Modelling, Simulation and Validation of Hybrid Vehicle Fuel Consumption

Imre Zsombok, Máté Zöldy

Budapest University of Technology and Economics, Faculty of Transport Engineering and Vehicle Engineering, Department of Automobile Technology, Muegyetem rkp 3, H-1111 Budapest, Hungary; imre.zsombok@edu.bme.hu; zoldy.mate@kjk.bme.hu

Abstract: Controlling, influencing and managing the fuel/energy consumption and refill frequency of hybrid vehicles will be essential in the coming decades of increasing vehicle autonomy and not have depleted or low battery vehicles, along the roadways. The presented research aims to establish a fuel consumption model with the vehicles' fuel consumption influencing factors, to simulate and evaluate the consumption and refill rate. The aim is to collect the effect of fuel consumption in a comprehensive literature overview. We defined the most relevant work for modelling and simulation. Results were validated in proving ground tests at a high-speed handling track. Several tests were done to validate different parameters' effects on fuel consumption and refine the models. As a result, we built a model that enables the correct prediction of reality in a model environment. It is valuable while autonomous vehicle testing is increasingly becoming simulations. Based on our results, autonomous vehicles can be developed with real environmental effects and fuel consumption behavior.

Keywords: autonomous vehicles; plug-in-hybrid vehicles; fuel consumption; simulation and validation

1 Introduction

Increasing the autonomy of cars and electrification are the two main automotive industry trends in the second decade of this century. There are scenarios in that they go hand-by-hand in other options, and one of them may spread faster [1]. Vehicles of the future will need energy – fuel, electricity or even an unknown source – and their independence will increase [2] [3]. Their effect on the environment [4] [5] and keeping their operation cost optimal is a focal area [6] [7]. In the vehicle industry, the manufacturers need to compliance standards and social pressure about fuel and exhaust emissions [8] [9]. Vahidi and Sciarretta [10] dealt with connected and Automated Vehicles (CAVs) energy-saving potentials based on motion, optimal control theory and eco-driving. Other vehicles' connectivity allows better anticipation of upcoming events (for instance: hills, curves, low traffic, state of traffic signals and measurement of neighboring vehicles). The paper created the first major analysis of connected and automated vehicles. It concluded that access to information (via advanced sensors and V2X communication [11] [12]) increased power, and precision positioning and control enable connected and automated vehicles to plan and execute eco-driving maneuvers much better than a human driver. Related literature to this paper specified energy-saving potentials. For instance, V2I causes 10% of energy savings, while connected and automated vehicles 20% (in platooning, where the vehicles communicate with each other, have 7-10% drag reduction). An interesting result, is that driving scenarios only have 3% of energy savings. These results and functions have a maximum advantage that does not need additional hardware costs, so it is not a significant effort from the manufacturer's side to develop these autonomous functions. Similar statements are presented in the paper of Barabas et al. [13]. He and Wu [14] presented mixed platoons with a mixed fleet of gasoline and electric vehicles. These vehicles have different characteristics as electric vehicles have high efficiency and energy recuperation. Their model uses a non-linear optimization depending on whether the platoon is led by an automated or a human-operated vehicle. This vehicle gets acceleration characteristics, which guarantees the lowest energy consumption of the platoon, while the following vehicles set targeted cruising speeds. The determination of the acceleration profile can be solved in many ways. One of these ways is with the continuum model. These models are usually used for hydrodynamic problems. However, Ronjung et al. [15] show that these models can describe the effect of acceleration changes with memory (that affects, for instance, fuel consumption, exhaust emission, velocity, or density) and give a proper solution with linear and non-linear stability checks too. These acceleration changes play a big role in traffic, causing traffic congestion or local clusters, and the model can reproduce these complicated traffic phenomena. This numeric solution is consistent with the theory. Fuel economy can be optimized in various ways. One of these ways introduced by Wu et al. [16] is an application designed for human drivers and autonomous vehicles. This FEOS (Fuel Economy Optimization System) system is designed for free-flow and car-following modes. It calculates the optimal acceleration and deceleration values by La-grange multipliers (considers even manual and automatic gear shifting and current gas pedal operations and calculates the optimal fuel usage with feedback). The system is based on previous optimization systems of sending the information to the autonomous vehicles, while the human driver gets the acceleration and deceleration information via an HMI (Human-Machine Interface). The system is tested and validated with a driving simulator experiment, where urban driving conditions gained more attention on saving gas than, for instance, freeway (because of the traffic conditions: more acceleration and deceleration is needed). Eight participants took the test from 24 to 34 years of age with normal vision and a valid driver's license. Four participants executed the test with FEOS and the other two without it, and the test concluded that the fuel usage and emission were significantly lower with FEOS (12-26%). This advantage with an autonomous vehicle can be even better with improved motion planning methods [17]. Fuel economy testing is important nowadays, and there is no accepted mechanism. One method was designed by Mersky and Samaras [18], where the main goal was to create a test method for autonomous vehicles for fuel economy testing. This new method is different because it considers how individuals drive and compares to autonomous vehicles. This way, we can get a clear picture of the advantages of autonomous vehicles on fuel economy. In other models, autonomous vehicles have unrealistic optimization decisions or have many requirements and non-public information. This model also can calculate fuel consumption if the vehicle follows another vehicle. The paper concludes that it is challenging to reduce fuel economy without predicting, and the performance can improve significantly by improving the amount of time a vehicle can predict actions in the future. Ross et al. [19] investigate four scenarios that can be seen in Figure 1. These scenarios can be partial or full automation, personal and shared vehicles, and these scenarios are a combination of these. Based on 2011 and 2014, an interpolation was done to 2017. These results are interesting: full automation is likely to result in more energy consumption mainly because it allows vehicles to travel faster (mainly because of travel demand). Shared vehicles' main energy saving potentials are because ridesharing can significantly reduce energy consumption.

