 40 min were included in Scenario 2. Table 1 shows the sample size and the activity type's percentages of each scenario. Scenario 2 contains 440 daily activity plans, Scenario 3 contains 1020 daily activity plans, and Scenario 4 contains 505 daily activity plans.

2.6. Parameter definition

In the AVs simulation, the identification of certain parameters are required, such as the AV capacity (in this case, four seats capacity is used), the pick-up duration (in this case 120 s), and the drop-off duration (in this case 60 s) (Bischoff *et al.* 2019b). Those travellers who travelled longer than 40 min and were classified as members of the high-income group and the travellers who were classified as part-time workers should have an average waiting time less than or equal to the average time needed for parking or un-parking a car (Bischoff, Maciejewski 2016). Thus, the travellers selected AVs if the waiting time was less than or equal to 10 min. A 1.5 traffic flow capacity factor was used to reflect the impact of AVs on the road capacity since a conventional car increases the congestion by 1.5 more than an AV (Huang *et al.* 2000; Meyer *et al.* 2017; Simoni *et al.* 2019). Maciejewski and Bischoff (2018) demonstrated that the capacity of roads increases when AVs fleet is operated on the market. In this study, the penetrations of the AVs were 10 and 20% of the sample size in each scenario. These penetration rates represent two scenarios of the AVs' acceptability by people.

The initial simulation of the daily activity plans was conducted to find the parameters that simulates the current travel behaviour of the travellers. The marginal utility of traveling by each transport mode was calibrated by using the collected data and by running the software many times to reach a point where the initial result of the software is very close to the statistics of the simulated data. The calibration results are presented in Table 2.

Table 2. Transport mode choice coefficients

Parameters	Calibrated values
Marginal utility of performing activity $B_{duration}$	+6
Marginal utility of money B_{money}	0.0018
Monetary distance rate $\gamma_{d,(M,i)}$	−0.40 car, −0.038 PT, −0.004 bike, −0 walking
Marginal utility of traveling for all modes B_{travel}	−2.5 car, −0.5 PT, −0.3 bike, −0.1 walking
Alternative mode-specific constant $C_{(M,i)}$	−0.2 car, 3.92 PT, 2.64 walking, −17.81 bike

Note: PT – public transport.

The marginal utility of performing an activity is 6, and the marginal utility of money is 0.0018, which are positive utility. The cost of using each transport mode per km is 40 Hungarian Forint (HUF) for a car, 0.038 HUF for public transport, 0.004 HUF for a bike, and 0 HUF for walking. The marginal utility of time and the constants by car, public transport (indicated as PT), bike, and walking are presented in Table 2 (BetterTec Gmbh 2021). Other parameters were set based on the default values of *MATSim* (Hörl *et al.* 2016).

The AV parameters are measured based on the parameters of a conventional car; the marginal utility of time is 35% less than the marginal utility of traveling by conventional car, and the travel cost is assumed to be 60% of the travel cost of the conventional car (Bösch *et al.* 2018; Fagnant *et al.* 2016). The parameters of the utility function, such as the routing algorithm, the transport mode cost, the pick-up/drop-off duration time, and the marginal utility of late arrival definitely influence the travel distance, the travel time, and the utility value of a particular traveller. During the simulation, events were created to evaluate the output of each step and the results of the newly added modifications.

3. Results

In this section, the results are presented in the following order: the simulation of the existing conditions of all scenarios, the simulation of the conventional transport modes with a 10% fleet size of AV, and the simulation of the conventional transport modes with a 20% fleet size of AV, and in the end, an additional simulation of a solely fleet of AVs is conducted for each scenario.

The simulation setting of each scenario was built based on the previously described parameters (Table 2), and the fleet sizes of AVs were 10 and 20% of the sample size in each scenario. 3 simulations of each scenario were conducted concerning the existing condition and the availability of the two different fleet sizes of AVs. The concept behind the selection of 10 and 20% is to simulate different penetrations of AVs, where the 1st simulation represents the case where AVs are getting accepted slowly, and the 2nd simulation shows the booming of the market where the AVs become more widespread. The selected percentages were used to simulate the initial demand, and they did not consider the extra demand that can be generated from the advancement of the AVs, as shown by Harper *et al.* (2016). The simulations were stopped when the system became stable, no further enhancement in the scoring, and no changes in the mode-share were noticed.

