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Autonomous vehicle impact on improving road network vulnerability

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Abstract

Purpose: This study first presents a method to identify the parameters increasing road vulnerability on a macroscopic road network model. The second part exploresthe effect size difference of the analyzed attributes on network vulnerability through the implementation of different autonomous vehicles (AVs) penetrations and automation levels.

Methods: The road traffic network of Budapest, Hungary on PTV VISUM is studied by adopting a passenger car unit factor procedure to simulate the effect of AVs on road saturation. Five link parameters were used: length, distance from the centre, speed, number of lanes, and number of connectors. Network vulnerability was studied by simulating a combination of road elimination process with different passenger car unit values for AVs.

Results: The analysis found the number of road lanes is the most significant parameter, affecting the link criticality; followed by road length and distance from the centre. The analysis of four AV scenarios with different AV penetration and level of automation showed huge effect differences ranging from 3.50% for a simple AV automation level with low AV percentage to as large to 28.53% for a fully automated fleet.

Conclusions: AV implementation has proved efficient in reducing the amount of travel delays in the case of road failure. Finally, it was found that the number of lanes remained the most significant influencing parameter on travel delay. The main question is to discover the effect size difference of the analyzed attributes on network vulnerability through the implementation of different AVs penetrations and automation levels.

Keywords: Network vulnerability, Critical links, Macroscopic, Autonomous vehicles, Travel delay, Passenger car unit

1 Introduction

Road networks are vulnerable to disasters, natural and human-made alike (earthquakes, floods, protests, terror attacks and catastrophic accidents). Damage caused by disasters on a given set of network element can affect the operability of the whole transportation system. However, not all network components equally jeopardise the system. Typically, some elements are more critical to the network functioning than others. Critical network components are those whose loss produces the greatest effects on the system [37]. Identifying the most critical system components is most vital for rescue operations in the case of a disaster,and it is also crucial to maintain the operability of the network to diminish substantial social and economic losses [22]. The identification of critical infrastructure components (links and nodes) is a crucial factor in vulnerability analysis,as it can help to reinforce these components, prioritising their maintenance or construct new alternative parallel paths [7, 23]. The disorder and interruption of links can change the shortest paths between node pairs and increase the travel distance between them, resulting in higher travel time and delay.

Nowadays, new technologies of autonomous vehicles (AVs), cooperative intelligent transport systems (C-ITS), and intelligent driving can be the most significant measures to reduce disaster impacts on road transportation operability. Communications between AVs and infrastructure (vehicle-to-vehicle and

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vehicle-to-infrastructure) are valuable for identifying the traffic states of urban roads, providing more information for road conditions and intersection control [26, 41]. The exchanged information helps vehicles choose and perform the best available action to improve traffic operations [25]. However, little research has been conducted on the expected impact of connected AVs on road network vulnerability and how the network operates if roads are eliminated.

The present article aims to identify critical roads on a macroscopic road network by the road characteristics and traffic parameters on the operability of the whole network; such as length, distance from the centre, speed, number of lanes, and number of connectors. This can provide a useful tool to have more understanding of which road characteristics have a higher impact on the network vulnerability. The second part of the article discusses a simulation of the predicted impact of AVs on the vulnerability of the network by analysing the effect of different AV scenarios on network operability in normal conditions and if roads are eliminated. In order to achieve these objectives, a case study area of Budapest, Hungary, was taken as the base model for the study.

This article is structured as follows: Sect. 2 describes the literature concerning road network vulnerability studies and the impact of AV technologies on traffic. Section 3 explains in detail the methodology used. Section 4 presents and discusses the results established from the case study. Finally, in the conclusion section, the authors describe the study findings, its limitations, and future research recommendations.

2 Literature review

2.1 Vulnerability

Vulnerability studies perform two tasks: some evaluate the reduction of transportation network performance under discomposure, and identify critical components of the transportation network [19, 27]. The latter task is accomplished by assessing the decrease in network performance indices when a given component is eliminated in [15]. Expert assessment is applied by [10, 28]. García Palomares and his colleagues' study in Spain developed a methodological framework to evaluate the critical road sections in terms of travel time. Their analysis concluded that radial highways are the most critical links [12]. Akbarzadeh's team also studied road network vulnerability by analysing travel time change, showing that links connecting neighbouring clusters are the most critical ones compared to links with the highest congestion [1].

Gecchele et al.'s vulnerability study used an activity-based model to evaluate travel demand changes due to link closure, and identified link criticality utilising a set of vulnerability indicators [14]. Cui and Levinson compared the cumulative opportunity accessibility before and after removing freeway segments in an urban zone in their model. They found that critical links are near freeways or at a freeway segment [9]. Calvert and Snelder presented a Link Performance Index for Resilience (LPIR) indicator, which evaluates the resilience level of specific road sections in a more comprehensive road network [6]. Gauthier and his colleagues chose the increase in overall travel cost as a parameter to measure road network performance in the presence of disruptions [13].

Another key issue involved in critical road identification is predicting the traveller's behavioural responses to road failure. Road failure causes changes in travel time uncertainty and travel behaviour regarding the transport mode choice, travel route or cancelling the whole trip [34]. Drivers under travel time uncertainty tend to choose a dependable shortest path with more travel time saving and reduction of travel time variability, which may have the inverse effect in the case of a road failure, showing that shortest routes aren't always the best choice in travel time saving in case of road failure [7]. AVs connected with each other and with the infrastructure can help find better routes to reduce uncertainty in the case of road failure [26].

2.2 Connected autonomous vehicles

Many studies have been conducted focusing on the future impact of AVs on a road network. The studies examine the six different automation levels, exploring the effect of basic automation levels to fully automated vehicles [17, 33]. Another factor influencing the effect of AVs on a network is the percentage of AVs in the total traffic flow (AV penetration) [8]. Human driving factors in a traffic network are expected to be partially eliminated using innovative AV technologies, such as 360-degree cameras and sensors [38]. AV platooning showed a 60% reduction in gap time between vehicles, showing a significant improvement in road capacity and congestion reduction [24, 31]. Several other studies investigated the impact of AVs on a network using different parameters, including reaction, acceleration and deceleration, and traffic flow [16, 35, 36, 39].