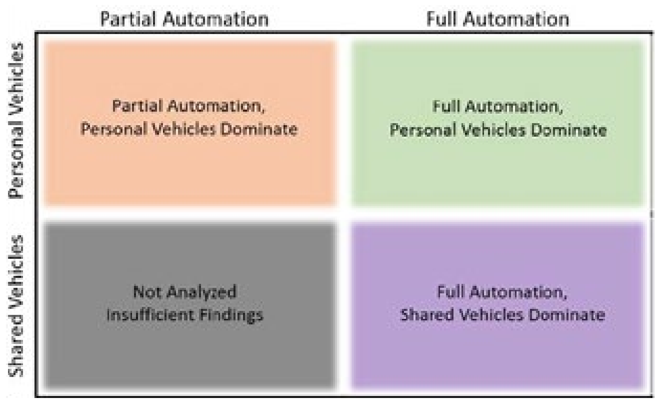

Figure 1
Autonomous vehicle driving scenarios [14]

According to these papers, reducing fuel consumption in vehicles is mandatory. In the case of full automation, if we do not reduce consumption, the pollution can gain too high a level, and it can affect health. That is why some regulations and testing standards need to be instituted to spread autonomous vehicles [20].

The self-driving vehicle can improve fuel consumption in different traffic situations, such as roundabouts, as Pokoradi et al. [21] described. Self-driving vehicles are much available to get information, communicate real-time data and co-operate with other road users. Evidence from current research indicates that in-vehicle systems positively impact fuel consumption and can improve fuel efficiency [22]. In-vehicle feedback systems are relatively new tools for driving more fuel and environmental consciousness to support driver behavior change. There are many devices on the board of the vehicles to be used to improve fuel efficiency, such as dashboard displays, heads-up displays etc. Barth and Boriboonsomsin [23] presented in their paper that speed feedback via in-vehicle dashboard displays can improve fuel efficiency by even 10-20%. Strömberg and Carlsson [24] report about a similar phenomenon in buses. Up to 6.8% in fuel consumption decreased when bus drivers received real-time feedback on their driving via in-vehicle eco-driving systems. Autonomous vehicle's potential role in future mobility emission control is highlighted by Babiak et al. [25].

