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MACROSCOPIC MODELLING OF PREDICTED AUTOMATED VEHICLE EMISSIONS

MOHAMMED OBAID*, ARPAD TOROK

Department of Automotive Technologies, Faculty of Transportation Engineering and Vehicle Engineering, Budapest University of Technology and Economics, Budapest, Hungary

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Abstract. This paper studies the effect of automated vehicle implementation on transport system emission from a macroscopic point of view. The paper considers several scenarios differing in passenger car unit (PCU) and the penetration share percent of automated vehicles in the system using PTV Visum software. The study presents that automated vehicles reduce total emission by both the effect of smooth driving of each automated vehicle independently and the spread of automated vehicles in the network. Furthermore, apart from considering the effect of different PCU values and penetration levels, the developed model takes into account three different types of emissions and seven different vehicle classes.

Keywords: automated vehicles, emissions, macroscopic, modelling, passenger car unit, penetration.

Introduction

The increased concentration of greenhouse gases (GHGs) (carbon dioxide, methane, nitrous oxide, and fluorinated gases) in the atmosphere, especially considering carbon dioxide (CO_2) concentration,

* Corresponding author. E-mail: Obaid.mohammed@mail.bme.hu

Mohammed OBAID (ORCID ID 0000-0003-3719-5019)
Árpád TÖRÖK (ORCID ID 0000-0002-1985-4095)

can intensify temperature rise. This process can further accelerate climatic changes, which can lead to disastrous outcomes for our civilisation. Increasing concentration of CO_2 and other GHGs can be strongly related to the increased level of human activities related emissions. It is estimated that the total CO_2 equivalent GHG emission increased from 22.5 gigatonnes to 50.9 gigatonnes between 1990 and 2018 with a 1.3% average yearly growth (Olivier & Peters, 2018).

Nitrogen oxide gases are formed from the reaction between nitrogen and oxygen during the burning of fuel. The emission of NO_x gases can result in smog and acid rain, strongly related to health effects. Particulate matters (PM) involve minuscular solid and fluid particles that can be inhaled, resulting in severe health issues for living beings.

The transportation sector is one of the major energy-consuming sectors responsible for 27% of global primary energy demand and is responsible for 14% of greenhouse emissions (WEC, 2016). It has to be mentioned as well that 95% of the world's transportation energy comes from petroleum-based fuels, largely gasoline and diesel (Kirby, 2008). Road transport gives 72.8% of the total emission of the transportation sector (European Union, 2016). Road transport is responsible for 39% of nitrogen oxide emissions and 11% of fine $PM_{2.5}$ emissions in Europe (European Environment Agency, 2020). The idea of automated vehicles (AV) appeared in the 1920s; the first driverless vehicle was introduced in 1921 at an airbase in Ohio, which was only a remotely controlled vehicle. This idea becomes more and more realistic and feasible over the years until it reaches the fully automated transport system concepts. However, numerous questions have emerged concerning the issues and challenges related to the future automated transport systems. Generally, the difference between automated and autonomous vehicles is the degree of human interaction. An autonomous vehicle decides the destination and what route to take; however, the automated vehicle would follow destination and route orders and then drive itself.

(Iacobucci, McLellan & Tezuka, 2018) have presented an up-to-date modelling framework to analyse the economic and financial sustainability of a connected and automated vehicle system. The investigation has shown that an automated vehicle in the analysed Tokyo model can replace about 7–10 vehicles. Barth and Boriboonsomsin's study proves that the eco-driving concept can reduce fuel consumption by 10–20%, where properly programmed automated vehicles will be able to fully operate in accordance with the principles of eco-driving (Barth & Boriboonsomsin, 2009). Studies conducted in the USA indicate that on motorways with an automated vehicle share of 90% of the total traffic, fuel consumption can be decreased by 25%, and delays can be decreased by 60% (Fagnant & Kockelman, 2015). With regard to the positive effects of automated vehicles on emissions, initial estimates related to GHG emissions can expect from slight increases to 80% reductions (Vimmerstedt et al., 2015). The estimated changes in the level of emission are mainly assumed to be affected by the following key factors: level of automation, the share of implementation, the type of automated vehicles, and behavioural responses. In accordance with the related SAE (Society of Automotive Engineers) level of Automation standard (Heinzelmann et al., 2012), the level of automation is classified into six levels: no automation, driver assistance, partial automation, conditional automation, high automation, and full automation. Potential energy consumption and GHG emission reduction are expected to be achieved through the positive factors of congestion mitigation and efficient routing caused by automated vehicles. On the other hand, these factors can also support the safety improvement of the system. Automated eco-driving is another important factor resulting in more efficient operation, less braking, and efficiently controlled acceleration and deceleration (Obaid & Szalay, 2019).

