https://doi.org/10.3311/PPtr.20655

Periodica Polytechnica Transportation Engineering, 51(2), pp. 126–132, 2023

Analysis of the Emergence of Autonomous Vehicles Using Simulation-based Dynamic Traffic Assignment – The Case of Budapest

Anas Alatawneh[1], Mohamad Shatanawi[1], Ferenc Mészáros[1*]

[1] Department of Transport Technology and Economics, Faculty of Transportation Engineering and Vehicle Engineering, Budapest University of Technology and Economics, Műegyetem rkp. 3, 1111 Budapest, Hungary
[*] Corresponding author, e-mail: meszaros.ferenc@kjk.bme.hu

Received: 15 June 2022, Accepted: 09 January 2023, Published online: 20 January 2023

Abstract

Traffic and transport researchers, policymakers, and vehicle manufacturers are interested in investigating the implications and the influence of autonomous vehicles (AV) because a gradual deployment of such new technologies is expected to take place in the future. This research investigates the impacts of the AVs emergence on traffic performance for the city of Budapest in three future traffic scenarios with different AV market replacement rates for the year 2030. The network was modeled using simulation-based dynamic traffic assignment in PTV Visum software. Four traffic performance parameters were analyzed to explore the impacts of AV's emergence on the network. The results showed noticeable improvements among the four investigated traffic performance parameters.

Keywords

autonomous vehicles, modelling, simulation-based, dynamic traffic assignment

1 Introduction

The first attempts to produce autonomous vehicles (AVs) were not meant for public use but for private road competitions such as the DARPA challenge (Ozguner et al., 2007). Currently, it can be seen that the idea is well-shaped and known to the public, seeing many high-level automated cars crossing highways. Waymo's vehicles, for example, have crossed over 2 million miles autonomously since they were launched in 2009 as Google's self-driving cars project (Muoio, 2017). Litman (2022) predicts that by 2025 AVs will be safe and reliable to drive, and the following few years will be needed for testing this technology and setting its regulations and restrictions. Therefore, AVs are projected to be available to the public and legitimized by 2030, and a transition from conventional vehicles to AVs is expected. Thus, it would be essential to smoothen the such transition to the extent that it serves the best experience for both users and operators.

AVs have a potential impact on influencing individual driving and the overall traffic network. AVs, for example, are expected to provide a high level of safety for road users (i.e., drivers, passengers, and pedestrians) and reduce vehicle crashes as the adverse effects of human driving will be reduced to the absolute minimum (Fagnant and Kockelman, 2015; Nadafianshahamabadi et al., 2021). Besides safety, AV integration will also benefit traffic network congestion due to their quick reaction time and complete comprehension of the surrounding environment compared to human-driven vehicles. Low reaction time will result in a less following distance between vehicles, and vehicles will move closer to each other. So, road capacity might be improved operationally without infrastructural extensions. On the other hand, the associated benefits of AVs will increase accessibility for more people (e.g., kids and people with disabilities) and vehicle distance traveled due to eliminating the responsibility of driving (Simoni et al., 2019). This increment at a certain level may increase congestion, raising the need for advanced demand management schemes e.g., dynamic road pricing (Shatanawi et al., 2021; 2022a; 2022b; Simoni et al., 2019).

This study investigates the change in traffic performance resulting from different replacement rates of privately owned passenger vehicles to privately owned AVs in Budapest in 2030. Three replacement rates were chosen to reflect the uncertainty of this technology's adoption rate:

1. relatively low private AVs uptake,
2. relatively high share of AVs, and
3. full AVs emergence.

Cite this article as: Alatawneh, A., Shatanawi, M., Mészáros, F. (2023) "Analysis of the Emergence of Autonomous Vehicles Using Simulation-based Dynamic Traffic Assignment – The Case of Budapest", Periodica Polytechnica Transportation Engineering, 51(2), pp. 126–132. https://doi.org/10.3311/PPtr.20655

These three scenarios were compared to the base scenario of the year 2030 for Budapest and the surrounding area, which was forecasted, calibrated, and validated by the Centre of Budapest Transport (BKK). The simulations in this research were performed during the morning peak period using simulation-based dynamic traffic assignment (SBA) in the traffic macroscopic simulation software Visum. Highly but not fully automated vehicles were considered in this research to avoid the demand shift that would be influenced from other modes of transport (e.g., conventional vehicles and public transport) to automated cars.