Similarly, to other characteristics, autonomous vehicles' fuel consumption measurement is hard to insert into the automotive industry's traditional type approval process, as Baranyi et al. [26] reported. The situation is much more complicated in the case of vehicles equipped with artificial intelligence. Aiming to reach a similar safety-critical failure level that is normal for human-driven vehicles, it would be necessary to test more than 4,000,000 km/s for an automated vehicle. It is not realistic, and this gap can be overburdened by using simulation environments combined with exceptional proving grounds [27].

Zöldy and Zsombók [28] research focused on determining the onboard (internal) and environmental (external) influencers of fuel consumption to be able to develop highly automated self-driving vehicles. They state that understanding and influencing fuel consumption is an excellent opportunity to utilize the driver assists systems for eco-driving in an increased way. This also provides a great help in assisting drivers in eco-driving training. Vehicle fuel- and energy consumption could depend on various reasons, and that is to be categorized as vehicle-driven parameters [29], road-related parameters [30], usage (driver) related parameters and ambient parameters. The four categories with their main contributors [31] and their magnitude [32] [33] are presented in Table 1. Related literature overview can be summarized as follows: autonomous and connected vehicles will have a significant role in future mobility. Testing and validation of automated vehicles make it necessary to test and measure the vehicle partially in virtual reality. Most of the aspects of self-driving vehicles are valid for energy consumption-related issues. As the future drivetrain technology is unclear yet, we focus on today's most complex solution, the plug-in hybrid technology, while it covers the two most potent applicants: electric vehicles and internal combustion engines. Focal research parameters were defined by Table 1 as follows: gear ratio, tire pressure, air conditioner use, vehicle speeds:

Table 1
Influencers and their magnitude on fuel consumption

Fuel consumption influencers (-%=increase fuel consumption			
Vehicle driven parameters		**Usage related parameters**	
weight	0.5 l/100 kg	total runtime	up to 8 %
gearbox	-3.3 %	severity of accelerations	down to -10 %
maintenance	up to 5 %	frequent braking	-1.4 %
engine oil	up to 2 %	over speeding	-2.6 %
tires (retreaded)	-1.8 %	driver style	up to 5 %
tires (low pressure	-0.2 %	short trips	down to 7 %
		engine start-up	up to 12 %
		air conditioning	-3.0 %
Road related parameters		**Ambient parameters**	
surface type	1.0 % wet	Intake air temperature	6.6 %
material	0.5 %	cold temperature	
		extra warm temperature	
		wind	
		landscape profile	

2 Materials and Methods

The literature review-based research program is presented in Figure 1. After capturing the relevant fuel consumption onboard influencers, a test track for real vehicle testing was chosen and modelled. Real vehicle tests validated the model-based simulations.

Figure 2
Block scheme of the research

The test program has two main parts: first, the real driving fuel consumption data was measured and evaluated. The focus was on the onboard fuel consumption influencers, while an autonomous vehicle can potentially affect fuel consumption.

Measurement results were incorporated into the modelling and simulation part. The number of measurements was determined for each measurement series during the measurements based on the following. For a population with unknown distribution, the sample size can be calculated from the Chebyshev equations as follows:

$$P\left(\bar{x} - k \cdot \frac{\sigma}{\sqrt{n}} \langle \mu \langle \bar{x} + k \cdot \frac{\sigma}{\sqrt{n}}\right) \geq 1 - \alpha \quad (1)$$

For simple random selection, the formula (1) is simplified to:

$$P(\bar{x} - \Delta \langle M(x) \langle \bar{x} + \Delta) = 1 - \alpha \quad (2)$$

Rearranging Equation (2) gives the number of samples needed to achieve the desired accuracy:

$$n = \frac{t^2 \cdot s_k^2}{\Delta^2} \quad (3)$$

Where:

n - required sample size

t - probability parameter

sk - corrected empirical standard deviation

D - accuracy range

Using the formula (3), the number of measurements performed can be examined in the appropriate standard deviation. To evaluate this, I have determined based on the literature how much spreading ranges are acceptable for each parameter under test with a propellant. The results are shown in Table 2. Here, it can be seen from formula (3) that the standard deviation calculated from the number of measurements carried out is lower than the standard deviation, s_{exp}, which characterizes the measurement's statistical robustness. Based on this, the results of the measurements are statistically acceptable.