AV will also operate in a smoother driving mode, which will expectedly result in reduced acceleration values. Based on the reviewed studies, it can be estimated that reducing the acceleration time from 0 to 60 mph by 1% can increase fuel consumption per distance unit by 0.44%. For this reason, instead of increasing the engine power and acceleration, it would be advisable to reduce fuel consumption (MacKenzie, 2013; Igliński & Babiak, 2017).

AVs will be able to be operated with a reduced following distance. As proved by Japanese research where three loaded lorries were platooned at a speed of 80 kmph in case of 4 m following distance, the fuel consumption reduction in the case of the first lorry achieved 8%, for the second lorry the reduction achieved the 23%, and for the last lorry fuel consumption reduction was 16% (Tsugawa, 2013). In light of these results, the fuel consumption reduction caused by AVs will expectedly reduce future greenhouse emissions.

The present research aims to study the effect of automated vehicles on a macroscopic level with regard to CO_2, NO_x, and $PM_{2.5}$ emission related to the transport sector. The effect is evaluated without considering significant fuel consumption reduction caused by technology development. The reason is the highlighted aim of the study, which intends to minimise the probability of overestimating positive effects. Therefore, a conservative estimation concept is applied during the research to determine if even automated vehicles consume the same amount of fuel without considering the possibility of an electrified vehicle fleet or the savings derived from the more efficiently organised transportation processes, especially considering junction crossings. The research investigates several scenarios differentiated by the considered parameters (PCU, penetration). Furthermore, the study aims to define the estimation model of the analysed emission categories with regard to the considered mobile parameters. This output makes it possible to provide an estimation framework depending on the combination of the considered model parameters. This concept allows us to predict the expected effects of certain interventions influencing the considered automated vehicle-related model parameters of the evaluated transport systems.

This article is structured as follows: Section 1 describes the selected model and explains the methodology used. Section 2 presents the results of model simulation and developed mathematical models for different road transportation pollutants. Section 3 discusses the results obtained. Finally, in the conclusion, the authors describe the contribution of this study, its limitations, and future research recommendations.

1. Experiments

In the next session, a short description of the used model and applied methods is presented.

1.1. Model description

The Hungarian EFM (Egységes Forgalmi Modell, Uniform Traffic Model) model is based on Budapest's official macroscopic model created and maintained by the Transport Corporation of Budapest. The macroscopic model of Budapest is developed in the PTV Visum software environment. The originate-destination structure of EFM has more than 920 internal zones and more than 20 agglomeration zones. There are about 1.7 million vehicle trips in the complete model; the map below describes an average weekday traffic structure. The network consists of more than 10 500 nodes and more than 30 000 connectors. The equilibrium assignment method of PTV Visum software has been used to demonstrate the daily transportation processes.

The model used real-world traffic parameters for the city of Budapest. Volumes, origin-destination matrices, road speeds, and capacities reflect the real conditions of Budapest. The model also considers both public and private transportation modes. The present research focuses on the private transportation modes, which contain three passenger car classes (cars, automated vehicles, and taxis) and 4 heavy vehicle classes. Figure 1 below shows the used EFM model.

2.2. Methodology

The research methodology aims to evaluate the impact of the considered model parameters related to the representation of automated vehicle characteristics. Accordingly, the first investigated parameter is the proportion of daily trips performed by AV compared to the total number of daily trips defined as penetration. Penetration values vary from minimum 0% penetration (all cars are traditional passenger vehicles) to maximum 100% penetration (all cars are automated vehicles). The complete interval of the investigated domain is divided equidistantly by 10% steps.

The second investigated parameter refers to the effect of Passenger Car Unit (PCU) values with regard to the automated vehicles. PCU reflects how much impact a specific transport mode has on traffic variables (density, saturation, speed) compared to one average passenger car (e.g., private car = 1, motorcycle = 0.5). In case of this study, PCU values are considered to be 0.50, 0.55, 0.60, 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, and 0.98 for AV (Árpád et al., 2018). The selected values are chosen to cover the expected range of AV effects since no exact value can be chosen. Also, a large dataset is needed to develop mathematical models for the three selected emission pollutants in the study.