The simulation of the existing condition of Scenario 1 shows that the average trip time per traveller is 33 min after 70 iterations. For certain travellers who spend more than 40 min for one trip and belong to the high-income class the simulation of the existing condition of Scenario 2 shows that the average trip time per traveller is 46 min after 100 iterations. Moreover, for Scenario 3, which consists of those elderly people who are more than 65 years old and retired, the simulation of the existing condition of these travellers shows that the average trip time per traveller is 33 min after 100 iterations. Finally, in Scenario 4, which includes those people who work on a part-time basis, the result of the simulation of the existing condition shows that the average trip time is 38 min after 100 iterations.

3.1. Current modal share

The modal share of each scenario, which contains the percentages of those travellers who use a particular transport mode is shown in Figure 4. Figure 4 presents four transport modes that are mainly used by travellers such as car, public transport, bike, and walking. From Figure 4, it can be concluded that the highest percentage of the travellers used public transport (37.4%), while the lowest used bike (2.3%), in case of Scenario 1. In Scenario 2, the car was more often used than any other transport mode. This can be explained as the travellers of long travel distances prefer to use car where other transport options are not suitable, such as walking is not that much popular for longer trips. Among the old travellers who are retired, the car was not so popular anymore since older people do not usually drive cars that much due to health and safety issues. Part-time workers travellers use public transport and walking more often because of the price benefits and their flexible work schedule. In all scenarios, the percentage of those travellers who used the bike mode was relatively low (1…2.3%) compared to other transport modes.

3.2. Travellers' trip time components in the presence of AVs

The inclusion of the AVs on the market was conducted through simulating the travellers in each scenario with the presence of certain fleet sizes of AVs. This was done to evaluate the impact of AVs on traveller behaviour, such impacts are evaluated based on the occurred changes on modal share, travel distance, travel time as well as show the differences among groups.

Table 3 shows the results of the simulations when the fleet size of AVs was the 10% of the sample size of each group. The average waiting time and the usage parameters of the AV fleet size were recorded, such as the empty time,