Table 2

Number of measurements to be performed and performed per measurement point

		$s_{exp.}$	$s_{calc.}$	**t**	**d**	**n [db]**
Power	W	0.07	0.040	1.96	0.05	6
fuel consumption	l/100 km	0.05	0.040	1.96	0.05	6
energy consumption	kWh/100km	0.03	0.031	1.96	0.05	10

2.1 Test Vehicle

A parallel, mild-hybrid vehicle was chosen for the Integrated Motor Assist system tests. It has an internal combustion engine with a volume of 1.5 liters with variable valve timing. Its transmission system is a 6-gear manual gearbox. A brushless DC motor is placed between these two, which also serves as a starter, rated at 10 kW. The system output is 90 kW. The battery is a Li-ion pack, with a capacity of 0.6 kWh, consisting of 84 cells, with a voltage of 12 V individually. The measurement was the following: the vehicle's cruise control was set at 110 km/h speed, and tests were carried out with Normal mode. Measured onboard consumers were air condition, headlights and audio system. The decrease of the vehicle's range on a 2 km long highway distance has been investigated.

Table 3
Technical specifications of the measured vehicle [28]

Engine	1.5 i-VTEC	
Displacement (cm^3)	1.499	
Bore (mm)	73	
Stroke (mm)	89.4	
Maximum Power (kW (LE)) /révolutions (1/min)	83(114) /6,100	
Maximum Torque (Nm)/révolutions(1/min)	145/4,800	
Compression ratio	10.4:1	
Maximum speed(km/h)	200	
Acceleration (0-100 km/h)	9.9	
Empty weight (kg)	1,147	
Fuel consumption (l/100km)	city	4.4
	highway	6.1
	mixed	5.0

2.2 Test Track Description

Two sets of tests were performed to verify the adequacy of the simulation results. The first was a measurement of consumption in an urban environment, where consumption variations were observed under identical traffic conditions but with variations in weather and day length. Analysis of the data from the measurements showed that the 40 cycles of measurements we carried out did not provide a sufficiently robust answer to whether our assumptions were sufficiently well founded.

As a second test environment, we chose a dedicated section of a test track on which we measured the effect of different consumers on fuel consumption at a constant average speed. During the measurements, the pressure in the vehicle's tires was varied intermittently, assuming that low pressure, which could be an indication of neglect or carelessness, was a clear indication of the vehicle's condition.

The effect of the mix of factors influencing consumption thus created was investigated as a function of speed and gear. In order to have a properly interpretable set of results, it was endeavored to compare the consumption measured at the same speed data in the simulations.

Each test track measurement cycle was run for 30 minutes at average speeds of 47 and 50 km/h.

In all cases, fuel consumption was measured at ambient parameters by preparing the vehicle's fuel supply system and dispensing it from a specially calibrated fuel tank using a top-up procedure to achieve the highest possible accuracy.

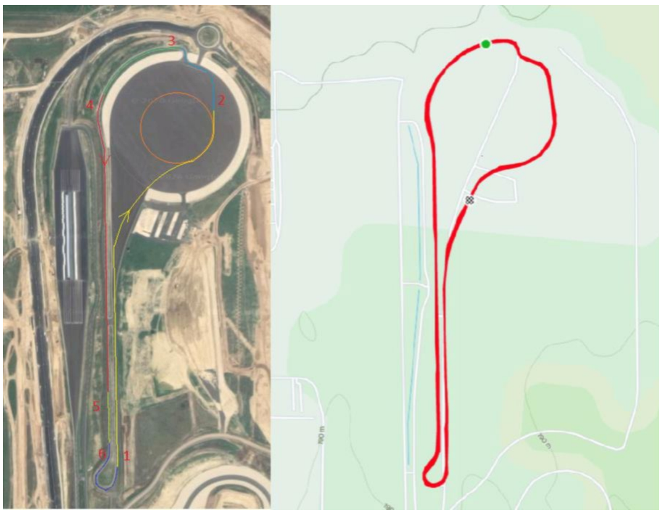

Figure 3
Test track for simulation (real picture and GPS tracked)