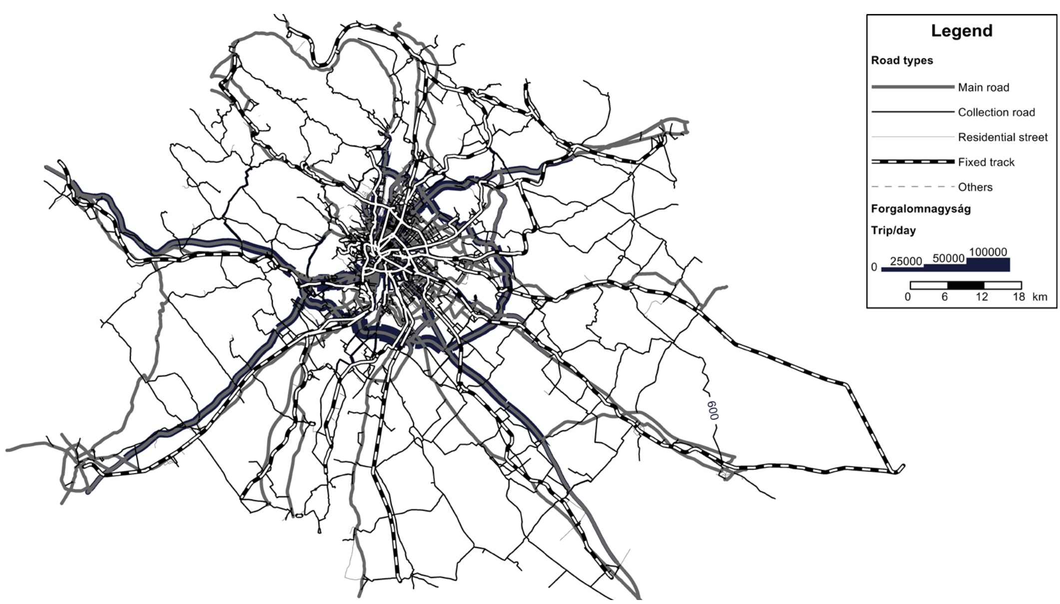

Figure 1. Budapest EFM model

The reason for modifying the PCU values of AV is their expected positive influence on network capacity and saturation characteristics (Bernhard, 2016). These factors are directly affected by PCU values. In the case of AV, a reasonably lower level of following distance can be assumed since following distance depends primarily on the path length needed to prevent the collision of the investigated vehicles. If a normal driver's stopping distance is investigated, its needed timeframe can be divided into reaction time and braking time (Green, 2000). However, in the case of automated vehicles, the effect of reaction time is expected to be minimised. This is assumed to decrease following distance and increase network capacity. Besides, the vehicle walking time and parking time are also expected to be reduced in the case of automated vehicles.

As mentioned previously, the research mainly focuses on the private transport modes; accordingly, Table 1 classifies each private transport mode and their considered PCU value.

Table 1. Private transport modes and their PCU (1 – Passenger Car, 2 – Heavy Vehicles)

Mode	Class	PCU
PC1	Automated vehicle	0.50–0.98
PC	Car	1.0
PC	Taxi	1.0
HV2	Light	1.0
HV	Medium	1.4
HV	Buses & Coaches	1.8
HV	Heavy	2.5

The evaluation process consists of repeated investigations regarding the combination of modified input parameters of penetration and PCU of AV. The task of the assignment problem is to program vehicles in every model step to routes characterised by the lowest travel cost. The problem is solved when an equilibrium state is achieved, and no trips can be programmed to other paths with lower travel costs (Piątkowski & Maciejewski, 2013). In the first phase, PCU values are modified as external variables, and penetration value remains unchanged. Then, when all the PCU values are utilised in the given penetration value, they can also be modified. This approach ensures to cover the predefined interval of the analysed model parameter domain. Accordingly, these steps are repeated until all penetration values are calculated.

The assignment of car trips onto the transport model method network helps us estimate any journey-related information such as travel time and distance, speed, and delay. The next step is to evaluate transport emission for each mode in the different scenarios using the calculated travel distance. As mentioned previously, the emission level is estimated in the case of the following gas: carbon dioxide (CO_2), nitrogen oxides (NO_x: NO_2 and NO) given as NO_2 equivalent, and particular matter ($PM = PM_{2.5}$) (Ntziachristos et al., 2019; Paton-Walsh et al., 2018). Figure 2 shows the framework of the selected methodology.