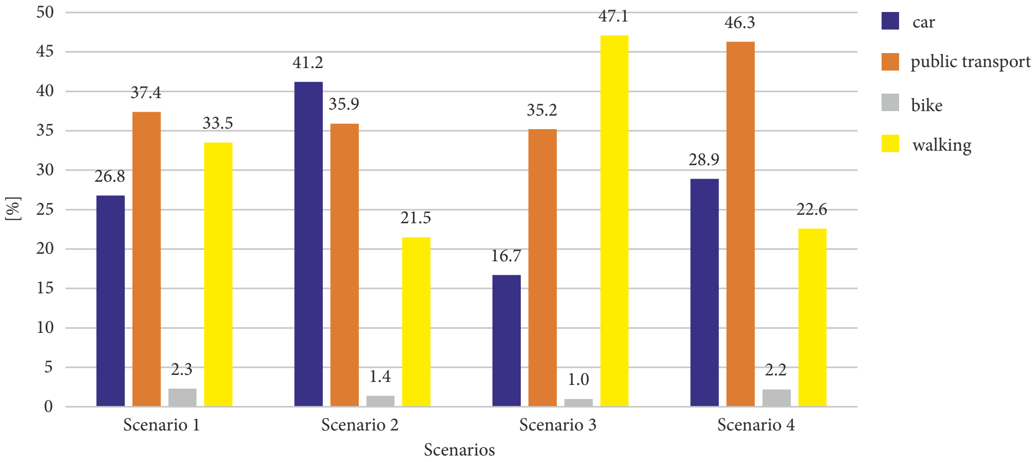

Figure 4. The current modal share of the simulations

the driven time, the occupied time, and the drop-off time. Scenario 1 reported 13.3 min of average waiting time when the fleet size of AVs was 850 AVs, and the average trip time was 18.75 min. The drop-off and the pick-up times represent the spent time for picking up the travellers and dropping them off in case of the AVs. The shown numbers stand for the fleet size per day, for example 344.27 h were needed to pick up the travellers in Scenario 1 and 172.13 h for dropping them off once using 850 AVs. It is shown that the ratio of the occupied time (i.e., the occupied, the pick-up, and the drop-off time) to the total operating time (i.e., the occupied, the pick-up, the drop-off, and the empty travel time) of the AVs fleet for Scenario 1 is 68% (fleet size utilization). Similarly, the fleet utilization of Scenarios 2, 3 and 4 was 69%, 64%, and 61%, respectively. The average waiting time was higher than the acceptable waiting time, which requires the increasing of the fleet size of AVs. In Scenario 2, 40 AVs were distributed randomly in the road network with other transport modes, and the people who used AVs were exposed to a 12.3 min of average waiting time, and the average trip time was 18.2 min per traveller. Moreover, the fleet size of AVs had 111.0 h empty driving to the locations of the travellers and had only 199.8 h occupied driven time. In conclusion, the travel distance (i.e., VMT) increased, which can be calculated by the ratio of the empty driven time to the occupied driven time, which is in this case 56%. In the case of Scenario 2, the additional VMT is high, and it can affect the cost of the travel negatively. The travellers of Scenarios 3 and 4 experienced a 4.7 min and 6.1 min of average waiting time, while the additional travelled distances by the fleets of AVs were 88.4% and 91.1%, respectively, based on the ratio of the empty to the occupied travel time. Moreover, the average trip time for Scenario 3 and Scenario 4 was 10.6 min and 11.5 min per travellers, respectively.

Table 4 shows the results of each scenario when AVs were included in the simulations with a 20% fleet size. The average waiting time and the usage parameters of the AV fleet size are recorded. In Scenario 1, the average waiting time per traveller was 10.5 min, where the fleet size was 1700 AVs, the fleet utilization was 68%, and the average trip time was 17.1 min per traveller. The drop-off and pick-up times were calculated based on the number of the trips. The result demonstrated that the AVs increased the travel distance of the travellers who switched to AVs by 55% compared to the conventional transport modes. In Scenario 2, the average waiting time was 8.0 min, the fleet utilization was 67%, the average trip time was 16.4 min per traveller, and the increase in the travelled distance was 62%. The high VMT of the fleet was generated because of the type of the travellers in this scenario, who typically travel for a long distance, thus the relocation of AVs requires more time on average. In the scenario of elderly and retired people (i.e., Scenario 3), the average travel time was 3.3 min, the fleet utilization was 72%, the average trip time was 9.85 min per traveller, and the additional travel distance was 62%, which means the utilization of the fleet size is not high. Finally, the part-time workers experienced 4.5 min, the average trip time was 10.2 min per traveller, and the extra travelled distance by the fleet size was 71%, which leads to a lower utilization ratio of the fleet size (i.e., the empty driven time is high).

As the ratio of the empty driven time to the occupied driven time decreases, the utilization of the fleet size of AVs increases. The average served request per one AV per day represents the number of the picked-up travellers per AV, which is the number of the travellers that each AV serves on average. As this number gets high, it brings more efficiency and profit to the operators. Figure 5 shows the fleet utilization ratio while Figure 6 shows the difference in the average requests served by an individual AV the fleet average when the fleet size of AVs is increased from 10 to 20% of the sample size. Figure 7 shows the additional VMT when the fleet size of AVs is increased from 10 to 20% of the sample size.

3.3. Modal shift in the presence of AVs

The inclusion of the new transport mode (i.e., AV) makes the travellers recalculate their utility based on the travel cost and the travel time between two consecutive activities. The results of the simulations produce new modal shares including AVs, as shown in Table 5 and Figure 8.

Table 3. The travellers' trip time components when the fleet size of AVs is 10% of the sample size

Sce-nario	Fleet size	Average waiting time [min/trip]	Empty driven time [vehicle·h/day]	Pick-up time [vehicle·h/day]	Occupied time [vehicle·h/day]	Drop-off time [vehicle·h/day]	Fleet utilization [%]	Additional VMT [%]	Average served request per one AV [#]
1	850	13.3	1696.25	344.27	3014.41	172.13	68	56	4.66
2	40	12.3	111.02	32.87	199.82	16.43	69	56	9.70
3	100	4.7	108.25	46.07	122.35	23.03	64	88	5.73
4	50	6.1	96.70	31.77	106.13	15.88	61	91	7.60

Table 4. The travellers' trip time components when the fleet size of AVs is 20% of the sample size