2.3 Modelling and Simulation

There are now many possibilities for simulating real-world consumption data with a high accuracy. The most widely used of these is the IPG Carmaker simulation environment, where arbitrary test programs can be run within a high-fidelity environment. Depending on the level of detail of the input data as well as the accuracy of the vehicle data to be tested, it can provide real-time results for vehicles in different environmental and driving situations.

In our case, we were looking for a more general solution to predict the measured data, so we chose to test in a simulation environment supported by neural networks. Simulation tools using neural networks, similar to the human brain, are able to predict fuel consumption and, thus vehicle range by taking into account a number of known or less known variables.

In choosing the right simulation network, we took into account, the complexity of each network and the computational capacity required, as well as the amount of empirical data needed to achieve sufficient accuracy. This grew from the simplest black-box model, which relies only on the anemometric data, to the more complex but significantly higher accuracy back propagation and radial basis neural networks, which empirically, achieve efficiencies of 95-98%.

According to the literature, there is a growing emphasis on the use of feed-forward neural networks.

In this model, neurons can be grouped into several hidden layers. The main features are an input layer, whose length depends on the number of inputs, an arbitrary number of so-called hidden layers, and an output part, whose size is equal to the number of desired outputs.

The size of the input and output layers were not varied and since no significant change was detected by varying the number of hidden layers, we worked with a network having only one hidden layer, varying only the number of neurons.

3 Results and Discussion

The main aim of the real-world test was to measure the effect of different onboard consumers on vehicle fuel consumption and distance prediction. The result can be summarized as it is presented in Table 4.

Table 4

Fuel consumption differences caused by the additional consumers

	l/100 km	**kg/h**	**difference**	**Power [W]**
no consumer	4.6	6.24	0	0
radio	4.65	6.31	1%	160
lightning	4.7	6.38	2%	200
air condition	5.3	7.19	15%	2,480
heating	5.4	7.33	17%	2,720
all consumers (radio, lightning, heating)	5.6	7.60	22%	3,080

Topological differences and environmental effects as wind were compensated so that the test was carried out in both directions, and the results were averaged. This approach helped to eliminate this effect and put onboard consumers in focus. A further research step could be to extend the investigations on the external effect on fuel consumption. Results of the simulation are presented in Figure 3. The baseline case was that no extra onboard consumers were added. The chart x-axis is the driven distance [m], and y is the fuel/electric consumption (absolute fuel consumption, actual fuel consumption, and actual electric consumption). Results are presented with and without extra onboard consumers in Figure 4. Four different onboard consumer level was simulated on the same track with similar environmental parameters: no consumer (left up), lightning as 200 W energy consumption (right up), air-condition with 2,500 W (right bottom) and radio, lightning and heating with 3,000 W (left bottom).