Research on connecting AVs and the use of communication between the vehicle and other network elements (V2X: other vehicles, infrastructure and central traffic system) showed improvement on traffic flow stability, significantly smoothened the shock waves of traffic flow, reduced delay and road traffic emitted pollutants [5, 20, 25, 32]. Studies on intersections showed a significant drop in vehicle travel time and travel delay in a connected vehicle environment [3, 11]

The above studies focused on either studying the vulnerability of a network or estimating the impact of future

AVs on the road transportation network. In this research, a framework will be developed to find the critical components by the different traffic parameters of roads in a macroscopic road network, and predict how AVs will impact the vulnerability of the network.

3 Methodology

This section first describes the macroscopic model used; then the assumptions for AV parameter identification inside the model are discussed. Finally, the framework used to study the sensitivity of different roads and the effect of AVs on the network are described.

3.1 Model description

The Hungarian EFM (Egységes Forgalmi Modell, Uniform Traffic Model) implemented in the PTV Visum software was used to construct the model in this study. The origin-demand matrices in the EFM represent real-life traffic data for Budapest and external zones connected to the city. The model also contains private transport data matrices and public transport data matrices. Private traffic matrices include four different vehicle categories: cars, taxis, bicycles, and cargo vehicles divided into four other cargo subcategories. The model consists of more than 30,000 roads corresponding to the whole road network of Budapest, including main roads, collector roads, and residential streets. Figure 1 below shows the EFM model.

The assignment was performed using the PTV Visum equilibrium assignment process, in which the assignment distributes the trips in several steps according to Wardrop's first principle [40]. The equilibrium assignment analyses the vehicle volumes on each road by dividing the demand constantly over several iterations. The system then searches for alternative routes with lower impedance, where vehicles will be moved to new roads to improve network operability. The procedure terminates when a balanced state is reached, meaning no more vehicles are to be moved between routes [29].

From the EFM model, 1000 zones inside Budapest and smaller clustered zones around the city were studied, focusing on private transport only Since most of the chosen roads only operates for private vehicles and the ones that don't have their private public transport lanes (bus lanes). The sensitivity of the road network was measured by the change in the total delay time parameter of the network. The improvement caused by AVs is also shown by the travelled kilometres and

Table 1 EFM model base scenario traffic parameters

Parameter	Unit	Total value
Total travel time by cars	vehicle × hour/day	582,739
Total travel distance by cars	vehicle × km/day	30,750,166
Daily total volume of cars	vehicle/day	81,686,075
Total network delay	vehicle × hour/day	136,911

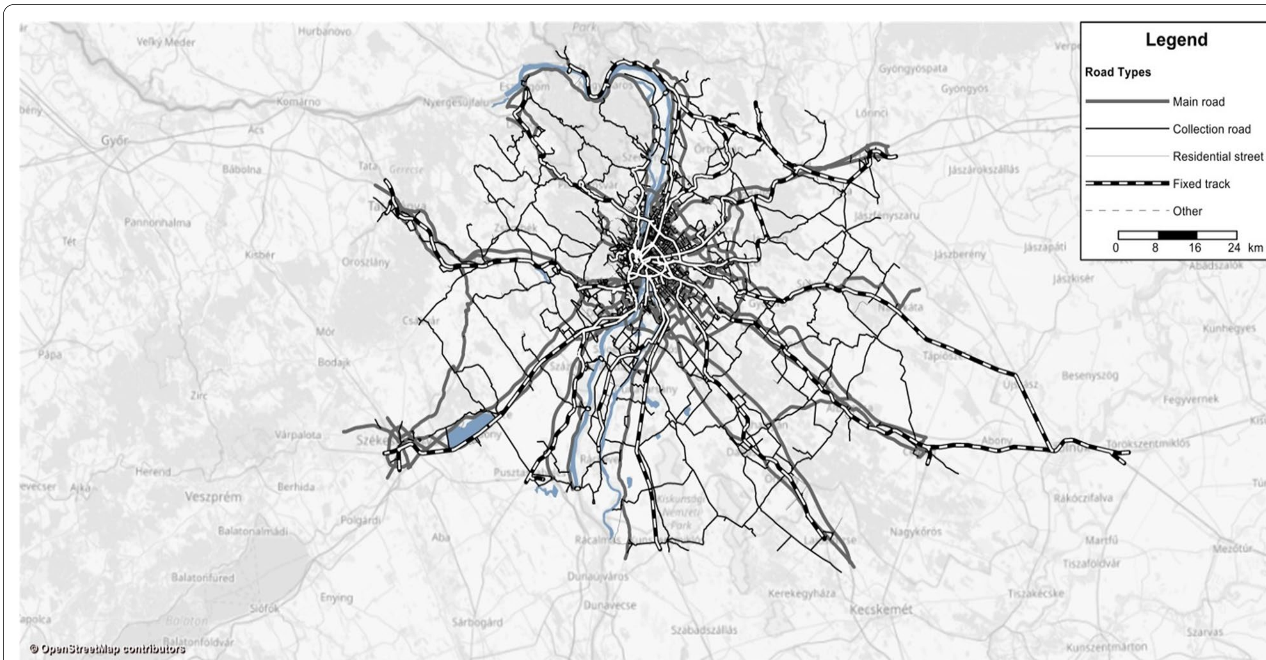

Fig. 1 EFM model

hours by car vehicle category. The base scenario model parameters are shown in Table 1 below. Since the study focuses on finding the change from a macroscopic point of view, the total delay of the whole network has been chosen as the key parameter to study the change in the whole network performance.

3.2 AV parameter identification

As mentioned in the literature review, the implementation of AVs in traffic fleet is expected to affect the capacity and saturation of the network due to different factors: the SAE (Society of Automotive Engineers) level of Automation, V2V and V2I communications, a smaller following distances (Space headways), a smaller required gaps for lane changing, lower driving reaction times, walking, and parking times. Communication between vehicles is maybe one of the strongest countermeasures in losing accessibility to part of the network. V2V and V2I communication provide AVs with a different alternative, replacing the eliminated roads due to emergencies, reducing jams resulting from vehicles being stuck in/near eliminated roads. These types of communications are currently provided by several navigation software and apps such as Waze and google maps.

The passenger car unit (PCU) parameter in the PTV Visum model was used to reflect the expected changes in network saturation and travel time reduction. PCU reflects how much impact a specific transport mode such as heavy trucks or buses has compared to a one small passenger car has on traffic network variables [4].