Sce-nario	Fleet size	Average waiting time [min/trip]	Empty driven time [vehicle·h/day]	Pick-up time [vehicle·h/day]	Occupied time [vehicle·h/day]	Drop-off time [vehicle·h/day]	Fleet utilization [%]	Additional VMT [%]	Average served request per one AV [#]
1	1700	10.5	2107.78	398.67	3807.39	199.33	68%	55%	2.76
2	80	8.0	137.7	34.9	222.21	17.45	67%	62%	5.24
3	200	3.3	79.12	47.83	127.36	23.92	72%	62%	2.86
4	100	4.5	74.78	33.57	104.71	16.78	67%	71%	3.98

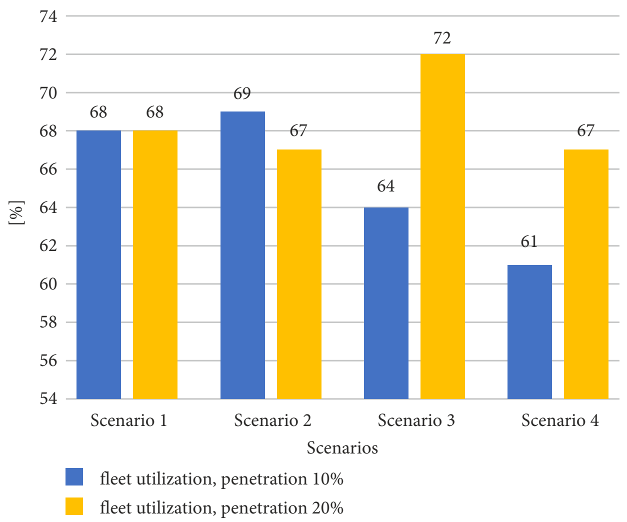

Figure 5. Fleet utilization differences across the two AVs penetrations

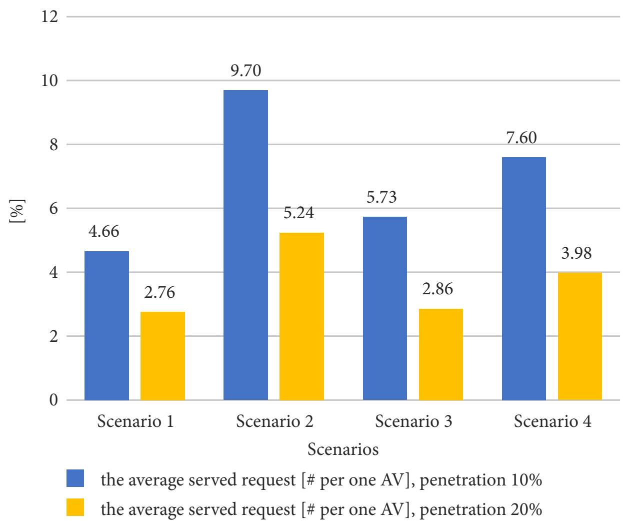

Figure 6. The average served request by an individual AV

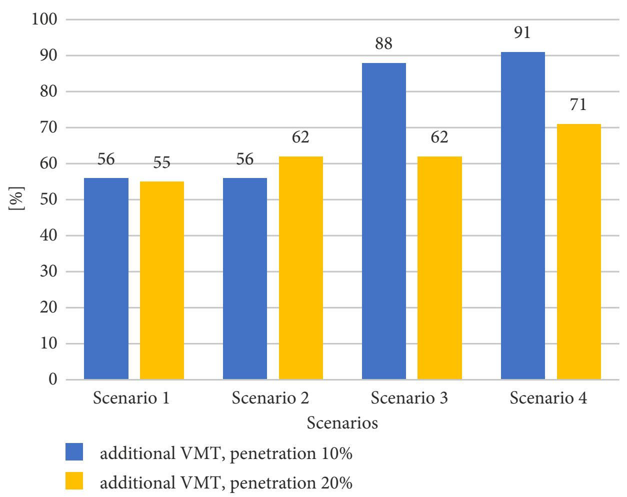

Figure 7. VMT differences across the two AVs penetrations

Some travellers switched to AVs to increase the utility of their traveling (i.e., decrease the disutility). The 23.6% of the people switched to AVs in Scenario 1 when the fleet size of AVs was 850, and 25.4% when the fleet size of AVs was 1700. The small increment in the AVs modal share was not the only result, since the quality of the service was enhanced by reducing the average waiting time when the fleet size of AVs is changed from 10 to 20%. Around the 47.5% of the long-trip travellers with high-income switched to AVs when the fleet size of AVs was 40 and 51.3% when the fleet size of AVs was 80. Additionally, the 19.5% of the elderly people who are retired switched to AVs when the fleet size of AVs was 100 and 21.9% when the fleet size was 200. Finally, the percentage of part-time workers who switched to AVs was 30.4% when the fleet size was 50 and 30.6% when the fleet size of AVs was 100.

