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Research Article

Simulating the alteration in energy consumption at a zebra crossing considering different traffic rates of electric and rule-following autonomous vehicles

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Abstract: The progressive integration of autonomous vehicle (AV) technology holds the potential to reshape the prevailing traffic landscape. AVs have different driving characteristics than human-driven vehicles, which manifests itself in the strict adherence to speed limit, in giving priority to pedestrians, and in the pre-set headways they can keep. A traffic simulation environment was built around an unsignalized pedestrian crossing to measure the energy consumption of vehicles in the presence of AVs. The simulation environment was modified to adhere pedestrian-accepted gaps between vehicles in case of crossing. Considered vehicle types are yielding or not yielding human-driven, and AVs. Scenarios were built to model the AV traffic share, the different headways kept by AVs, and the various traffic volumes in each direction. The different driving behaviour and traffic share of AVs led to energy consumption changes, which were modelled through scenario analysis. The maximum energy consumption reduction of human-driven vehicles was 10.67% for yielding vehicles and 12.41% for non-yielding vehicles compared to the 0% AV traffic rate. Although, in case of AVs, the energy consumption increased in all scenarios compared to the basic version with only human-driven vehicles. In higher traffic scenarios, where only AVs were on the road, there was a substantial 35,92-96.55% increase in energy consumption, compared to the 0% AV ratio case. Thereby speed of vehicles, following distance and the number of stops affected the overall system efficiency. The results of this study can contribute to the understanding the impact of AVs which can support their introduction.

Keywords: Traffic simulation; energy consumption; autonomous vehicle; electric vehicle; pedestrian crossing

I. INTRODUCTION

The automotive industry has undergone significant changes in the past decade. New drive modes and advanced driving support technologies were introduced. Electric drive is one of the most dynamically developing vehicle propulsion techniques, which is clearly shown by the fact that the electric car market sales exceeded 10 million in 2022 globally. The 14% of new cars sold were electric, up from 9% in 2021 and 5% in 2020. Also, a total increase of 35% in sales was forecast for the year 2023 [1]. The rise of battery electric vehicles in Europe is also remarkable, an increase of 83% was observed between 2019-2020 and 76% between 2020-2021 [2]. To facilitate the transition from internal combustion engines to zero-emission ones, the European Commission has stipulated that from 2035, only zero-emission new vehicles can be sold [3].

Besides the emergence of EVs, highly automated vehicles are spreading which can assist or even replace human driving operations [4]. Autonomous vehicles (AVs) have the potential to reduce human error due to the more accurate and faster environment sensing and control [5].

Our research focused on energy consumption simulation at an unsignalized pedestrian crossing in the era of autonomous and electric vehicles. The aim was to examine how energy consumption varies as a function of speed, acceleration, and deceleration according to simulation time steps. Energy consumption is influenced by many things, including the speed and weight of the vehicle, the elevation of the route, and the driving style. In the simulation, only electric vehicles (EVs) were modeled, which could be traditional human-driven or autonomous vehicles (AVs). AVs have a different driving behavior than traditional human-driven vehicles, which manifests itself in the strict adherence to the speed limit, in giving priority to pedestrians, and in the pre-set headways they keep. The rule-following behavior of AVs was achieved by modifying the simulation parameters. Scenarios were built to model the AV traffic share, the different headways, and the various traffic volumes in each direction. The different driving behavior and traffic share of AVs led to energy consumption changes, which were modeled through scenario analysis.

The structure of the paper is the following: a brief literature review is followed by the description of previous related research in Section II. In Section III, the simulation methodology and the implemented scenarios are discussed. Section IV contains the results of the study. Finally, the conclusions were summarized.

II. LITERATURE REVIEW

Energy consumption was studied in different approaches in previous studies. These are either based on measurements in a real environment [6-9] or based on mathematical modelling and simulation [10-14]. Most of the research rely on VSP (Vehicle Specific Power) models, which estimates instantaneous power requirement based on vehicle kinematic parameters. Parameters that are frequently used to calculate VSP are vehicle speed, acceleration, frontal area of the vehicle, mass, rolling resistance coefficient, drag coefficient, and road grade. The first VSP model was defined by J. L. Jimenez-Palacios in 1998 [15]. An interpretation of the power-based model for electric vehicle consumption was discussed in a study by Fiori et al [16]. They modelled the instantaneous energy consumption of EVs using second-by-second vehicle speed and acceleration as input variables. Their proposed model had an average error of only 5.9% relative to the empirical data. Results also showed that a higher amount of energy is recovered in urban environments compared to higher-speed highway driving. Wu et al. examined real-time power consumption in relation to vehicle speed, acceleration, and road grade [17]. Other studies estimate the effects of ambient temperature [18-19] and road gradient [20] on vehicle energy consumption. Another important factor that can influence energy consumption is driver behaviour, which has also been addressed by several studies [21-22].