Table 2 Assumed passenger car units associated with each SAE category [2]

SAE category	SAE PCU
SAE0	1.00
SAE1	0.98
SAE2	0.95
SAE3	0.90
SAE4	0.80
SAE5	0.65

Modifying PCU values for the AV class is based on the expected positive effect of connected AVs on road capacity and saturation characteristics. The methodology created by Török and his colleagues was adopted for five different scenarios, including the base scenario with no fully automated vehicles [2]. The methodology focuses on changing PCU value depending on the SAE level and AV penetration value. Simple polynomial regression was used to define the PCU value associated with each SAE level, as shown in Table 2. We expect a positive impact in the case of the different key performance indicators, however the main question is to discover the effect size difference of the analysed attributes on network vulnerability through the implementation of different AV penetrations and automation levels.

The scenarios mix the different AV PCU factors with the five SAE penetration values. Table 3 below shows the chosen scenarios, with the corresponding SAE proportion, and PCU values.

3.3 Network sensitivity analysis framework

To study the sensitivity of different roads on a transport network, 30 roads with different characteristics were selected, shown in Fig. 2. The figure focuses mostly on showing the distribution of the selected roads since some of the roads are really close which can be identified as one The first characteristic of the chosen roads is the number of driving lanes in each direction. The 30 selected roads were divided into three groups of one, two, and three lanes in each direction with ten roads in each group. The second characteristic is the distance from the mid-point of the road to the model centre. Another characteristic is the number of connectors. These are the points in which vehicles can enter/exit the selected road from/to other roads. The last two characteristics are the maximum allowed speed and the length of the roads. Table 4 summarises the selected road characteristics.

The adopted methodology to study network sensitivity eliminates one road each time by reducing the capacity of the eliminated road to zero so no vehicles can use it. And runs the five chosen AV scenarios by modifying the PCU, and executes the equilibrium assignment for each scenario. Changes in traffic parameters are analysed for

Table 3 SAE level proportion in each scenario [2]

SAE Category	SAE0	SAE1	SAE2	SAE3	SAE4	SAE5	Scenario PCU
AV0	1	0	0	0	0	0	1.000
AV30	0.70	0.18	0.07	0.03	0.02	0	0.986
AV50	0.50	0.19	0.12	0.11	0.06	0.02	0.960
AV80	0.20	0.08	0.13	0.13	0.26	0.20	0.856
AV100	0	0	0	0	0	1	0.650

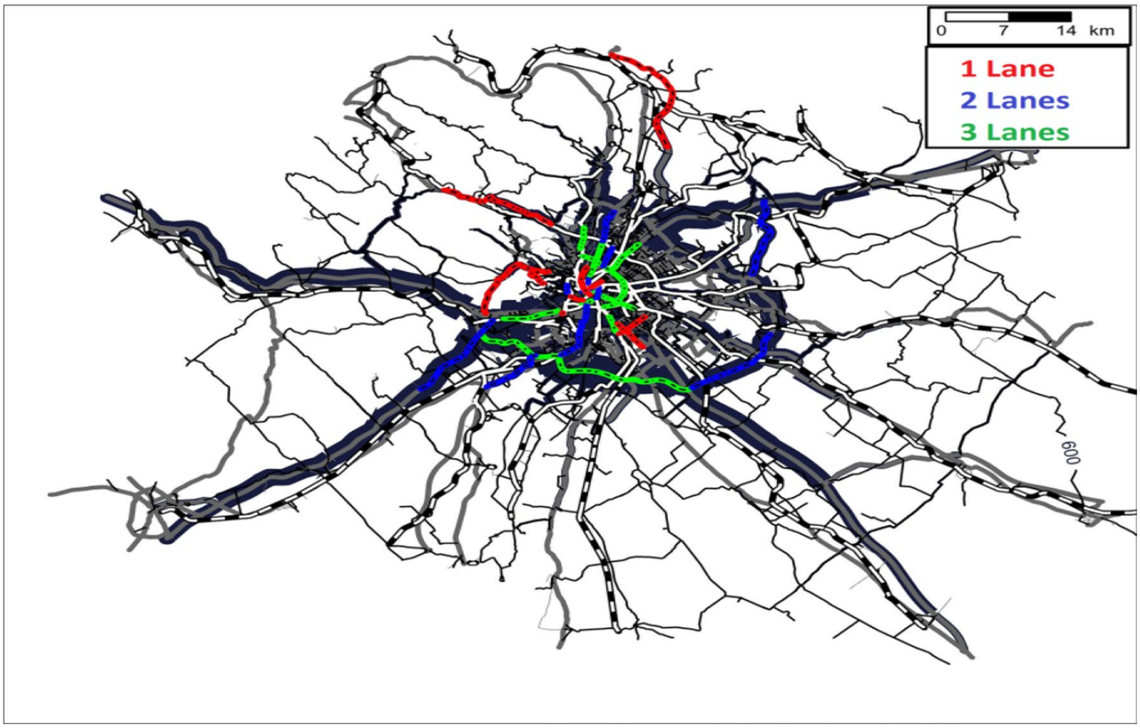

Fig. 2 Roads selected for elimination

each scenario. Then another road is selected and eliminated until all 30 roads are eliminated. Figure 3 shows the framework of the used methodology.

3.4 Regression model and model validation

Multiple linear regression was applied to estimate the most significant parameter affecting road criticality. Normality, collinearity, and heteroscedasticity conditions were checked to make sure that linear regression is applicable. The data were put into a correlation coefficient matrix to check for collinearity between the parameters. The matrix showed no high colinearity between the parameters, with the highest value of 0.63 between speed and road length, which is lower than the accepted maximum value of 0.80. The normal P–P plot was used to check normality, and a scatterplot of the residuals was used to check heteroscedasticity [21]. Due to the frequent appearance of tie values in the sample and due to our goal to apply transparent and explicit methods we decided to use Shapiro Wilk test and Jarque–Bera tests [18]

Due to the frequent appearance of tie values in the sample and due to our goal to apply transparent and explicit methods we decided to use the Jarque–Bera test [18]. On the other hand, as far as tests for normal distributions are concerned, Shapiro–Wilk is one of the most popular and widely used tests for small sample sizes, accordingly, we also investigated the sample with the Shapiro–Wilk test [30]. At the same time, we considered the results of the Jarque–Bera test more relevant in this case, since the Jarque–Bera test is one of the most transparent and explicit since it captures a combination of Skewness and Kurtosis which are the two dimensions that capture divergence from a Normal distribution. *p* value for Jarque–Bera tests and Shapiro–Wilk is shown in Table 5 below. Jarque–Bera test shows *p* value higher than 0.05 showing that the data are consistent with having skewness and excess kurtosis zero, while Shapiro–Wilk gives mostly lower *p* value than 0.05 giving some doubts about the normality of the residuals.