Table 5. The mode-share shift results of the simulations

Transport mode	The fleet size of AVs is the 10% of the sample size				The fleet size of AVs is the 20% of the sample size			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4
AV	23.6	47.5	19.5	30.4	25.4	49.5	21.9	30.6
Car	12.8	6.3	2.6	2.9	7.5	2.3	2.2	1.8
Public transport	21.5	31.2	29.0	36.1	25.2	33.0	29.2	39.4
Bike	3.0	2.7	3.0	2.6	2.8	2.4	3.1	2.8
Walking	39.1	12.3	46.3	27.9	39.1	11.8	43.2	25.4

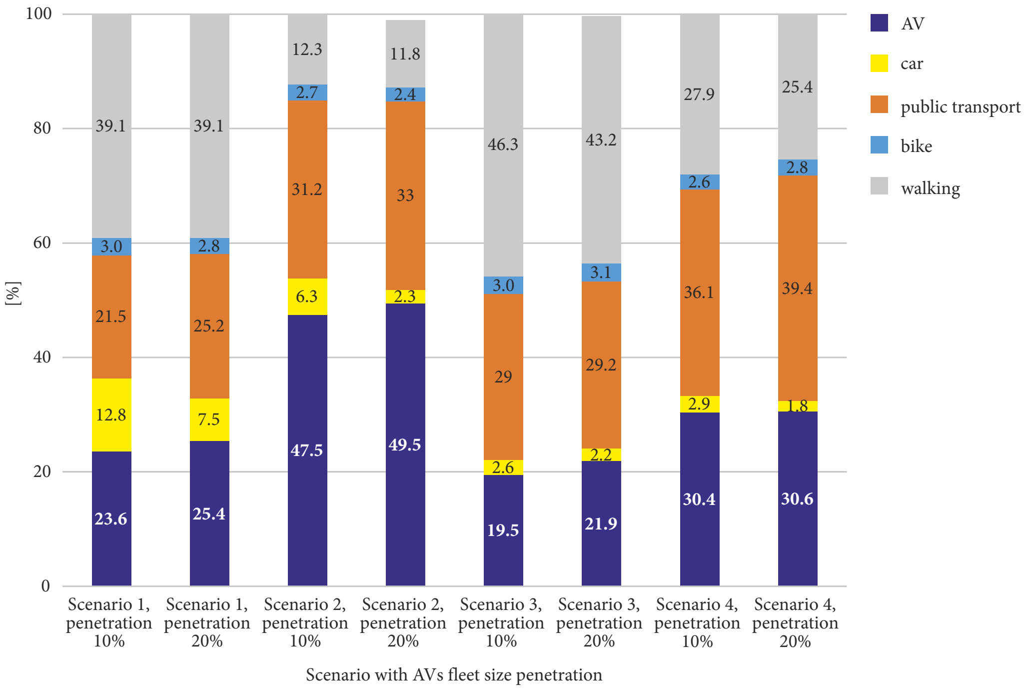

Figure 8. The mode-share shift results when the AVs penetration increases from 10 to 20%

The results showed that the rise the fleet size of AVs did not attract more travellers, but it impacted the average waiting time positively. The inclusion of additional AVs on the market impacted other transport modes negatively, especially the car and the walking modes. The decrease in the car and walking modal splits when the additional AVs were introduced into the market produced an increase in the public transport and AVs modal splits. For example, in Scenario 1, the car modal share decreased from 12.8 to 7.5%, while the public transport increased from 21.5 to 25.2%, and the AVs share increased from 23.6 to 25.4%. The results lead to the conclusion that increasing the fleet size of AVs will mainly increase the quality of the service based on the assumption that decreasing the waiting time enhances the quality of the service. The interpretation of the additional shift from the non-motorized transport modes when the additional AVs are on the market can be obtained from the time allocation strategy and the reasonable walking time. The time allocation is affected by the average waiting time, which impacts the usage of AVs. The characteristics of a traveller determines whether to use AV or not since the arrival and the departure as well as the availability of AV within the schedule should coincide. Therefore, more AVs on the market can lead to less waiting time and more usage of AVs concerning other factors, such as the VOT of the travellers.