The remainder of this paper is structured as follows: Section 2 covers the case study and the data used in this research. Section 3 describes the framework of this research paper, including the process of applying SBA to the model. Section 4 presents the results of analyzing the four transport performance parameters (TPPs), and Section 5 highlights the conclusion.

2 Case study and data

Budapest is the capital of Hungary and its most populated city, with a population of over 1.7 million and a land area of 525 km^2 (HCSO, 2021). The transport network of the city and the surrounding area, see Fig. 1, is macroscopically modeled through the so-called Unified Transport Model (EFM) by the BKK in Visum software. It contains over 30,000 links with their traffic parameters (i.e., speed, number of lanes, permitted vehicle types, among others), over 15,000 nodes, and 1200 zones. The model was created and calibrated based on an extensive analysis of the traffic status in 2014, considering various aspects such as demographical, social, and economic factors. Moreover, the EFM model provides a forecasted demand for 2030 with 2.23 million daily private transport trips; this projected demand was utilized in this research's simulation process. To obtain this future demand, the developers of the model (BKK, 2020) applied the traffic forecasting equation, illustrated in Eq. (1):

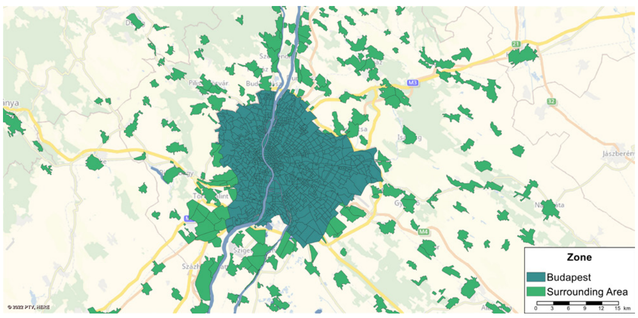

Fig. 1 Simulation area including Budapest network and its surroundings

$$C_t = s\Big/\left(1+\left(\left(S-C_0\right)/C_0\right)\times e^{-g_0\times S\times t/\left(S-C_0\right)}\right), \quad (1)$$

where C_t is motorization level of a specific year; S is automobile saturation level; C_0 is the level of motorization of the predefined base year, g_0 is a growth factor, and t is the number of years between the forecasted and the base year. Moreover, the EFM model was calibrated using the data of over 240 cross-sections distributed throughout the city to imitate the actual network behavior with a modest margin of error. The Geoffrey E. Havers (GEH) function was utilized to define the accepted tolerance between the modeled and actual flow. As the EFM model was calibrated on the static assignment method, new calibration was performed when altering to SBA to ensure the stability of the model. Similar to the BKK calibration, an acceptable tolerance limit of value 5 in the new calibration was achieved according to the GEH function.

The transport and traffic network of Budapest was modeled in Visum software. Visum is a global traffic planning software widely known and used by transport professionals. It can perform a macroscopic digital replica of mobility, land use, and socio-demography to gain a deeper insight into the challenges of today and the future (i.e., what-if scenarios). It can also model and simulate the behavior of various advanced transport modes such as automated vehicles. Considering these features and the availability of the EFM model in Visum software, this study was performed using it.

This research studies Budapest's 2030 transport network and traffic demand and the surrounding areas during the morning peak from 05:00-10:00, containing 36% (i.e., +800 thousand trips) of Budapest's total daily private transport demand. The morning peak was chosen as it has the highest share of the daily trips in Budapest, representing the worst-case scenario.

For more information about the EFM model and Visum Software, see (BKK, 2020; PTV Group, 2021).