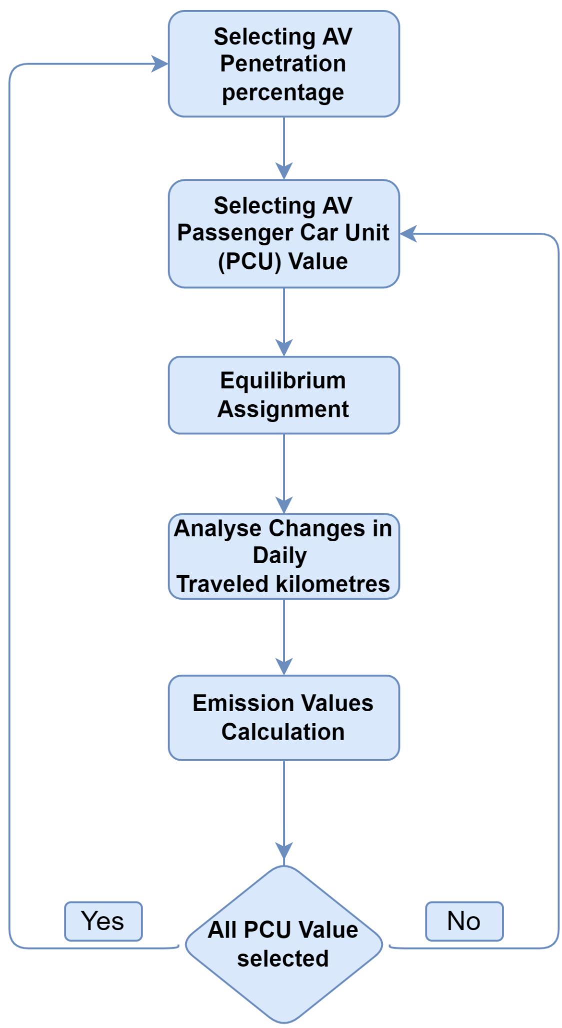

Figure 2. Methodology framework

Vehicular emission models calculate the level of emissions for different pollutants. The models depend on several factors: emission factor, fuel consumption, average speed, volume and traffic composition of the road network (Esteves-Booth et al., 2002). Emission factor models use simple calculation for finding emission levels. They use a mean calculated emission factor for a specific class of vehicles for a specific road type (Fallahshorshani et al., 2012). Average speed models are built on speed-emission functions. These functions are calculated by measuring emission rates over several trips with different speeds (Knez, 2013). Average speed models are regularly used in measuring emission inventories on a road network scale (Esteves-Booth et al., 2002).

Traffic models depend on the average traffic volume and the traffic composition (vehicle categories). Traffic models calculate emissions in terms of the mass of pollutants produced per vehicle distance of fuel and are usually used in regional and national emission estimations (Fallahshorshani et al., 2012). As described before, the model used for the study is the city of Budapest. Since traffic volumes and vehicle categories are the main inputs, the traffic emission model is used for emission calculations. Table 2 shows the unit factors for each gas emission and transport mode, in grams/kilometres based on the European Environment Agency (EEA) guidebook (Ntziachristos et al., 2019).

The emissions unit factors for AV in Table 2 were calculated using anticipated emission reductions factors of smoother driving by AV; 19.09% for $PM_{2.5}$, 15.51% for NO_x, and 6.55% for CO_2 (Liu, Kockelman, & Nichols, 2017). The reduction factors were used on the EEA CAR emissions factors (Ntziachristos et al., 2019).

Table 2. Private transport mode emission factors

Mode	Carbon Dioxide CO_2, g/km	Nitrogen Dioxide NO_x, g/km	Particular Matter $PM_{2.5}$, g/km
Automated vehicle	207.30	0.516	0.0017
Car	221.83	0.611	0.0021
Light	237.675	1.030	0.0783
Medium	253.52	1.193	0.1220
Buses & Coaches	1584.5	6.500	0.0100
Heavy	760.56	8.010	0.2260
Taxi	221.83	0.611	0.0021

The result of the PCU and penetration scenarios for each considered emission (CO_2, NO_x and $PM_{2.5}$) has been analysed for both passenger cars and heavy vehicles. Since a reasonably complex relationship structure can characterise the analysed data, the nonlinear regression analysis was chosen to find the best model. In general, the statistical analysis of nonlinear regression function 'f' relates a vector x (independent variables) and y (dependent variable) using components of the vector of parameters β, which is nonlinear to function f: $y \sim f(x, \beta)$.

TableCurve 3D has been used to identify the proper estimation model, which can provide a more efficient estimation with regard to the amount of emission reduction compared to the other investigated functions. TableCurve 3D software uses a wide collection of linear and nonlinear models: linear equations, Polynomial and rational functions, logarithmic and exponential functions, nonlinear peak functions, nonlinear transition functions and nonlinear exponential and power equations. Nonlinear exponential and power regression were used in TableCurve 3D software to find the best-fitted surface for the three factors: penetration, PCU and emission reduction. They were chosen since they gave the most minor statistical errors, shown in the values of R^2 calculated for each developed model (Obaid & Torok, 2021).

2. Results

2.1. Baseline emissions and attributes

There have been no automated vehicles considered in the model in the baseline scenario, so the penetration is assumed to be 2% since a basic level of automation is already available on the market. Accordingly, the baseline emission values are the reference point for the evaluation focusing on the effect of automated vehicles. Table 3 presents the baseline emission values and daily travelled kilometres.