An 80/20 percent for model developing/validation has been chosen, where 24 roads have been chosen for the development of the model. Roads 2, 8, 13, 16, 28, and 30 have been selected randomly to validate each developed model. Root Mean Square Error (RMSE) value was calculated to give the average distance between the predicted total delay from the developed models and the total delay values from the simulation in the dataset for the validation process.

Table 4 Selected roads characteristics

Number	Length	Nr. lanes	Speed	Distance	Capacity	Nr. of connectors
1	1.80	1	40	2.18	900	5
2	4.39	1	45	6.01	1000	7
3	3.87	1	50	7.97	1200	15
4	1.54	1	40	1.11	900	9
5	22.41	1	65	24.51	1000	8
6	19.73	1	90	31.65	1500	6
7	4.34	1	45	8.84	1000	14
8	4.57	1	50	0.82	1200	8
9	12.84	1	50	10.29	1400	7
10	15.44	1	80	16.41	1400	7
11	1.60	2	50	0.22	2400	12
12	8.80	2	60	6.69	2800	15
13	12.19	2	115	21.25	4000	3
14	1.87	2	50	1.64	2400	16
15	7.89	2	100	15.31	3200	4
16	2.97	2	55	5.38	2400	9
17	14.45	2	115	21.39	4000	6
18	5.04	2	60	9.35	2800	11
19	13.55	2	115	18.06	4000	6
20	1.05	2	50	0.56	2600	5
21	6.26	3	100	7.82	5100	7
22	4.57	3	60	6.29	4200	10
23	6.90	3	60	4.21	4200	14
24	3.63	3	60	3.92	4200	16
25	24.93	3	100	13.27	4800	9
26	5.07	3	50	3.41	3900	19
27	1.26	3	50	2.66	3900	6
28	5.63	3	60	4.72	4200	31
29	2.62	3	60	6.95	4200	5
30	3.88	3	60	7.45	4200	11

4 Results and discussion

The first part of the analysis focused on finding the increase in total delay by eliminating each road to find the most important road characteristics affecting the network for AV0 scenarios. The total daily delay (hours) for the whole network was calculated. Thus, the baseline value of the total daily delay is 136 911 h. Each scenario was compared to this value. Figure 4 below shows the impact of the elimination of 30 roads on network delay, presented in percentage.

The developed vulnerability function, using multi-linear regression, is shown below with the R squared value of 89.1%. The normal P–P plot of the dependent variable is given in Fig. 5, and Table 6 presents the estimated p value of each parameter, showing the residuals are approximately linear, which supports the condition that the error is normally distributed.Table 6 also shows VIF value which all are between 1 and 5 indicating moderate correlation between the given variables in the mode. The result indicates that the road length, number of lanes, speed, and number of connectors have a positive impact on delay. In contrast, the distance from the centre has a negative impact on the total delay increase. The regression also indicated that the number of lanes has the highest impact on the network delay, seconded by length and distance, which almost have similar effects, which were all expected results.

$$\begin{aligned} \textit{Increase in Total Delay} =& 352.49L + 1017.3N + 55.69S \\ & - 319d + 127.6Co - 4109.5 \end{aligned}$$

where

L: Length of the eliminated road [km].

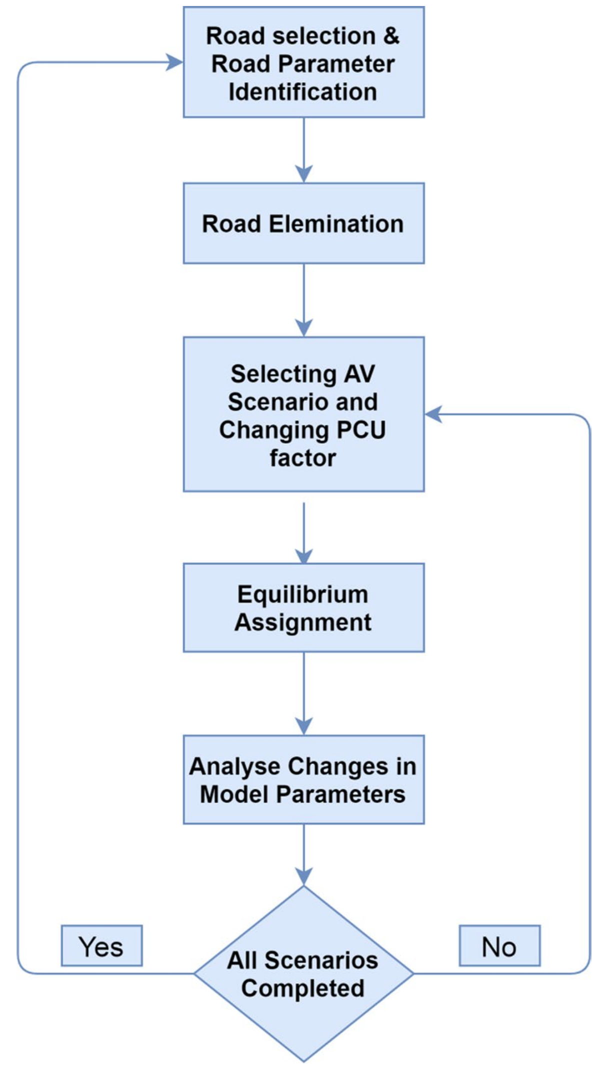

Fig. 3 Methodology framework for sensitivity analysis

Table 5 Jarque–Bera and Shapiro–Wilk *p* value associated with each parameter

Parameter	Jarque–Bera *p* value	Shapiro–Wilk *p* value
Length	0.1065	0.0022
Nr. lanes	0.3247	0.0003
Speed	0.1636	0.0010
Distance	0.0721	0.0136
Nr. of connectors	0.4956	0.2685

N: Number of lanes of the eliminated road.

S: Maximum speed allowed on the eliminated road in [km/h].

d: Distance of the middle of the road from the centre of the model [km].

Co: Number of connectors along the eliminated road.