3 Methodological approach

This section presents the framework to model the effect of various replacement rates of human-driven passenger cars by AVs in the mid-size city network. As AVs drive themselves with the ability of automated speed and tighter headways, a link capacity would increase (van den Berg and Verhoef, 2016). Therefore, capacity is considered the controlling factor in modeling AVs in this research via a simplified car-following model. The well-known four-step modeling was adopted in this study because it is often applied for predictions of long-term scenarios (Levin and Boyles, 2015). The fourth step of the four-step planning model (i.e., traffic assignment) is then defined with its controlling parameters as the SBA in this research. Factors related to the model run (e.g., termination conditions and additional iterations) control the overall computing process. After running the model and producing the results, analysis is performed, and findings are discussed.

3.1 Scenarios

This study investigates the impact of replacing different ratios of private travel demand with privately owned AVs on traffic performance. Because the future market share of AVs is still vague and will emerge gradually over time, a possible sequence of scenarios for introducing AVs into the Budapest network is adopted, according to Davidson and Spinoulas (2015). The three proposed scenarios representing different possibilities of AV emergence are: Scenario 1 is mixed traffic with one-third of the fleet being AVs, Scenario 2 replaces two-thirds of human-driven cars with AVs, and Scenario 3 considers complete replacement of human-driven cars by AVs. In all scenarios, AVs as highly automated vehicles, are all privately owned, and they are not allowed to drive while unoccupied.

The demand share of AVs replacing the demand share of passenger cars is described in Eq. (2) and Eq. (3):

$$d_{pc} = \left(1 - p_{\mathrm{AV}}\right) \times d_{\mathrm{total}} \tag{2}$$

$$d_{\mathrm{AV}} = p_{\mathrm{AV}} \times d_{\mathrm{total}} , \tag{3}$$

where d_{pc} and d_{AV} are the demand assigned to human-driven passenger cars and AVs, respectively, d_{total} is the total demand in the network, and p_{AV} is AV replacement rate.

3.2 AV modeling using SBA

Budapest transport model has six private transport systems, i.e., passenger car, bicycle, and four types of cargo vehicles. The main focus of this study is to model AVs as a new transport system and examine their impact on traffic performance using SBA. The AV impact on transport operation is mainly described by the reduction in network saturation caused by a lower following distance (Torok et al., 2018). There are also other factors contributing to this impact such as level of automation, Car-to-Car (C2C) and Car-to-Infrastructure (C2X) communications, shorter gap for lane changing, and shorter walking and parking time (Obaid and Torok, 2021). Nevertheless, for each network segment, SBA can determine network saturation level, C2C and C2X communications, and level of automation compared to conventional passenger cars. In this study, such network segments are referred to as "AV-ready".

In SBA, loading the network is carried out by a simulation with a simplified car-following model. That means the following behavior depends not only on the vehicle itself but also on the vehicle in front. This option is possible by the link attribute "SBA reaction time factor" in Visum. A human-driven car in normal circumstances will have an SBA reaction time factor of 1. The lower the factor value means that vehicles can drive close to each other because of the lower reaction time needed to brake. For example, if an SBA reaction time factor of link (A) was 0.7 for all its transport systems, and the SBA reaction time factor of a link (B) was 1.2, and both links have the same specifications (i.e., number and dimensions of lanes, speed limit, etc.), then the capacity of link (A) would be larger than the one of link (B) as vehicles drive in tighter headways. However, the SBA reaction time factor considers only one value for all transportation systems in the network. In this case, the more detailed link attribute "SBA is reaction time factor transport system dependent" is used, which allows for different reaction time values for different vehicle combinations. For example, if an AV is following another AV, the headway will be smaller than if the followed vehicle was a conventional one.

Three different categories were adopted considering the different combinations of private transport systems. This classification was developed depending on the fact that the lower the SBA factor value results in a larger capacity on the link. (Simoni et al., 2019) used a 1.5 capacity increment factor when modeling fully automated vehicles, in SBA, this can be interpreted into a reaction time factor using the SBA capacity equation (PTV Group, 2021), as shown in Eq. (4):

$$C = l\frac{3600}{d};\ \text{where } d = r + \frac{e}{v} , \tag{4}$$

where C is capacity as calculated in SBA [veh/h], l is the number of lanes, d is temporal headway [s], r is factored SBA reaction time, e is factored SBA effective vehicle length [m] (default value = 7 m), and v is link permitted speed [m/s]. With Eq. (4), increasing the capacity by 1.5 times the original capacity (with the other factors being constant) would reduce the SBA reaction time factor by 0.5. Table 1 illustrates these categories and shows that the SBA reaction time factor values are the lowest in case both combination's vehicles are autonomous. This is mainly because braking requires a shorter reaction time, implying tighter headways and larger link capacity. If the leading vehicle is not autonomous, the ‚SBA reaction time factor' value increases to 0.65 between other transport systems (TSys) followed by AV and to 1 in case the leading and the following vehicle are not AV.