To increase the range of electric vehicles, regenerative braking is a frequently used solution. Several research focus on the issue of calculating the efficiency of regenerative braking. Some of these models consider constant regenerative braking efficiency [23-24], while others study regenerative braking as a linear function of vehicle speed [25] or its deceleration [16].

Fuel consumption reductions by AV traffic was also studied in some articles [35-36]. However, fewer studies focus on the energy consumption of electrically powered AVs. Most of them are researching the possibilities in optimizing the relocation of shared AVs [26-27] and connecting them with the smart grid [28]. Other studies in this field rather focus on vehicle-level energy consumption modeling [29-30].

Traffic simulation studies related to AVs are also getting more attention nowadays. Research indicates that AVs may enhance traffic characteristics in both on freeways [31-32] and in urban areas [33]. At the same time, we found only one example of simulating AVs in the environment of a pedestrian crossing [34].

Based on our literature review, it can be stated that the simulation of energy consumption in a specific traffic situation, such as at a pedestrian crossing is a less researched area. The novelty of our research comes from modeling electric-powered AVs in the vicinity of a pedestrian crossing and analyzing the effects of their different behavior characteristics on energy consumption.

III. SIMULATION METHODOLOGY

An unsignalized pedestrian crossing on a 2x1 lane road was modeled in Vissim (2020) microsimulation software. The road section was characterized by straight alignment on a flat terrain, with lane widths of 3.5 meters. Overtaking was not permitted in the vicinity of the pedestrian crossing.

Road-side video camera measurements were carried out in Budapest, Hungary to assess pedestrians' vehicle distance-based crossing decisions. Data collection was conducted over four days, with time intervals typically set at 1.5-2 hour. Pedestrian traffic was normalized to 1 hour, which resulted in 87 pedestrians in west-to-east direction and 91 pedestrians in east-to-west direction. Pedestrian groups were formed according to gender and age categories. We found that the majority of pedestrians chose to cross if the vehicle distance was 50 meters or more.

The drivers' yield ratio was measured 69%, which was also implemented in the model by separating yielding and not yielding human-driven vehicles in the simulation model with different vehicle classes. Speed distributions remained at the default Vissim setting. However, for AVs, a fixed maximum speed limit of 50 km/h was enforced.

Given that pedestrian behavior in the Vissim simulation environment does not inherently consider vehicle proximity, model calibration became necessary. To address this, we deployed detectors with 10 meters range to detect vehicle positions. Subsequently, signal heads were placed on both ends of the pedestrian crossing, permitting access to pedestrians based on their gender, age category, and the proximity of the approaching vehicle. The logic between the detectors and the signal control that handled the signal heads was set with the VisVAP module.

We defined mathematical formulas for energy consumption and regeneration, and subsequently provided these as input parameters to the Vissim software for energy calculations. To accomplish this, we employed the Vissim External Emission Model, and the energy model itself was programmed in the C++ language. Due to the substantial data volume, an Excel macro was written for data processing. Finally, to measure the impact of traffic volumes, AV traffic ratios, and the different headways maintained by AVs on energy consumption, various scenarios were built in the simulation framework.

It is important to emphasize that present study focused on the pedestrian crossing area. Consequently, we examined the area within a 100 meter radius in both directions. Vehicle data beyond this range was excluded with data filtering.

The calibration processes of Vissim with the VisVAP module, incorporating energy consumption calculation formulas, and the development of the simulation scenarios are summarized in **Fig.1**.

1. Scenario building

The simulation model was constructed utilizing data derived from roadside observations. In accordance with the discerned patterns of pedestrian decision-making in response to varying vehicle distances, we established specific vehicle headway values of 50 meters, 60 meters, and 70 meters for AVs. Conversely, for conventional vehicles, we retained the default model parameters.