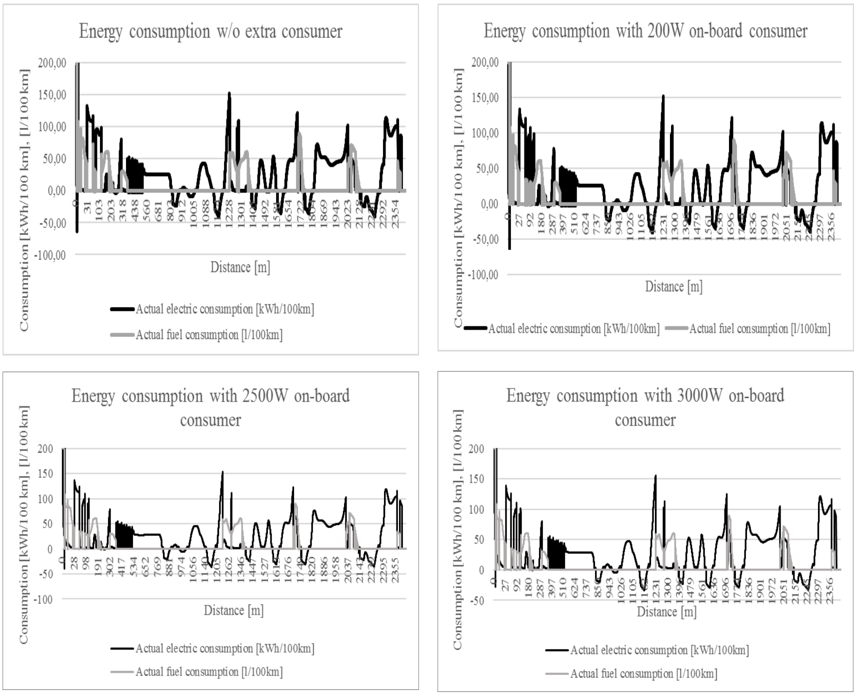

Figure 3

Results of fuel and energy consumption simulation

Figure 3 shows the simulations results in the distance function in all cases. The length of the testing curve is 2.4 km. The fuel and energy consumption profiles of the four cases are very similar. The main difference in energy/fuel utilization is seen in the first part of the track between 0 and 180 meters and the closing part after 2,300 meters. In the first track, the start-up energy consumption of the vehicle is the reason for the different behavior. In the last part, the accumulator charge appears. During the intermedium parts of the track, only a slight difference is to realize that the tendencies (start and stop of ICE, start and stop of electric engine, recharge of accumulator) are the same. Table 5 gives an overall picture of the measured and simulated fuel consumption. In the third row of Table 5, the raw simulation data is compared to the measurement. It is to recognize that increasing onboard energy consumption increases the difference between simulated and measured values.

Table 5
Average fuel and energy consumptions

Fuel consumption [l/100 km]	**w/o consumer**	**200 W load**	**2500 W load**	**3000W load**
Simulation (Sim)	4.6	4.66	4.85	5.02
Measurement (Meas)	4.6	4.70	5.3	5.6
Sim - Meas difference	0%	1%	8%	10%
Corrected simulation (Corr Sim)	4.60	4.70	5.34	5.62
Corr Sim - Meas. Difference	0%	0%	1%	0%

After evaluating the data, it is proposed to use a correction that is a multiplication of a z constant and the extra load as presented in Equation 6:

$$B_{corr} = B_{sim} + (Z * L) \tag{6}$$

where B_{corr} is the corrected simulated fuel consumption, Bsim is the simulated fuel consumption, Z is the constant correction factor of 0.0002, and L is the actual extra load of the onboard consumers. As Table 5 last row shows with the proposed correction, the simulation results were in the 1% range of the measured results.

Conclusions

This work established a correction factor, to correlate fuel consumption simulation results, with onboard consumers and road test data. A comprehensive literature overview in the research paper highlights the importance of fuel consumption prediction of autonomous plug-in-hybrid vehicles. These vehicles contain all state-of-the-art propulsion technologies that will play an essential role in the mobility of the following decades [37]. The basis of the forecasting is a simulation model that correlates with the actual consumption. Development and testing of autonomous vehicles will be done partially in virtual reality. To have accurate fuel consumption simulation results, it is crucial to have correct fuel consumption data connected to that realistic emission and environment load. The three commonly used models and simulation environments were examined, and one was chosen, based on the potential for utilization. In this test environment, a basic setup was built, to do a basic test concerning the potential utilization and validate it with our tests. Our tests concluded that, the modelled fuel consumption method could be verified in simulations, for hybrid autonomous vehicles, in the future, with an accurate correction factor.

Acknowledgement

Project no. 2019-1.3.1-KK-2019-00004 has been implemented with support from the National Research, Development and Innovation Fund of Hungary, financed under the 2019-1.3.1-KK funding scheme.