3.3 SBA parameters and factors

SBA models use a traffic simulator to dynamically model complex traffic flow, which helps design operating solutions for real-time implementation. For more in-depth literature, refer to Mahmassani (2001); Matalqah et al. (2022); Peeta and Mahmassani (1995); Peeta and Ziliaskopoulos (2001) and Shatanawi and Mészáros (2022). The process of deploying SBA can be divided into three main parts: network, demand, and SBA parameters.

Network: the EFM model of Budapest is an independent, continuously maintained, and regularly updated macroscopic model that forecasts future transport changes and developments in Budapest and the area around it. In this step, all network segments were modified to be AV-ready to distinguish the features of each transport system separately.

Demand: the EFM model was created based on the demand share of the total volumes. In other words, a percentage share of the total demand was specified for each time interval, e.g., morning peak and evening peak. From 05:00 to 10:00 am, the morning time interval was defined as the analysis period (AP) in this research. This partially long period will provide this project with more stable results than choosing a shorter one. It is essential to define the AP in this step to be used afterward in the assignment procedure.

SBA parameters: the SBA assignment procedure in Visum consists of various fundamental parameters and factors that control the results of the assignment. At first, the "Termination conditions" define when the assignment stops. There are two main conditions; once one of them is achieved, the assignment will end, namely the *Maximum number of iterations* and *maximum gap*. The higher the iteration number, the more statistically reliable the results; however, it is a trade-off with the computational time. The *maximum gap*, on the other hand, is a well-known approach that defines the level of tolerance. The reliability of a solution obtained using an SBA model is calculated by determining the deviation in volume pattern in each iteration and comparing it to a predefined tolerance rate (Ahmed, 2015). The tolerance threshold determines the amount of error tolerated in the final solution. While a lower tolerance level is optimal, it will significantly increase the computational time. In this research, a *maximum gap* of 0.03 was used. If the maximum gap was reached, but not all cars could leave the network, the termination condition might not be fulfilled. Therefore, and in addition to the two main termination conditions, the *maximum number of additional iterations* can be predefined and calculated to guarantee that all vehicles exited the network if any were left after the last iteration.

The *Assignment Time Interval* parameter is defined to determine which time slot should be calculated in the assignment. Peak hours are often investigated as they provide the worst-case scenario; as mentioned earlier, this study adopted the period from 05:00 to 10:00 am.

Table 1 Categories of SBA reaction time factor

Category No.	Transport system combination		SBA reaction time factor
	Leading vehicle	Following vehicle	
1	AV	AV	0.5
2	Other TSys	AV	0.65
3	Other TSys	Other TSys	1

4 Results

This section discusses and compares the impact of AVs emergence on four traffic performance parameters (TPPs) in the different proposed future traffic scenarios. The investigated TPPs are delay, traffic density, queue length, and link speed.

4.1 Delay

In SBA, the delay is calculated from the travel time in the network without volume (t_0), taking SBA length and first-in-first-out (FIFO) t_0 functions into account, and from travel times with volume (t_{Cur}) calculated from the FIFO t_{Cur} functions that are intersected to the analysis time intervals (PTV Group, 2021). A total delay reduction of 6.5% occurred when replacing 33.3% of the human-driven vehicles with AVs and further decreased by nearly six times when AVs replacing 67.7% of Budapest's private cars fleet. Moreover, a full AV replacement rate (i.e., 100%) eliminated 58.7% of the total delays. Fig. 2 illustrates the total reduction in delay distributed between the different