The marginal utility of the travel time of a particular transport mode impacts the possibility of changing a transport mode considering the cost, the departure and the arrival times. From the above tables, it can be concluded that the waiting time is decreased as the fleet size of AVs is increased, and as the fleet size of AVs is increased the additional empty driven time/distance is decreased. As the travel distance increases, the empty driven time increases, as well, as demonstrated in Scenario 1. Increasing the fleet utilization is a target because it indicates a high efficiency of the fleet. As the number of requests per AV increases the efficiency of the fleet increases, and the number of idle AV hours decreases. The bike and walking modes are less affected by the inclusion of AVs because the users of those modes have different characteristics from other travellers'. For example, people using bike or walking enjoy non-motorized modes in addition to the low cost. The occurred shift to the AVs from the non-motorized modes appeared because of those travellers who travelled long distances, for example 2 h walking in one trip. The previous simulations that are mentioned in Table 5 were conducted by using *Intel® Core*^{TM} I7-7500U CPU @ 2.70 GHz-2.9 GHz and 8 GB RAM laptop, and the simulations' average running times lasted for 18.5, 5.6, 7.4, and 6.5 h for Scenario 1, Scenario 2, Scenario 3, and Scenario 4, respectively. The number of the conducted iterations was 80 for Scenario 1 and 200 iterations for the others.

Another paradigm of using AVs is presented in this research, as well. The simulation of the activity chain plans was conducted with AVs to determine the required fleet size thus serving all the demand. In this new calculation, the transport modes in all daily activity plans were replaced by AVs. The results were defined as the required fleet size of AVs to serve all the demand, in which 3000 AVs were required for Scenario 1, 90 AVs for Scenario 2, 70 for Scenario 3, and 65 for Scenario 4. These fleet sizes were determined after several trials, and the acceptable waiting time (i.e., less than 10 min) controlled the fleet size. This concludes that a relatively small number of AVs can serve a large demand compared to conventional transport modes. The increase in the usage of AVs can be occurred due to the ease of traveling by AVs without needing a driving license, as an example. Additionally, the results demonstrated that an extra VMT was accompanied by the use of AVs, which leads to an increase in the fuel consumption and the depreciation of the infrastructure (i.e., the maintenance of the roads related to the usage of the roads). The simulations were conducted by using *Intel® Core*^{TM} I7-7500U CPU @ 2.70 GHz-2.9 GHz and 8 GB RAM laptop, and the simulations' average running times were 31.5, 5.5, 5, and 4 h for Scenario 1, Scenario 2, Scenario 3, Scenario 4, respectively. The number of the conducted iterations in this paradigm ranges from 100 to 350 iterations.

4. Discussion

The travel behaviour of people toward the presence of AVs is evaluated in this study. The evaluation consists of, first of all, the evaluation of the current travel behaviour by simulating the daily activity plans of the travellers, and second, the examination of the impacts of AVs among certain groups of users when AVs are introduced into the market. 4 scenarios were presented, where Scenario 1 includes the behaviour of all travellers while Scenario 2, Scenario 3, and Scenario 4 consist of the behaviour of three groups of users. In studying the travel behaviour, both the conventional transport modes and AVs were simulated separately and then together. In the simulation, several variables that impact the travel behaviour, such as the road capacity factors, the fleet size, the speed, the acceptable waiting time, the travel distance, and the distribution of AVs on the network, were considered. The results of the simulations demonstrated differences among the groups regarding AV usage. Moreover, in line with the concept of the utility function, the traveling ((dis)utility) is improved in case of AVs because the VOT was smaller than the conventional cars'. Furthermore, other factors pertaining to the traveller preference, such as arrival time and travel distance or time impact the improving the travel utility by using fast and cheap transport mode.