Table 3. EFM model baseline emissions and attributes

	Unit	Car	Taxi	Light	Medium	Buses & Coaches	Heavy	Total
Travelled, km	1000 km	32 369	616	6069	581	6271	2865	48 771
CO_2	Metric Ton	7180	137	1446	148	9964	2185	21 060
NO_x	Kilogram	19 777	377	6268	695	40 875	23 015	91 007
PM	Kilogram	67.97	1.30	477	71.1	62.9	649	1329

2.2. Emissions

2.2.1. Passenger car

Figs. 3–5 represent the model calculated output values (generated from the combination of the different PCU and penetration values) and the fitted function concerning passenger car relative emission reduction factors for CO_2, NO_x, and $PM_{2.5}$, respectively. The three figures also represent the best-fitted surface developed for the three emissions. CO_2 reduction varies from a minimum of 0.65% to a maximum of 7.93%

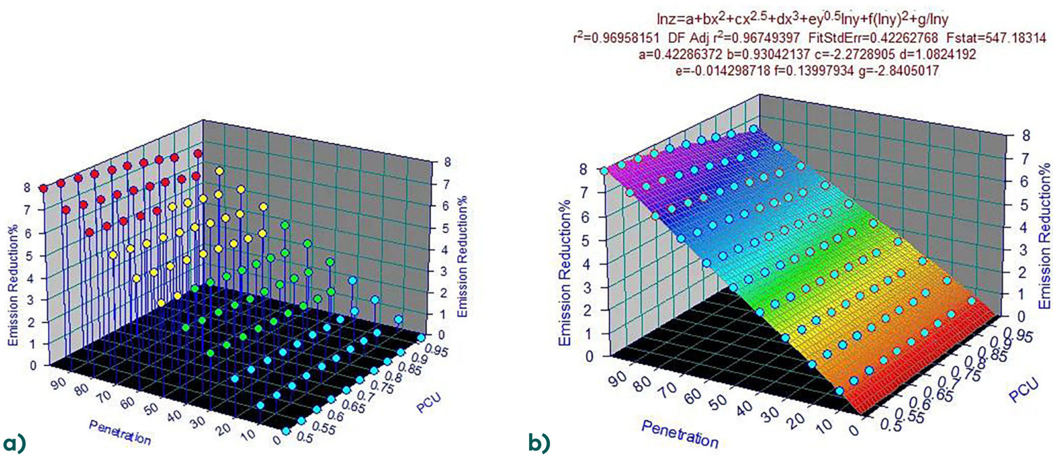

Figure 3. Carbon dioxide emissions of passenger cars: (a) passenger car CO_2 relative emission reduction; (b) best-fit surface model for passenger car CO_2 emission reduction

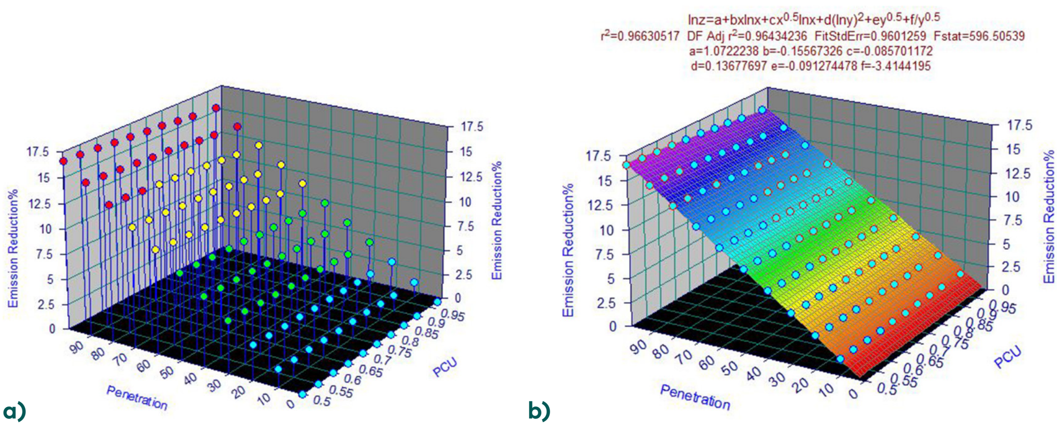

Figure 4. Nitrogen oxide emissions of passenger cars: (a) passenger car NO_x relative emission reduction; (b) best-fit surface model for passenger car NO_x emission reduction

reduction, NO_x varies from a minimum of 1.53% to a maximum of 16.59%, and $PM_{2.5}$ varies from a minimum of 1.89% to a maximum of 20.04% reduction.