The second part of the analysis focuses on finding the impact of implementing AVs into the model. The four AV scenarios were compared with the base scenario described in Table 1 in the methodology section (AV0). The travelled daily kilometres showed a reduction ranging from 0.19 to 1.29%, also, travelled hours reduction ranged from 0.73 to 5.78% of the total daily travelled hours. The most significant improvement induced by AVs is witnessed in total daily delay. AV30 scenario showed that even with only introducing 30% AVs of the entire traffic fleet with zero SAE5 automation level, a 3.5% reduction was achieved. AV50 and AV80 lowered the delay by 6.89% and 14.81%, respectively, which also introduced a low percentage of SAE5 AVs. The most significant decrease in the delay is achieved by introducing a whole fleet of SA5 AVs, reducing total daily delay by 28.52%. The result is shown in Fig. 6 below.

The analysis of introducing AVs into the traffic fleet also reduced the rise in delay in the case of road obstructions and elimination. For each of the presented AV scenarios, the total daily delay was estimated for the whole network and also calculated for the 30 road elimination process and compared. The results are shown in Fig. 7 below. For example, the highest increase in delay is for road number 25, with a rise of 8.26% in the case of zero AVs (AV0). This increase is reduced to 7.68%, 7.14%, 5.95%, and 4.26% for AV30, AV50, AV80 and AV100 scenarios, respectively, showing a 50% decrease in the rise of delay. An improvement as big as 60% is reached with fully SA5 AVs for road number 5. The average reductions in delay are 7.78%, 15.43%, 24.96% and 43.08% for AV30, AV50, AV80 and AV100, respectively. Figure 8 shows the results for each AV scenario and road.

Vulnerability functions for the increase in total delay were developed for each AV scenario to understand improvements caused by AVs on network sensitivity in the case of road blockage. The four developed regression models are shown below with R squared values of 86.5%, 88.6%, 87.6%, and 83.9% for AV30, AV50, AV80, and AV100, respectively. Table 7 shows the estimated

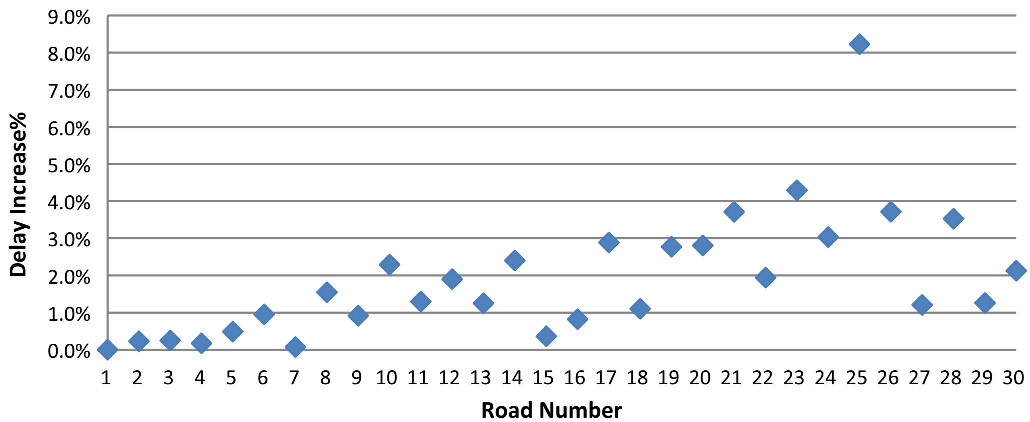

Fig. 4 Delay increase percentage for each eliminated road for AV0 scenario

p value for each developed model. Further analysis of each independent variable weight compared to all variable values are shown in Fig. 9. The speed, distance, and the number of connectors weights are nearly unchanged if AVs are implemented. The most significant change is shown in the increase in the number of lanes weight of the eliminated road in the vulnerability equation with more AVs in the traffic flow and road length–weight reduction for the same condition. The changes in weights mean that roads with higher number of lanes are more sensitive to a fully automated flow network than to road length. Another is that the number of lanes significantly impacts the network delay.

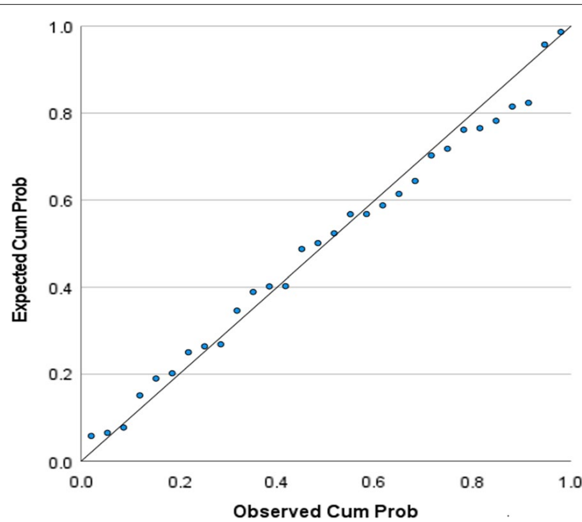

Fig. 5 Normal P–P plot of regression residual of independent variable increase in total delay

Table 6 *p* value associated with each parameter of AV0 model

Parameter	*p* Value	VIF value
Length	3.03×10^{-6}	3.70
Nr. lanes	0.006	1.97
Speed	0.0019	3.46
Distance	2.28×10^{-5}	4.68
Nr. of connectors	0.0266	1.30

$$AV30\ Increase\ in\ Total\ Delay = 278.98L + 1000N + 58.69S - 296d + 150.36Co - 4410$$

$$AV50\ Increase\ in\ Total\ Delay = 306.93L + 886.72N + 49.769S - 282d + 113.02Co - 3630$$

$$AV80\ Increase\ in\ Total\ Delay = 264.72L + 747.8N + 40.29S - 243.5d + 86.17Co - 2767$$

$$AV100\ Increase\ in\ Total\ Delay = 183.64L + 618.96N + 30.05S - 183.44d + 63.14Co - 2054$$

Validation for the five developed mathematical models has been made using 20% of the total 30 selected roads. RMSE values calculated for the six roads were evaluated firstly by comparing them with RMSE values of the dataset used for developing the model and secondly by calculating the normalized RMSE values. Table 8 below presents the validation process results. The first comparison between RMSE of the validation dataset and the training dataset shows a low difference. The Normalized RMSE shows values of 0.23 and lower; these two findings with the calculated R^2 indicate that the developed models can relatively predict the data accurately.