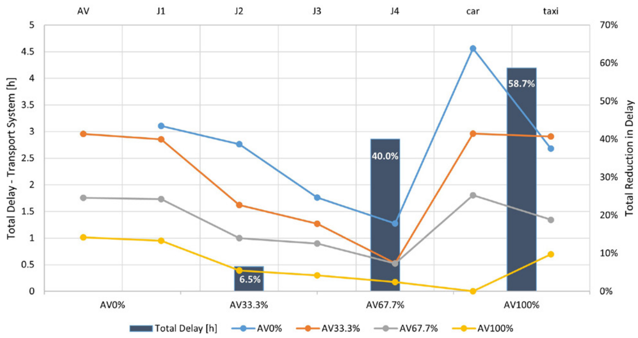

Fig. 2 Total reduction in network delay and total delay for each transport system during the analysis period

transport systems in the city due to the integration of AVs into the Budapest network.

The delay for different transport systems showed that the reduction in the total delay follows an S-shaped curve depending on the AV replacement rate applied, which is divided into three stages:

1. slow increment in the reduced delay percentages with increasing AV replacement rate from 0% to 33.3%,
2. fast increase in the reduction percentage of the total delay while altering AV replacement rate from 33.3% to 67.7%, and
3. slower growth in the delay compared with stage 2 between 67.7% and 100% replacement rates of AVs.

4.2 Traffic density

SBA density in Visum is the average number of vehicles per km per lane [veh/km]. The five-hour simulation time interval was divided into 30-minutes subintervals to explore the dynamic influence of AVs on the average density as they enter the network. As illustrated in Fig. 3, the average traffic density in all scenarios continued to rise during the investigated period to reach 31 [veh/km] in the base scenario; however, the increment pace was lower

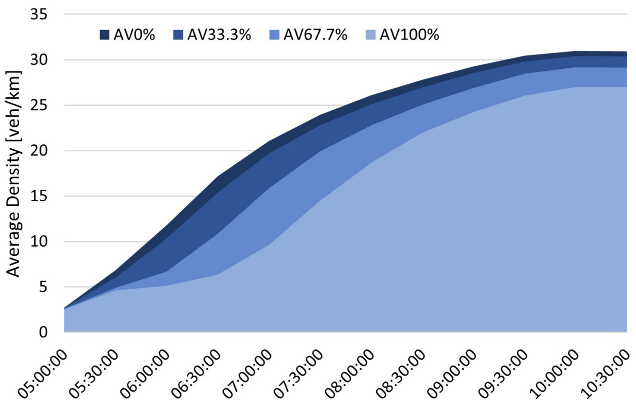

Fig. 3 Average density over the 5-hour time interval

when the fleet consisted of AVs. Increasing the AV replacement rate up to 33.3%, the average density decreased by more than 4%. Moreover, 67.7% and 100% share of AVs would reduce the average density by approximately 16% and 30%, respectively, compared to the base scenario.

4.3 Queue length

One of the advantages of dynamic assignments is that queue lengths can be examined and, thus, compared with other scenarios. SBA is able to handle queues dynamically and pass on congestion to the next time interval (or if it was the last ATI, the queue will dissolve using the extension time interval) and provide a better way to estimate the total delay.

An examination of the average and summation of queues in each scenario is illustrated in Fig. 4. It can be noticed that the greater the AV replacement rate is, the lower the average queue length would be. The reduction in queue length is not linear; when replacing AVs at a 33.3% rate in the Budapest network, the average queue length was reduced by 2.4% compared to the base scenario. However, between AV33.3% and AV67.7% scenarios, the total reduction in average queue lengths was 9%, and 20% reduction was observed between AV67.7% and AV100% scenarios. The full emergence of AVs into the Budapest transport network would eliminate approximately 430 km of total queues in the city, resulting in a less congested area.