These predefined vehicle headway values constituted the initial phase in scenario building. We adjusted the proportions of AV traffic, encompassing a spectrum from 0% to 100% in increments of 25%. Subsequently, we introduced five discrete levels of traffic flow rates for each direction, specifically 200, 400, 600, 800, and 1,000 vehicles per hour. Accordingly, a total of 65 distinct scenarios were built. It is noteworthy to mention that the predefined headway settings were not applied if the AV traffic ratio is 0%.

In each scenario, three simulation runs were performed and the average values of them were considered for further calculations. To model the stochastic variations of vehicle and pedestrian arrivals, different random seeds were implemented in Vissim. The chosen random seed values were 5, 7, 9 and 11. Each simulation run lasted for 3600 simulation seconds.

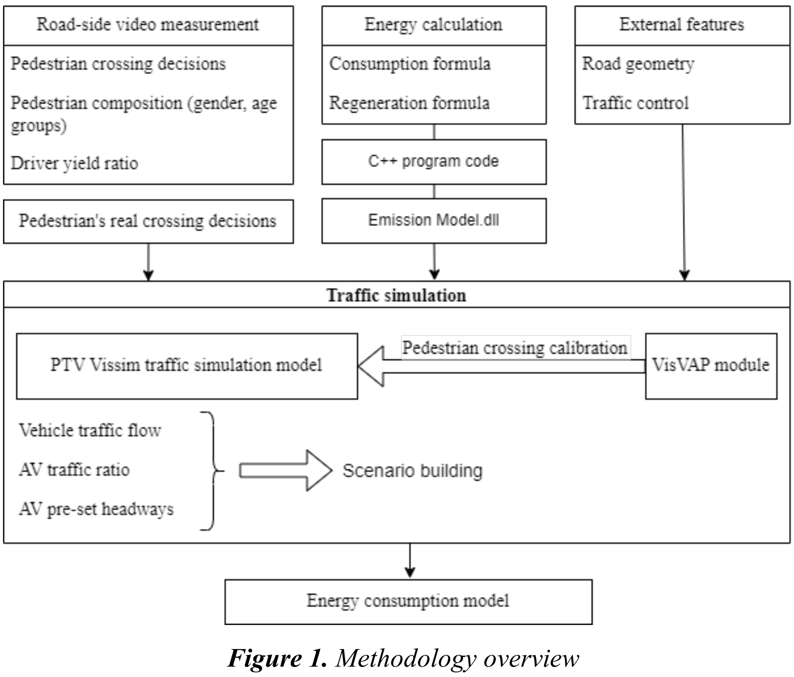

Figure 1. *Methodology overview*

2. Energy consumption and regeneration calculation

Since energy consumption of the EVs is not constant over time, a time step approach was used in the simulation. Vissim generated the speed, acceleration (deceleration), and position data for each vehicle in every t time step which was 0.25 seconds.

The energy consumption model was derived from vehicles' kinematic parameters, with the summation of the forces acting on a moving vehicle by equation (1):

$$\sum F = F_{acc} + F_{roll} + F_{air} \tag{1}$$

Where F_{acc} is the acceleration force acting on the vehicle - equations (2), F_{roll} is the rolling resistance force - equation (3), and F_{air} is the aerodynamical drag force - equation (4).

$$F_{acc} = M \cdot a_t \tag{2}$$

Here M denotes the vehicle mass in kilograms, a_t is the acceleration in t time step of the EV in m/s^2.

$$F_{roll} = \mathrm{M} \cdot g_t \cdot C_R \tag{3}$$

Where g_t is the gravitational acceleration in m/s^2 in t simulation time step, and C_R is the tires' rolling resistance coefficient.

$$F_{air} = \frac{1}{2}\, \rho_a \cdot C_D \cdot A_{front} \cdot v_t^2 \tag{4}$$

Where symbol ρ_a represents the air mass density in kg/m$_3$, C_D is the aerodynamic drag coefficient, A_{front} is the frontal area of the vehicle in m^2, and v_t is the vehicle speed in m/s in the t time step.

The power requirement (measured in KWh) for moving the vehicle at a given velocity v was determined with equation (5):

$$P_{acc} = \frac{\sum F \cdot v}{3{,}600{,}000} \tag{5}$$

Regarding deceleration, the regenerated energy (in KWh) was determined by computing the alteration in kinetic energy by equation (6):

$$P_{dec} = \frac{\frac{1}{2} M \cdot (v_{t-1}^2 - v_t^2)}{3{,}600{,}000} \tag{6}$$

The regenerated energy calculated within this expression has a negative sign, signifying the directional vector of energy transfer is opposite to the energy consumption. We note that, due to the inefficient regeneration at low vehicular speeds, data associated with EVs operating at velocities below 10 km/h were omitted.