The developed model for the best-fit surface for the relative passenger car emission reduction presented in Figs. 2–4 is represented in Eqs. (1)–(3) regarding CO_2, NO_x and $PM_{2.5}$. The value of the R^2 statistics measure is 96.7% for CO_2, 96.4% for NO_x, and 92.8% for $PM_{2.5}$.

$$\text{PC } CO_2 \text{ Relative Emission Reduction (\%)} = \\ e \wedge [0.423 + 0.93X^2 - 2.27X^{2.5} + 1.08X^3 - 0.014\sqrt{Y}\ln Y + 0.14(\ln Y)^2 - (2.84/\ln Y)], \tag{1}$$

$$\text{PC } NO_x \text{ Relative Emission Reduction (\%)} = \\ e \wedge [1.072 - 0.16X\ln X - 0.086\sqrt{X}\ln X + 0.14\,(\ln Y)^2 - 0.086\sqrt{Y^2} - (3.41/\sqrt{Y})], \tag{2}$$

$$\text{PC } PM_{2.5} \text{ Relative Emission Reduction (\%)} = \\ -17.43 - 0.81X + 7.60\ln Y - 0.60X^2 + 0.011(\ln Y)^2 - 0.0025X\ln Y, \tag{3}$$

where: X – PCU factor, Y – penetration in percentage.

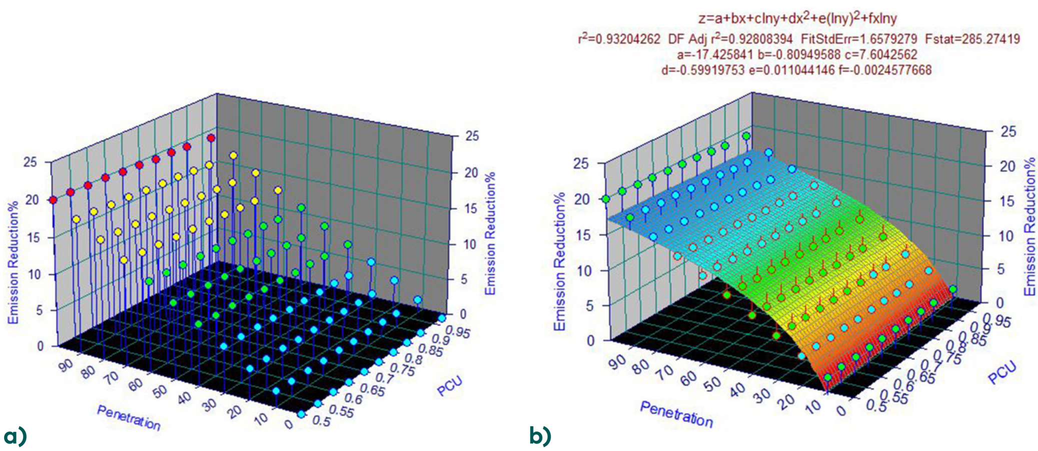

Figure 5. Fine Particulate Matter emissions of passenger cars: (a) passenger car $PM_{2.5}$ relative emission reduction; (b) best-fit surface model for passenger car $PM_{2.5}$ emission reduction

2.2.2. Heavy vehicles

Since four different heavy vehicle categories have been differentiated in the model, and the passenger car-related input parameters and the heavy vehicle-related output parameters are proved to be related in a completely different way in case of the different emission factors, the relative reduction for all three emissions has been separately investigated in the certain scenarios.

Emissions of heavy vehicles are calculated for each scenario to investigate whether the penetration of automated vehicles influences

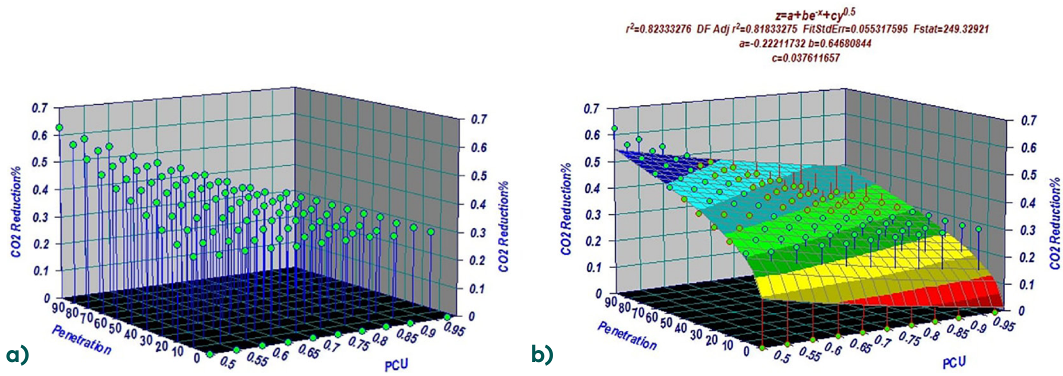

Figure 6. Carbon dioxide emissions of heavy vehicles: (a) heavy vehicle CO_2 relative emission reduction; (b) best-fit surface model for heavy vehicle CO_2 emission reduction