A visualization of queues is presented in Fig. 5, showing the distribution of queues in the AV100% scenario (blue color) during the 08:00-08:30 subinterval. The congestion is distributed across the network in different links; however, no congested area (several links in a place) was spotted. Fig. 5 also compared queue lengths between AV100% and base scenarios. The width of the green bars represents the length of the eliminated queues because of AV emergence, while the red color means that the queue

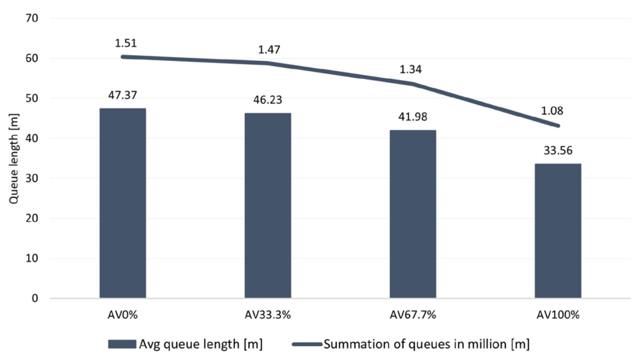

Fig. 4 Average and summation of queues across the four scenarios

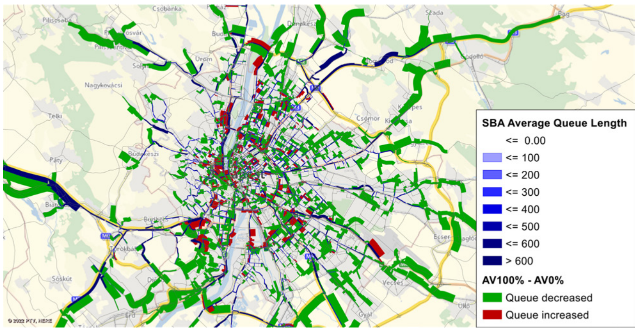

Fig. 5 Visualization of queue length in AV100% scenario and the difference with AV0.0%

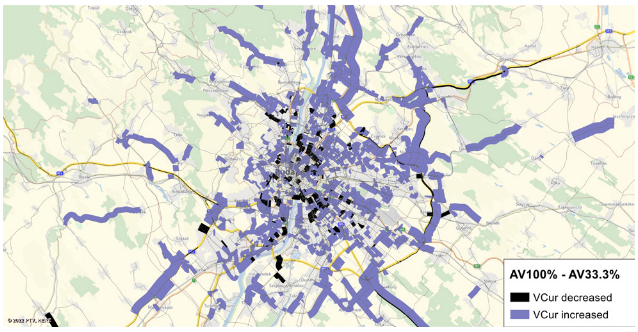

Fig. 7 AV travel speed difference between AV100% and AV33.3% scenarios

length has increased. The green color is dominant; however, it is also seen that the red color is mainly observed in the downtown area more than outside, yet in small values and only a few links experienced long queues compared to the base scenario.

4.4 Link speed

Link speed (V_{cur}) mainly depends on density and volume. Once a link has a high volume, then the density will increase, resulting in a decrement in travel speed according to the fundamental equation of traffic stream flow.

The impact of integrating AVs on the network has a positive influence in general (e.g., density and delays), meaning that travel speed is also expected to be positively affected. In Budapest, the deployment of AVs with different replacement rates increased travel speed whenever the AV's market share went up. Fig. 6 represents a visualization that compared the travel speed between AV100% and AV67.7% scenarios. It is noticeable that the purple color is dominant, meaning that the increment in travel speed is higher in the AV100% scenario. On the other hand, the downtown area of Budapest is experiencing an increment in queue length, resulting in a decrement in average link speed.

Fig. 7 reveals the differences between AV100% and AV33.3% in terms of AV travel speed. The average travel speed in the AV33.3% scenario for automated cars was spotted at 31.00 [km/h], while in AV100% is expected to reach 31.18 [km/h]. Furthermore, comparing Fig. 6 and Fig. 7 showed that the variation in speed between the AV100%–AV33.3% is greater than between AV100%–AV67.7%, which means that increasing the percentage of AVs in the network would result in higher speed until reaching a point where the supply cannot serve the demand, causing an opposite effect to the network.