3 simulations were conducted for each scenario, a simulation of the existing conditions, and 2 simulations with the presence of AVs on the market with two penetration levels, i.e., the 10 and the 20% of the demand. Scenario 1 simulated all travellers, in which the travel behaviour measures were presented, such as 33 min was the average trip time per traveller. The results demonstrated a travel time reduction compared to the average trip time of the existing conditions due to the shift to the AVs. Scenario 2 simulated the long commuters with high-income, where the average trip time was 46 min per traveller, and it decreased when AVs entered the market. The largest shift to the AVs was in this group of users, which concludes that as travel time increases the shift to AVs increases considering the smaller VOT of AV than the car. In Scenario 3, the average trip time was 33 min per traveller, and it decreased when AVs were introduced into the market because of the occurred shift to the AVs from other modes of travel. In Scenario 4, the part-time workers were simulated, and the average trip time was 38 min per traveller. The average trip time decreased when AVs were used due to the occurred shift to the AVs. The reduction in the average trip time comes from the removed parking time, the minimized travel delay, the removed access and egress times (i.e., AV is a door-to-door service), and the percentage of users who shift from slower transport modes to faster modes or AVs, as a result of introducing the new mode to the market.

In all scenarios, the results of the simulations showed a large shift to the AVs, which means the travellers were attracted to the AVs more than to the conventional transport modes, especially, cars. The large shift is justified by several factors, for instance, the VOT of using AVs was evaluated less than that of the conventional cars, where the score was evaluated as the highest. It is worth mentioning that the variations in the results of the simulations between the scenarios refer to the variations in the characteristics of each scenario, for example a larger shift (i.e., 47.5%) to AVs was demonstrated in Scenario 2, while the lowest was in case of Scenario 3. Furthermore, the simulations showed a considerable shift from public transport to AVs because some travellers received the highest utility when they shifted to AVs. The new modal share did not show large differences in the bike and the walking modes compared to the original modal share (Figures 4 and 8). Practically, the users of the bike and the walking modes usually optimize their daily activities based on different factors, such as health, than those who choose motorized modes. While the motorized modes are normally selected based on the availability of car or public transport, weather, cost, and travel time. The obtained small shift from non-motorized modes to the AVs were justified based on the pre-set criterion of the simulations about the maximum walkable distance (i.e., 800 m) as well as a small percentage of the travellers reported long walking distances in their daily activity plans. Moreover, the changes in the arrival and departure times of a traveller (see the re-planning step) determine the use of a specific mode based on the obtained utility (see the scoring step). For instance, in Scenario 2 the decrease in the modal share of walking was caused by the travellers who reported long time walking, such as a 2 h walking time. Additionally, the simulation demonstrated that the shift to AVs does not follow a linear relationship with the fleet size of AVs since the shift was already relatively high when the AVs fleet size was 10% and did not change dramatically when the fleet size of AVs became 20% (Figure 8).

Furthermore, the availability of idle AVs affects the usage of AVs because the travellers will schedule their travel based on such preferences as departure time and arrival time. Additionally, increasing the larger fleet size of AVs enhances the quality of the service to the travellers rather than to the operators because travellers tend to have as small waiting time as possible. The waiting time is an important factor that affects the usage of AVs in addition to other factors, such as sharing acceptability and service trust. The waiting time is controlled by the fleet size, as the fleet size is increased, the waiting time is decreased, as demonstrated in Tables 3 and 4. Therefore, in the future, the operators should consider the waiting time when operating AVs because the willingness of people to use AV depends on the quality of the service that is connected to the available fleet size, where one of the quality indicators is having as small waiting time as possible. The changes in the modal share are not affected only by the fleet size of AVs but by other factors, too, such as the VOT of the travellers, the time preferences regarding the time schedules of the individuals and the activities.

The results of the simulations demonstrated that as the fleet utilization increases, the extra driven distance decreases. Additional AVs on the market lead to a smaller number of served orders per AV, while the high utilization ratio leads to more profit for the operators and gives an indication of the efficiency of the AV fleet size. Additional VMT is not preferable because it increases the energy consumption, the deterioration of the roads, and the depreciation of the vehicles. AVs remove the parking time, which was 9 min for conventional car travellers that were estimated from the travellers' records. This advanced technology (i.e., AV) decreases the delay generated from human behaviour and traffic congestion. Additionally, the AVs will enhance the safety, the comfort, the privacy, and other features, which make the travel time more productive and enjoyable. Additionally, the fleet size of AV that is required to serve each demand of the four scenarios was determined considering the average waiting time is not more than 10 min. The results demonstrated that the demand can be served with a smaller fleet of AV compared to conventional car.