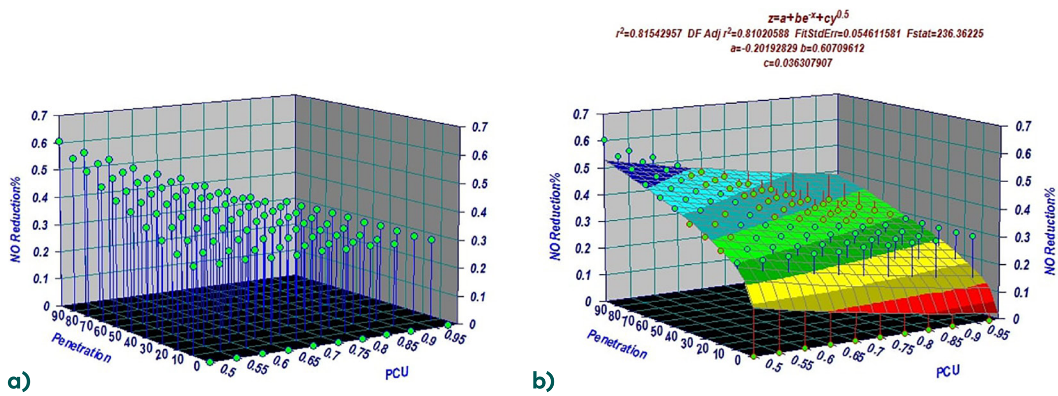

Figure 7. Nitrogen oxide emissions of heavy vehicles: (a) heavy vehicle NO_x relative emission reduction; (b) best-fit surface model for heavy vehicle NO_x emission reduction

other vehicle classes through the network. Figs. 6–8 illustrate the change in CO_2, NO_x, and $PM_{2.5}$ and the best model for each in case of the heavy vehicle class. CO_2 varies from a minimum of 0.29% to a maximum of 0.63% reduction, NO_x varies from a minimum of 0.29% to a maximum of 0.60%, and $PM_{2.5}$ varies from a minimum of 0.30% to a maximum of 0.77% reduction.

Eqs. (4)–(6) represent the estimation model of relative emission reduction with regard to CO_2, NO_x, and $PM_{2.5}$ in the case of heavy vehicle class. The value of R^2 statistics measure is 82.3% for CO_2, 81.2% for NO_x, and 85.9% for $PM_{2.5}$.

$$\text{HV } CO_2 \text{ Relative Emission Reduction (\%)} = -0.2221 + 0.6468(e^{-X}) + 0.03761\sqrt{Y}, \quad (4)$$

$$\text{HV } NO_x \text{ Relative Emission Reduction (\%)} = -0.2019 + 0.6071(e^{-X}) + 0.03631\sqrt{Y}, \quad (5)$$

$$\text{HV } PM_{2.5} \text{ Relative Emission Reduction (\%)} = 0.741 - 0.7772\sqrt{X} + 0.0459\sqrt{Y}, \quad (6)$$

where: X – PCU factor, Y – penetration in percentage.

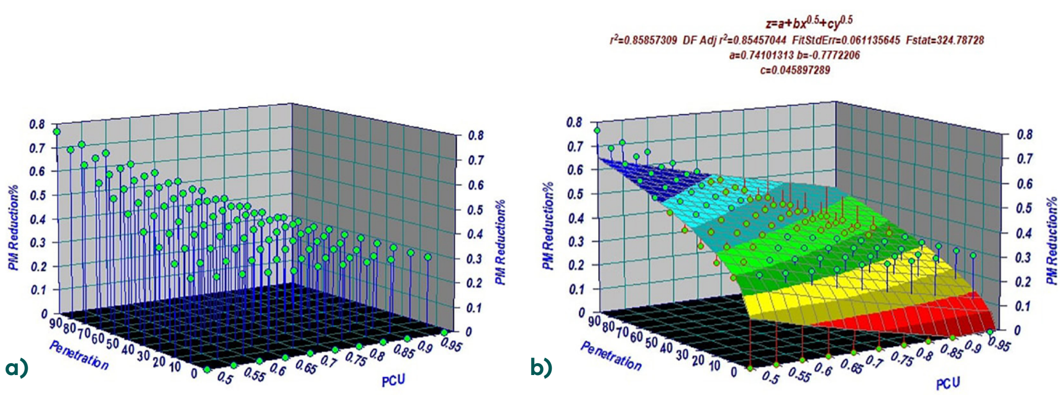

Figure 8. Fine Particulate Matter emissions of heavy vehicles: (a) heavy vehicle $PM_{2.5}$ relative emission reduction; (b) best-fit surface model for heavy vehicle $PM_{2.5}$ emission reduction