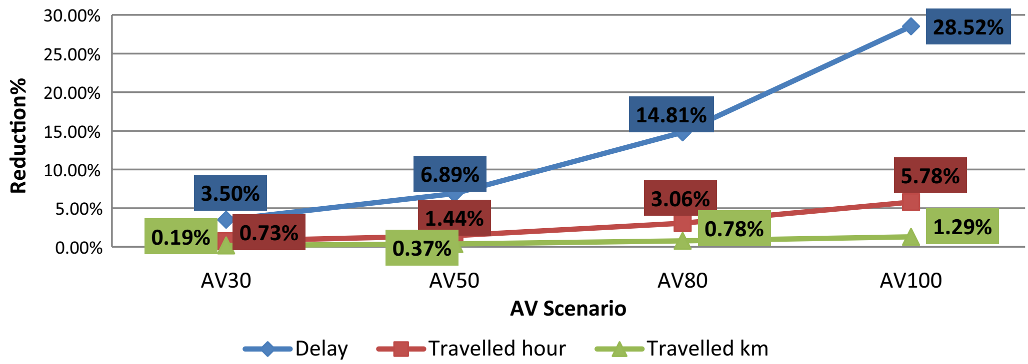

Fig. 6 Delay, travelled hours and travelled km reduction percentage for each scenario

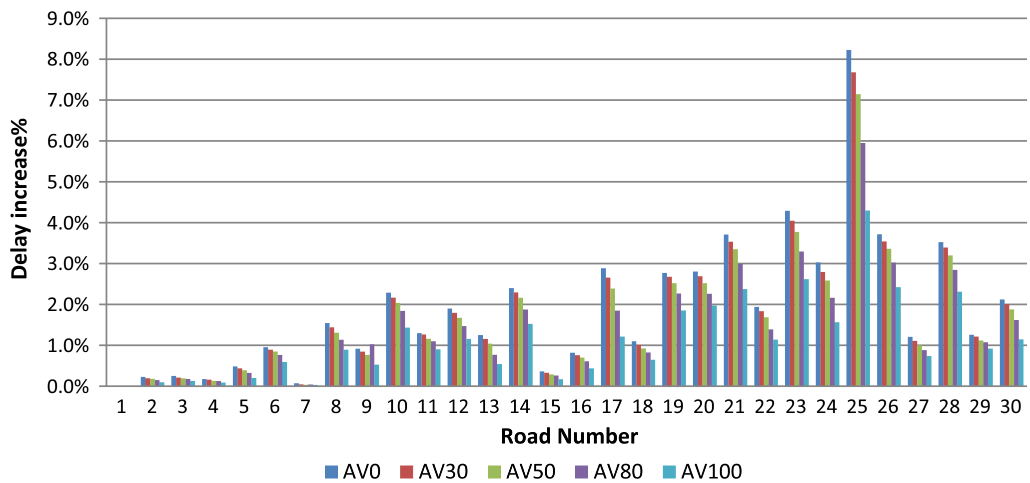

Fig. 7 Delay increase percentage of different AV scenarios for each eliminated road

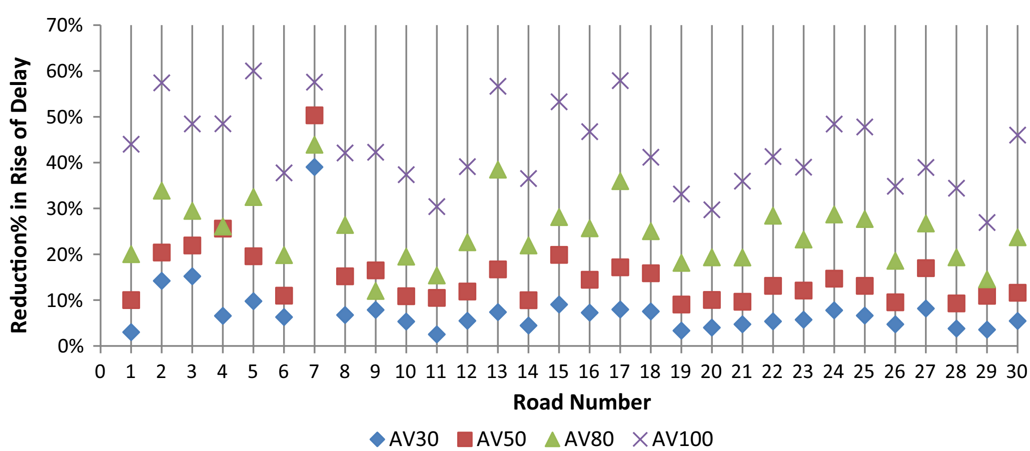

Fig. 8 Delay reduction percentage comparison between all scenarios

Table 7 *p* value associated with each parameter of AV30, AV50, AV50, and AV100 models

Parameter	AV30	AV50	AV80	AV100
Length	0.0001	4.83×10^{-6}	6.22×10^{-6}	8.83×10^{-5}
Nr. Lanes	0.0104	0.0075	0.001	0.0133
Speed	0.0021	0.002	0.0038	0.0107
Distance	0.0001	2.91×10^{-5}	3.64×10^{-5}	0.00024
Nr. of connectors	0.016	0.029	0.045	0.101

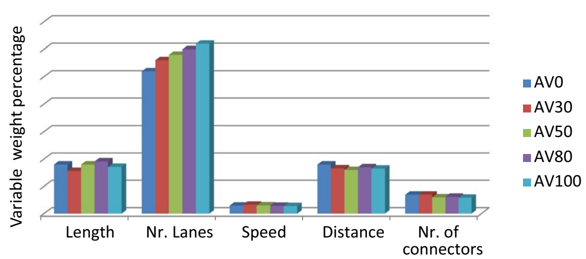

Fig. 9 Independent variable weight compared to all variables values

Table 8 Models validation results

Model	RMSE of the validation dataset	RMSE Of the training dataset	Normalized RMSE	R^2 (%)
AV0	832.5	806.8	0.18	89.1
AV30	989.9	889.8	0.23	86.5
AV50	695.0	728.4	0.17	88.6
AV80	516.2	640.9	0.14	87.6
AV100	376.8	556.9	0.12	83.9

5 Conclusion

This research studied road network vulnerability in terms of daily travelled hours, daily travelled km and total delay by eliminating roads with different characteristics (length, distance from the centre, speed, number of lanes, and connectors). Simulations and the development of a multi-linear regression statistical model of 26 different eliminated roads concluded that the number of lanes in a road has the most significant effect on delay. The second high impact characteristics are road length and distance from city centre, followed by the remaining characteristics.