The indirect consequences of using AVs can be realized from this study. AVs decrease the travel time for the travellers based on the locations of the travellers and their destinations as well as the traffic condition, which is affected by the time of the travel during the day. The decreased number of vehicles on the street and the reduction of using the parking spaces will influence the price of the properties in the urban areas and converting many parking spaces to serve other useful aims, such as into public spaces. Budapest is classified as a historic city where a lot of buildings do not have parking garages, and widening the streets is not a solution to satisfy the increasing demand of the travellers. Moreover, taxes and fees should be applied to parking and driving to discourage people from using cars in the city centre. The AVs will provide a solution for the parking areas and narrow roads as well as might motivate people to redistribute the existing urban formation at the city centre. In this study, the AVs were assumed to be parked at the last place after the last traveller is served when there was no call to pick up a traveller.

Future works are included in this section. Parking was not included in this study due to the absence of suitable data to provide the minimum requirement of input data to *MATSim*, but it is recommended to be examined in a further study. The fleet size of AVs is affected by the number of people who request an AV before a certain time, for example travellers can order an AV for 8:00 AM of the following day, and the AVs have to consider this (i.e., pre-bookings), which means that the AVs should be available with priority to those who booked earlier. Pre-booking was not simulated in this paper because currently, *MATSim* does not support it, but it is an interesting concept, which should be elaborated on in the future. AVs will affect the choice of the locations of the people, which means the travel distance will increase with similar travel times, and people will tend to buy houses in areas further from their destinations if they can reach their activity locations within the same travel time. However, studying the impact of AVs on the land use and the relocation of the people's places is still a hot topic. Studying the impacts of AVs on the location choice requires to expand the knowledge about the impacts of AVs on both the short- and the long-term future. For example, the saved parking places can be obtained within a short term, while the travellers' housing relocation can be obtained within a long term. The analysis of AVs still needs more research and different methods in predicting the implications of AVs on the mobility of people and the surrounding environment until it appears on the market (i.e., empirical studies are needed).

Conclusions

The simulation of the daily activity chain plans of the different types of people in the presence of future technology (i.e., AV) was conducted. Previous studies focused on studying the impacts of AVs on people in general through simulations, while this study examined the impact of AVs on different groups of users. In this research, a large-scale open-source agent-based simulation model was used to study the impacts of AVs on the travel behaviour of people in general and on three selected groups, which are more likely to use the AVs in the future. To simulate the activity plans of the travellers based on flexible functions, the *MATSim* software tool was chosen because it has the power to apply a co-evolutionary algorithm. The introduction of AVs into the market was examined through two cases, first, with a penetration of 10% of the demand, and second, with the 20% penetration of the demand. The study included four scenarios with the following groups of people: all travellers, long commuters with high-income, elderly people who are retired, and part-time workers. The scenarios were examined through simulations, in which different variables were assessed, such as the modal share, the waiting time, an additional VMT, the AV fleet utilization, the travel time, and the travel distance. The results demonstrated differences between the groups of people when AVs were introduced, as shown in the new developed modal share. The differences in the characteristics of the travellers definitely affect the travel behaviour, which is manifested in the result of the four scenarios. The VOT, the travel cost, and the fleet size of AVs were the main determinants that participate in either encouraging the acceptance of AV as a new transport mode or not. As a result, it can be stated that the availability of AVs is expected to decrease the usage of conventional cars and public transport and will slightly impact the non-motorized modes. The percentage of the travellers who shifted to AVs increased slightly when the fleet size of AVs increased from 10 to 20%. This leads to the conclusion that the determination of the fleet size of AVs is important for both the operator and the travellers since providing a larger fleet size than the required increases the satisfaction of the travellers, while the utilization ratio of the AV fleet decreases significantly, which causes an unsustainable situation for the fleet operator due to the increase in the operating cost. Additionally, the fleet size of AVs, in which a full replacement for the conventional transport modes was determined. The output of this study can be fruitful for policy-makers, urban planners, transport modes operators, and vehicle manufacturers.

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