3. Discussion

Implementing AV in the network traffic flow with different penetration levels affected several traffic key factors: travelled distance, travelled time, speed and delay (Obaid & Torok, 2021). The adopted methodology predicted the percentage of reduction in three types of GHG emissions resulting from the decrease in total travelled kilometres only. Road transport emission reduction resulted from replacing conventional cars with AVs is mainly because of smoother driving of AVs. However, the result showed that the spread of AVs in the whole network resulted in an additional decrease in emissions. The improvement in emission reduction can be mostly shown in the 100% penetration scenarios where reduction of all three emissions is higher than the expected reduction from the smoother driving factor alone. Although it is a relatively small effect, even by ignoring the factor of efficiency improvement effect of automated transport modes or the electrified vehicle fleet, there will be a positive effect in reducing environmental pollution (Csiszár et al., 2019; Aradi, Becsi & Gaspar, 2014; Bartolini, Tettamanti & Varga, 2017; Ma & Zhang, 2018; Tettamanti et al., 2016; Szalay et al., 2017). The additional improvement can be shown by comparing CO_2 7.93%, NO_x 16.59%, and $PM_{2.5}$ 20.04% reduction results with Liu et al. finding of 6.55% for CO_2, 15.51% for NO_x, and 19.09% for $PM_{2.5}$ (Liu, Kockelman & Nichols, 2017; Obaid, Torok & Ortega, 2021).

The results also validate that AV presence affects the emission of other vehicle classes as well, even if only marginally. The impact on other vehicles classes may be explained by reducing congestion, travel time and travelled trip distances in a more efficient road network caused by AV spread.

Automobile manufacturers have invested significant resources in AV technology development; however, studies of the expected impacts of AVs on the transportation system are minimal. The six developed mathematical percentage of reduction models for the three selected emissions will assist stakeholders in predicting future road transport emissions for various AV penetration rates. The findings may help authoritsies and decision-makers better understand the opportunities of AVs in reducing GHG emissions and mitigating global warming.

Conclusions

This paper has investigated the estimated emission values of CO_2, NO_x, and $PM_{2.5}$ assuming the spread of automated vehicles in a macroscopic model framework. The study has analysed the real urban framework of the Budapest EFM model using Visum software. Automated vehicles have only been considered the class of passenger cars (automated vehicles) where several scenarios have been performed; the scenarios differ in assumed PCU of AV and AV penetration compared to the total number of passenger cars used in the model. The results have been classified into two classes:

firstly, passenger car class has been evaluated, where the relative reduction in emission varies:

- CO_2 reduction varies from a minimum of 0.65% to a maximum of 7.93%;
- NO_x varies from a minimum of 1.53% to a maximum of 16.59%;
- and $PM_{2.5}$ varies from a minimum of 1.89% to a maximum of 20.04% reduction.

The reduction is due to automated vehicle smooth driving and the deployment of automated vehicle fleets in the transportation network at various penetration levels (lower travelled kilometres in the whole network).

The second class is heavy vehicles where:

- CO_2 emission reduction varies from 0.29% to 0.63%;
- NO_x emission reduction varies from 0.29% to 0.60%;
- and $PM_{2.5}$ emission reduction varies from 0.30% to 0.77%.

This result shows that the emission values of other vehicle classes using the network are also slightly affected by the spread of automated vehicles.

The final part of the study introduces the developed multiple mathematical models applicable to predicting the relative emission reduction for both passenger car class and heavy vehicle class. The applied explanatory variables of the model are the PCU of automated vehicles and the penetration of automated vehicles. The R^2 values for the passenger car class are CO_2 96.7%, NO_x 96.4% and 92.8% for $PM_{2.5,}$ while the R^2 values for the heavy vehicle class are CO_2 82.3%, NO_x 81.2%, and 85.9% for the $PM_{2.5}$ model. The developed models can be a helpful tool for future stakeholders and decision-makers to have a deeper understanding of AV future on the road transportation network. The results can also provide local government with a valuable opportunity to address their road transportation-related environmental issues.

The study has only focused on private transportation modes, not taking into account public transportation services; this is due to the lack of data available for public transport. This study can also be further extended by examining the impact of AVs combined with different mobility policies and technologies, park and ride (P&R), ride-sharing and car-sharing. Future research also includes focusing on the analysis of the expected change in car-ownerships with AV implemented in the transportation network.

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