A methodology was adopted to study the impact of autonomous vehicles (AVs) on the network model using different passenger car values (PCU) for AVs. Four scenarios were chosen with different combination of SAE levels of automation and AV proportion in the traffic flow. Total delay showed significant improvement reaching a 28.52% reduction in a fully automated fleet scenario. Travelled daily kilometres and hours were also reduced by 0.19–1.29% and 0.73–5.78% with the various AV scenarios, respectively.

Finally, the proposed model vulnerability based on delay was examined for all 30 selected roads for the four AV scenarios. The introduction of AVs resulted in a significant reduction of the increased delay caused by eliminated roads. The average decrease proved to be up to 43.08% from the base scenario with all conventional vehicles. The findings were further analysed by developing a statistical delay model for the four AV scenarios and compared with the zero AV statistical model. It was found that the impact of the road number of lanes parameter on delay has significantly increased with higher AV penetration. At the same time, the number of lanes remained the most significant one in this respect.

This research did not consider the change in speed caused by the failure of the selected road on other roads, especially adjacent roads. Future work will focus on studying and applying a speed correlation matrix for the whole network. The study also focused on eliminating one road at a time; a good extension is examining how eliminating a combination of roads or on the influenced region with AV implementation; consequently, it would be possible to model AVs in a more dynamic methodology. Such work could also explain the relationship between AV implementation, number of eliminated road lanes, and delay relation found in this paper. Future work will also focus on terminating the roads and re-routing all public services using the eliminated road to different routes.

Abbreviations
AV: Autonomous vehicle; PCU: Passenger car unit; C-ITS: Cooperative Intelligent Transport Systems; EFM: Egységes Forgalmi Modell; SAE: Society of Automotive Engineers.

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Author contributions
MO: conceptualization, formal analysis, writing and editing, methodology. AT: supervision, validation, review and editing. Both authors have read and agreed to the published version of the manuscript.

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Declarations

Competing interests
The authors declare no conflict of interest.