References

[1] Madanipour, V., Montazeri-Gh, M., Mahmoodi-k, M. Clean Techn Environ Policy (2017) 19: 291, https://doi.org/10.1007/s10098-016-1195-y

[2] Szauter, F., Péter, T., & Lakatos, I. (2014, September) Examinations of complex traffic dynamic systems and new analysis, modeling and simulation of electrical vehicular systems. In 2014 IEEE/ASME 10th International Conference on Mechatronic and Embedded Systems and Applications (MESA) (pp. 1-5) IEEE

[3] Lakatos, I., Szauter, F., Pup, D., & Nagy, A. (2020, November) Alternative Propulsion Buses in the Metropolitan Public Transport. In Vehicle and Automotive Engineering (pp. 49-66) Springer, Singapore

[4] Palevičius V, Podviezko A, Sivilevičius H, Prentkovskis O. (2018) Decision-Aiding Evaluation of Public Infrastructure for Electric Vehicles in Cities and Resorts of Lithuania. Sustainability. Vol. 10, p. 904, https://doi.org/10.3390/su10040904

[5] Matijošius, J., Juciūtė, A., Rimkus, A., & Zaranka, J. (2022) Investigation of the concentration of particles generated by public transport gas (CNG) buses. Cognitive Sustainability, 1(1) https://doi.org/10.55343/cogsust.10

[6] Gáspár, P., Bokor, J., Mihály, A., Szabó, Z., Fülep, T., & Szauter, F. (2015) Robust Reconfgurable Control for In-wheel Electric Vehicles. IFAC-PapersOnLine, 48(21), 36-41

[7] Zoldy, M., Szalmane Csete, M., Kolozsi, P. P., Bordas, P., & Torok, A. (2022) Cognitive Sustainability. *Cognitive Sustainability*, *1*(1) https://doi.org/10.55343/cogsust.7

[8] Szabó M, Szalmáné Csete M, Pálvölgyi T. (2018) Resilient Regions From Sustainable Development Perspective, European Journal Of Sustainable Development 7: 1 pp. 395-411, 17 p.

[9] Čokorilo, O. (2008) Risk management implementation in aircraft accident cost analysis. The 12th Annual World Conference, Air Transport Research Society (ATRS) World Conference, July 6-10, 2008, Athens, Greece

[10] Vahidi A, Sciarretta A (2018) Energy-saving potentials of connected and automated vehicles, Transportation Research Part C, https://www.elsevier.com/locate/trc

[11] Péter, T., Háry, A., Szauter, F., Szabó, K., Vadvári, T., & Lakatos, I. (2021) Analysis of Network Traversal and Qualification of the Testing Values of Trajectories. Acta Polytechnica Hungarica, 18(10), 151-171

[12] Torok, A., & Pauer, G. (2022) Safety aspects of critical scenario identification for autonomous transport. *Cognitive Sustainability*, *1*(1) https://doi.org/10.55343/cogsust.23

[13] Barabás I., Todoruț A., Cordoș N., Molea A.: Current challenges in autonomous driving, IOP Conf. Series: Materials Science and Engineering 252 doi:10.1088/1757-899X/252/1/012096 (2017)

[14] He X, Wu X (2018) Eco-driving advisory strategies for a platoon of mixed gasoline and electric vehicles in a connected vehicle system, Transportation Research Part D, https://www.elsevier.com/locate/trd

[15] Rongjun C, Hongxia G, Fengxin S, Jufeng W (2018) An extended macro model accounting for acceleration changes with memory and numerical tests, Physica A, https://www.elsevier.com/locate/physa

[16] Wu C, Zhao G, Ou B (2011) Fuel economy optimisation system with applications in vehicles with human drivers and autonomous vehicles, Transportation Research Part D, https://www.elsevier.com/locate/trd

[17] Antonya C., Butnariu S., Beles H.: Parameter Estimation from Motion Tracking Data. In: Duffy V. (eds) Digital Human Modeling. Applications in Health, Safety, Ergonomics and Risk Management: Ergonomics and Health. DHM 2015, Lecture Notes in Computer Science, Vol. 9185, Springer, Cham https://doi.org/10.1007/978-3-319-21070-4_12 (2015)