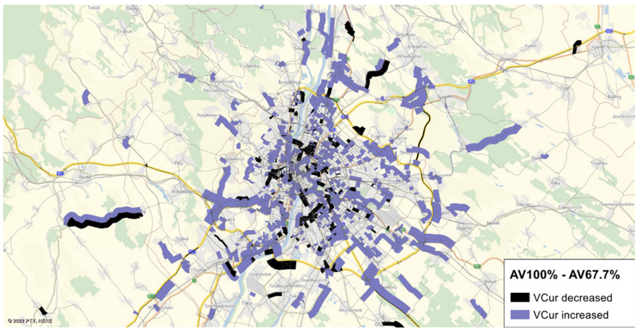

Fig. 6 AV travel speed difference between AV100% and AV67.7% scenarios

5 Conclusion

This research deployed SBA to incorporate AVs into the Budapest traffic network to predict the impact of AVs on TPPs. It can be concluded that cities with similar factors as this study's case can benefit from AVs to improve traffic performance. This study also illustrated that using the reaction time factor in simulation-based dynamic traffic assignment for implementing AVs would primarily control (i.e., increase) link capacity, which in return would decrease traffic congestion. Table 2 summarizes the differences in these attributes among the four developed scenarios in this paper.

Acknowledgment

Both PTV Group and the BKK generously provided their full technical support in order to bring the best out of this research. The research was supported by OTKA - K20 - 134760 - Heterogeneity in user preferences and its impact on transport project appraisal led by Dr. Ádám Török.

Table 2 Summary of traffic performance parameters TPPs

	Reduction in total delay	Reduction in density	Reduction in queue length	Change in AV speed
Compared with	Base scenario			Previous scenario
AV0.0%	-	-	-	-
AV33.3%	6.5%	4.44%	2.40%	-
AV67.7%	40%	16.47%	11.37%	+0.59%
AV100%	58.7%	29.93%	29.14%	+4.10%

References

Ahmed, A. (2015) "Integration of Real-time Traffic State Estimation and Dynamic Traffic Assignment with Applications to Advanced Traveller Information Systems", [pdf] PhD Thesis, University of Leeds. Available at: https://core.ac.uk/download/pdf/30268362.pdf [Accessed: 12 March 2022]

BKK (2020) "Egységes forgalmi model" (Unified traffic model) [online] Available at: https://bkk.hu/fejlesztesek/egyseges-forgalmi-modell/ [Accessed: 12 March 2022] (in Hungarian)

Davidson, P., Spinoulas, A. (2015) "Autonomous Vehicles - What Could this Mean for the Future of Transport?", [pdf] In: AITPM 2015 National Conference, Brisbane, Qld, Australia, pp. 1–15. Available at: http://transposition.com.au/papers/AutonomousVehicles.pdf [Accessed: 08 March 2022]

Fagnant, D. J., Kockelman, K. (2015) "Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations", Transportation Research Part A: Policy and Practice, 77, pp. 167–181.
https://doi.org/10.1016/j.tra.2015.04.003

HCSO (2021) "Területi Statisztikai Évkönyv, 2020 / Regional Statistical Yearbook of Hungary, 2020", [pdf] Hungarian Central Statistical Office (HCSO), Budapest, Hungary. Available at: https://www.ksh.hu/docs/hun/xftp/idoszaki/evkonyv/teruleti_evkonyv_2020.pdf [Accessed: 12 March 2022] (in Hungarian and in English)

Levin, M. W., Boyles, S. D. (2015) "Effects of Autonomous Vehicle Ownership on Trip, Mode, and Route Choice", Transportation Research Record: Journal of the Transportation Research Board, 2493(1), pp. 29–38.
https://doi.org/10.3141/2493-04

Litman, T. (2022) "Autonomous Vehicle Implementation Predictions: Implications for Transport Planning", [pdf] Victoria Transport Policy Institute, Victoria, BC, Canada. Available at: https://www.vtpi.org/avip.pdf [Accessed: 05 September 2022]

Mahmassani, H. S. (2001) "Dynamic Network Traffic Assignment and Simulation Methodology for Advanced System Management Applications", Networks and Spatial Economics, 1(3–4), pp. 267–292.
https://doi.org/10.1023/A:1012831808926

Matalqah, I., Shatanawi, M., Alatawneh, A., Mészáros, F. (2022) "Impact of Different Penetration Rates of Shared Autonomous Vehicles on Traffic: Case Study of Budapest", Transportation Research Record: Journal of the Transportation Research Board, 2676(12), pp. 396–408.
https://doi.org/10.1177/03611981221095526