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References

1. Akbarzadeh, M., Salehi Reihani, S. F., & Samani, K. A. (2019). Detecting critical links of urban networks using cluster detection methods. *Physica A: Statistical Mechanics and Its Applications, 515*, 288–298. https://doi.org/10.1016/j.physa.2018.09.170
2. Árpád, T., Zsolt, S., Gábor, U., & Bence, V. (2018). Modelling urban autonomous transport system in Budapest. In *8th International scientific conference CMDTUR 2018*, *October*.
3. Baz, A., Yi, P., & Qurashi, A. (2020). Intersection control and delay optimization for autonomous vehicles flows only as well as mixed flows with ordinary vehicles. *Vehicles, 2*(3), 523–541. https://doi.org/10.3390/vehicles2030029
4. Bernhard, F. (2016). The effect of autonomous vehicles on traffic. In M. Markus, J. Christianerdes, B. Lenz, & H. Winner (Eds.), *Autonomous driving* (pp. 317–334). Berlin: Springer. https://doi.org/10.1007/978-3-662-48847-8_16
5. Calvert, S. C., Klunder, G., Steendijk, J. L. L., & Snelder, M. (2020). The impact and potential of cooperative and automated driving for intelligent traffic signal corridors: A field-operational-test and simulation experiment. *Case Studies on Transport Policy, 8*(3), 901–919. https://doi.org/10.1016/j.cstp.2020.05.011
6. Calvert, S. C., & Snelder, M. (2018). A methodology for road traffic resilience analysis and review of related concepts. *Transportmetrica A: Transport Science, 14*(1–2), 130–154. https://doi.org/10.1080/23249935.2017.1363315
7. Chen, B. Y., Lam, W. H. K., Sumalee, A., Li, Q., & Li, Z. C. (2012). Vulnerability analysis for large-scale and congested road networks with demand uncertainty. *Transportation Research Part A: Policy and Practice, 46*(3), 501–516. https://doi.org/10.1016/j.tra.2011.11.018
8. Chen, D., Ahn, S., Chitturi, M., & Noyce, D. A. (2017). Towards vehicle automation: Roadway capacity formulation for traffic mixed with regular and automated vehicles. *Transportation Research Part B: Methodological, 100*, 196–221. https://doi.org/10.1016/j.trb.2017.01.017
9. Cui, M., & Levinson, D. (2018). Accessibility analysis of risk severity. *Transportation, 45*(4), 1029–1050. https://doi.org/10.1007/s11116-017-9837-4
10. Dvořák, Z., Sventeková, E., Řehák, D., & Čekerevac, Z. (2017). Assessment of critical infrastructure elements in transport. *Procedia Engineering, 187*, 548–555. https://doi.org/10.1016/j.proeng.2017.04.413
11. Elhenawy, M., Elbery, A. A., Hassan, A. A., & Rakha, H. A. (2015). An intersection game-theory-based traffic control algorithm in a connected vehicle environment. In *IEEE conference on intelligent transportation systems, proceedings, ITSC*, *2015-Octob* (August 2019) (pp. 343–347). https://doi.org/10.1109/ITSC.2015.65.
12. García-Palomares, J. C., Gutiérrez, J., Martín, J. C., & Moya-Gómez, B. (2018). An analysis of the Spanish high capacity road network criticality. *Transportation, 45*(4), 1139–1159. https://doi.org/10.1007/s11116-018-9877-4
13. Gauthier, P., Furno, A., & El Faouzi, N. E. (2018). Road network resilience: How to identify critical links subject to day-to-day disruptions. *Transportation Research Record, 2672*(1), 54–65. https://doi.org/10.1177/0361198118792115
14. Gecchele, G., Ceccato, R., & Gastaldi, M. (2019). Road network vulnerability analysis: Case study considering travel demand and accessibility changes. *Journal of Transportation Engineering, Part A: Systems, 145*(7), 05019004. https://doi.org/10.1061/jtepbs.0000252
15. Gu, Y., Fu, X., Liu, Z., Xu, X., & Chen, A. (2020). Performance of transportation network under perturbations: Reliability, vulnerability, and resilience. *Transportation Research Part E: Logistics and Transportation Review, 133*(218), 1–16. https://doi.org/10.1016/j.tre.2019.11.003
16. Hartmann, M., Krause, S., Hoffmann, S., Motamedidehkordi, N., Vortisch, P., & Busch, F. (2017). Impact of automated vehicles on capacity of the German Freeway Network VISSIM View project Virtual Reality and Pedestrian Simulation View project Impact of Automated Vehicles on Capacity of the German Freeway Network. November.
17. Heinzelmann, B., Indinger, T., Adams, N., & Blanke, R. (2012). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. *SAE International Journal of Commercial Vehicles, 5*(1), 42–56. https://doi.org/10.4271/2012-01-0107
18. Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters, 6*, 255–259.
19. Jenelius, E., Petersen, T., & Mattsson, L. G. (2006). Importance and exposure in road network vulnerability analysis. *Transportation Research Part A: Policy and Practice, 40*(7), 537–560. https://doi.org/10.1016/j.tra.2005.11.003
20. Jia, D., & Ngoduy, D. (2016). Enhanced cooperative car-following traffic model with the combination of V2V and V2I communication. *Transportation Research Part B: Methodological, 90*, 172–191. https://doi.org/10.1016/j.trb.2016.03.008
21. Jun, N. (2014). Graphical methods for data analysis. by J. M. Chambers; W. S. Cleveland; B. Kleiner; P. A. Tukey Review by: N. I. Fisher Stable URL : http://www.jstor.org/stable/2531418. *40*(2), 567–568.
22. da Martins, M. C., Rodrigues da Silva, A. N., & Pinto, N. (2019). An indicator-based methodology for assessing resilience in urban mobility. *Transportation Research Part D: Transport and Environment, 77*(January), 352–363. https://doi.org/10.1016/j.trd.2019.01.004
23. Matisziw, T. C., & Murray, A. T. (2009). Modeling s-t path availability to support disaster vulnerability assessment of network infrastructure. *Computers and Operations Research, 36*(1), 16–26. https://doi.org/10.1016/j.cor.2007.09.004
24. Milanes, V., Shladover, S. E., Spring, J., Nowakowski, C., Kawazoe, H., & Nakamura, M. (2014). Cooperative adaptive cruise control in real traffic situations. *IEEE Transactions on Intelligent Transportation Systems, 15*(1), 296–305. https://doi.org/10.1109/TITS.2013.2278494
25. Obaid, M., & Szalay, Z. (2019). A novel model representation framework for cooperative intelligent transport systems. *Periodica Polytechnica Transportation Engineering, 48*(1), 39–44. https://doi.org/10.3311/PPtr.13759
26. Obaid, M., Szalay, Z., & Török, Á. (2020). Reconsidering the cybersecurity framework in the road transportation domain. *Acta Polytechnica Hungarica, 17*(9), 57–83. https://doi.org/10.12700/aph.17.9.2020.9.4
27. Obaid, M., Torok, A., & Szalay, Z. (2019). Network vulnerability of road infrastructure. *East West Cohesion*.
28. Ortega, E., Martín, B., & Aparicio, Á. (2020). Identification of critical sections of the Spanish transport system due to climate scenarios. *Journal of Transport Geography, 84*(March), 102691. https://doi.org/10.1016/j.jtrangeo.2020.102691
29. Piątkowski, B., & Maciejewski, M. (2013). Comparison of traffic assignment in visum and transport simulation in MATSim. *Transport Problems, 8*(2), 113–120.
30. Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika, 52*, 591–611.
31. Shladover, S. E., Su, D., & Lu, X. Y. (2012). Impacts of cooperative adaptive cruise control on freeway traffic flow. *Transportation Research Record, 2324*(Idm), 63–70. https://doi.org/10.3141/2324-08
32. Suzuki, H., & Marumo, Y. (2018). A new approach to green light optimal speed advisory (GLOSA) systems for high-density traffic flowe. In *IEEE conference on intelligent transportation systems, proceedings, ITSC*, *2018-November* (pp. 362–367). https://doi.org/10.1109/ITSC.2018.8569394.
33. Szalay, Z. (2021). Next generation X-in-the-loop validation methodology for automated vehicle systems. *IEEE Access*. https://doi.org/10.1109/ACCESS.2021.3061732
34. Szarata, A., & Nosal Hoy, K. (2019). The impact of road infrastructure failures on traffic conditions and travel behaviour in urban areas—the case of the Lazienkowski Bridge in Warsaw. *MATEC Web of Conferences, 284*, 01006. https://doi.org/10.1051/matecconf/201928401006
35. Talebpour, A., & Mahmassani, H. S. (2016). Influence of connected and autonomous vehicles on traffic flow stability and throughput. *Transportation Research Part C: Emerging Technologies, 71*, 143–163. https://doi.org/10.1016/j.trc.2016.07.007
36. Talebpour, A., Mahmassani, H. S., & Bustamante, F. E. (2016). Modeling driver behavior in a connected environment: Integrated microscopic simulation of traffic and mobile wireless telecommunication systems. *Transportation Research Record, 2560*(January), 75–86. https://doi.org/10.3141/2560-09
37. Taylor, M. A. P., Sekhar, S. V. C., & D'Este, G. M. (2006). Application of accessibility based methods for vulnerability analysis of strategic road networks.

Networks and Spatial Economics, 6(3–4), 267–291. https://doi.org/10.1007/s11067-006-9284-9
38. Tilg, G., Yang, K., & Menendez, M. (2018). Evaluating the effects of automated vehicle technology on the capacity of freeway weaving sections. *Transportation Research Part C: Emerging Technologies, 96*(September), 3–21. https://doi.org/10.1016/j.trc.2018.09.014
39. Varga, B., Szalai, M., Fehér, Á., Aradi, S., & Tettamanti, T. (2020). Mixed-reality automotive testing with sensoris. *Periodica Polytechnica Transportation Engineering, 48*(4), 357–362. https://doi.org/10.3311/PPTR.15851
40. Wardrop, J. G. (1952). Some theoretical aspects of road traffic research. *Proceedings of the Institute of Civil Engineers., 1*(3), 325–362. https://doi.org/10.1680/ipeds.1952.11259
41. Yang, K., & Menendez, M. (2017). A convex model for queue length estimation in a connected vehicle environment. In *Transportation Research Board 96th Annual Meeting*.

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