[18] Mersky A C, Samaras C (2016) Fuel economy testing of autonomous vehicles, Transportation Research Part C, http://www.elsevier.com/locate/trc

[19] Ross C, Guhathakurta S (2017) Autonomous Vehicles and Energy Impacts: A Scenario Analysis, ScienceDirect, https://www.sciencedirect.com

[20] Robinson I: The End of Emissions with Self-Driving Cars, 2018.04.11, https://www.azocleantech.com/article.aspx?ArticleID=706 (2018)

[21] Pokorádi, L., Koçak, S., & Tóth-Laufer, E. (2021) Fuzzy Failure Modes and Effects Analysis Using Summative Defuzzification Methods. Acta Polytechnica Hungarica, 18(9), 111-126

[22] Rastelli J P, Milanés V, De Pedro T, Vlacic L: Autonomous driving manoeuvres in urban road traffic environment: a study on roundabouts. Proceedings of the 18th World Congress the International Federation of Automatic Control, Aug 2011, Milan, Italy

[23] Barth M, Boriboonsomsin K: Energy and emissions impacts of a freeway-based dynamic eco-driving system, Transportation Research Part D: Transport and Environment, Vol. 14, pp. 400-410, 2009

[24] Strömberg H K, Karlsson I M: Comparative effects of eco-driving initiatives on urban bus drivers–Results from a field trial. Transportation Research Part D: Transport and Environment, Vol. 22, pp. 28-33, 2013

[25] Babiak, M., Iglinski H.: Analysis of the potential of autonomous vehicles in reducing the emissions of greenhouse gases in road transport, Procedia Engineering 192, pp. 353-358 (2017)

[26] Baranyi, P., Csapó, Á., Budai, T., & Wersényi, G. (2021) Introducing the Concept of Internet of Digital Reality. Acta Polytechnica Hungarica, 18(7) 225-240

[27] Szalay, Z., Tettamanti, T., Esztergár-Kiss, D., Varga, I. and Bartolini, C. Development of a Test Track for Driverless Cars: Vehicle Design, Track Configuration, and Liability Considerations, Periodica Polytechnica Transportation Engineering, 46(1), pp. 29-35, doi: https://doi.org/10.3311/PPtr.10753 (2018)

[28] Zöldy M., Zsombók I.: Modelling fuel consumption and refuelling of autonomous vehicles Horizons of Railway Transport 2018 37, MATEC Web of Conferences 235, 000 https://doi.org/10.1051/matecconf/2018235000 (2018)

[29] Široký J, Schroder S, Gašparík J (2017) Comparison of operational and economic aspects of direct road transport and continental combined transport. Communications - Scientific Letters of the University of Zilina, 19, 109-115

[30] Geiger A., Holló A., Thernesz A., Durgo R., Czibor S., Bartha L, Gergó P. Chemically Stabilized Rubber Bitumen, Proceedings of EEC, Istanbul, Turkey, Volume: ISBN/EAN 978-90-802884-0-9, 1-8 (2012)

[31] Zöldy M, Zsombók I. (2019) Influence of External Environmental Factors on Range Estimation of Autonomous Hybrid Vehicles, System Safety: Human - Technical Facility - Environment, 1(1), 472-480, doi: https://doi.org/10.2478/czoto-2019-0061

[32] Zanne M, Groznik A, (2016) The impact of traffic flow structure on traffic safety: the case of Slovenian motorways. Transport. 1-7, https://doi.org/10.3846/16484142.2016.1153519

[33] https://en.wikipedia.org/wiki/Honda_CR-Z

[34] Prescan TASS – Users Manual, © 2018 TASS International Version 8.4.0

[35] IPG Carmaker – Users Guide, User's Guide Version 7.0.1

[36] ITD Vires- Format Specification, Rev. 1.4 – DRAFT

[37] M, Baranyi P: Cognitive Mobility – CogMob. 12th IEEE International Conference on Cognitive Infocommunications – CogInfoCom 2021 • September 23-25, 2021 pp. 921-925