Muoio, D. (2017) "RANKED: The 18 companies most likely to get self-driving cars on the road first", INSIDER, Sep., 27. [online] Available at: https://www.businessinsider.com/the-companies-most-likely-to-get-driverless-cars-on-the-road-first-2017-4#7-waymo-12 [Accessed: 08 March 2022]

Nadafianshahamabadi, R., Tayarani, M., Rowangould, G. (2021) "A closer look at urban development under the emergence of autonomous vehicles: Traffic, land use and air quality impacts", Journal of Transport Geography, 94, 103113.
https://doi.org/10.1016/j.jtrangeo.2021.103113

Obaid, M., Torok, A. (2021) "Macroscopic Traffic Simulation of Autonomous Vehicle Effects", Vehicles, 3(2), pp. 187–196.
https://doi.org/10.3390/vehicles3020012

Ozguner, U., Stiller, C., Redmill, K. (2007) "Systems for Safety and Autonomous Behavior in Cars: The DARPA Grand Challenge Experience", Proceedings of the IEEE, 95(2), pp. 397–412.
https://doi.org/10.1109/JPROC.2006.888394

Peeta, S., Mahmassani, H. S. (1995) "Multiple user classes real-time traffic assignment for online operations: A rolling horizon solution framework", Transportation Research Part C: Emerging Technologies, 3(2), pp. 83–98.
https://doi.org/10.1016/0968-090X(94)00016-X

Peeta, S., Ziliaskopoulos, A. K. (2001) "Foundations of Dynamic Traffic Assignment: The Past, the Present and the Future", Networks and Spatial Economics, 1(3–4), pp. 233–265.
https://doi.org/10.1023/A:1012827724856

PTV Group (2021) "PTV Visum Online Manual", [online] Available at: https://cgi.ptvgroup.com/vision-help/VISUM_2021_ENG/Content/TitelCopyright/Index.htm [Accessed: 12 March 2022]

Shatanawi, M., Ghadi, M., Mészáros, F. (2021) "Road pricing adaptation to era of autonomous and shared autonomous vehicles: Perspective of Brazil, Jordan, and Azerbaijan", Transportation Research Procedia, 55, pp. 291–298.
https://doi.org/10.1016/j.trpro.2021.06.033

Shatanawi, M., Alatawneh, A., Mészáros, F. (2022a) "Implications of static and dynamic road pricing strategies in the era of autonomous and shared autonomous vehicles using simulation-based dynamic traffic assignment: The case of Budapest", Research in Transportation Economics, 95, 101231.
https://doi.org/10.1016/j.retrec.2022.101231

Shatanawi, M., Hajouj, M., Edries, B., Mászáros, F. (2022b) "The Interrelationship between Road Pricing Acceptability and Self-Driving Vehicle Adoption: Insights from Four Countries", Sustainability, 14(19), 12798.
https://doi.org/10.3390/su141912798

Shatanawi, M., Mészáros, F. (2022) "Implications of the Emergence of Autonomous Vehicles and Shared Autonomous Vehicles: A Budapest Perspective", Sustainability, 14(17), 10952.
https://doi.org/10.3390/su141710952

Simoni, M. D., Kockelman, K. M., Gurumurthy, K. M., Bischoff, J. (2019) "Congestion pricing in a world of self-driving vehicles: An analysis of different strategies in alternative future scenarios", Transportation Research Part C: Emerging Technologies, 98, pp. 167–185.
https://doi.org/10.1016/j.trc.2018.11.002

Torok, A., Szalay, Z., Uti, G., Verebelyi, B. (2018) "Modeling urban autonomous transport system in Budapest", In: 8th International Scientific Conference CMDTUR 2018, Zilina, Slovakia, pp. 89–94. ISBN 978-80-554-1485-0 [online] Available at: https://www.researchgate.net/publication/340022955 [Accessed: 05 March 2022]

van den Berg, V. A. C., Verhoef, E. T. (2016) "Autonomous cars and dynamic bottleneck congestion: The effects on capacity, value of time and preference heterogeneity", Transportation Research Part B: Methodological, 94, pp. 43–60.
https://doi.org/10.1016/j.trb.2016.08.018