The comprehensive energy equilibrium of the vehicle through the entire time frame can be evaluated by the difference of energy dissipation and energy regeneration by equation (7):

$$P_{consumed} = \sum P_{acc} + \sum P_{dec} \tag{7}$$

The parameters employed in the emission modelling process are depicted in **Table 1**. The selected parameters fell within the range of values identified in the existing literature.

IV. RESULTS AND DISCUSSION

The energy consumption was calculated for vehicles giving priority, not giving priority, and AVs. Results are showcased for traffic volumes.

In scenarios considering 800 and 1000 vehicles per hour, it was observed that not all vehicles could trespass the area. The resulted traffic congestion may have influential and distorting impact on the energy consumption results. Accordingly, the result of scenarios considering 200, 400, and 600 vehicles per hour are only further discussed in this paper. **Table 2**, **Table 3**, and **Table 4** shows the energy consumption per vehicle under the considered traffic volumes, respectively.

Table 1. *Parameters used in the energy consumption calculation*

Parameter	***Ref.*** [16]	***Ref.*** [24]	***Ref.*** [37]	***Ref.*** [38]	***Ref.*** [39]	***Chosen value***	***Unit***
Mass of the vehicle (M)	1521	1500	2169	1480	2791	2000	[kg]
Rolling resistance coefficient (C_R)	0.0328	0.005	0.013	0.013	0.006	0.01	-
Aerodynamic drag coefficient (C_D)	0.28	0.25	0.23	0.34	0.8	0.3	-
Frontal area (A_{front})	2.3316	2.25	2.341	2.713	2.666	2.3	[m^2]
Air mass density (ρ_a)	1.2256	1.275	1.293	1.204	1.2	1.275	[kg/m^3]

Table 3. *Energy consumption per vehicle [KWh] (traffic volume: 400 veh./h)*

Headway/ AV ratio	***AV 0%***	***AV 25%***	***AV 50%***	***AV 75%***	***AV 100%***
50 m	0.1297	0.1358	0.1453	0.1501	0.1607
60 m		0.1376	0.1467	0.1546	0.1703
70 m		0.1398	0.1498	0.1576	0.1762

Table 2. *Energy consumption per vehicle [KWh] (traffic volume: 200 veh./h)*

Headway/ AV ratio	***AV 0%***	***AV 25%***	***AV 50%***	***AV 75%***	***AV 100%***
50 m	0.1205	0.1200	0.1246	0.1279	0.1310
60 m		0.1198	0.1254	0.1295	0.1350
70 m		0.1212	0.1273	0.1317	0.1381

Table 4. *Energy consumption per vehicle [KWh] (600 veh./h)*

Headway/ AV ratio	***AV 0%***	***AV 25%***	***AV 50%***	***AV 75%***	***AV 100%***
50 m	0.1444	0.1599	0.1765	0.1910	0.2098
60 m		0.1639	0.1839	0.2115	0.2569
70 m		0.1680	0.1909	0.2300	0.2838

Besides the absolute energy consumption values, we illustrate the relative change compared to the 0% AV traffic ratio. These results are also presented with respect to headways kept by AVs and the level of AV traffic penetration. With the rise of AV traffic ratio, headway kept and the amount of road traffic, the energy consumption increased significantly, as presented in **Fig. 2.**, **Fig. 3.**, and **Fig. 4.**

In the context of all three traffic scenarios, energy consumption exhibited an upward trend with the rise of AV traffic ration. In the case of 200 vehicles per hour traffic volume, a 100% AV ratio, and 70 m headway, the energy consumption was 14.57% greater than the scenario without AVs. As traffic density increased, this disparity further magnified. Specifically, in scenarios involving 400 vehicles per hour, the difference surged to 35.92%, and in the context of 600 vehicles per hour, it escalated to 96.55%. This increase can be attributed to the rule-following behavior of AVs, as they consistently yielded to pedestrians, while 31% of human drivers did not yield. Rule-following behavior results in more acceleration phase thus higher energy consumption. It is also noteworthy that the rise in energy consumption correlated with the augmentation of the headway maintained by AVs. This additional energy consumption is likely attributed to minor accelerations and decelerations required to uphold the desired inter-vehicle spacing. Furthermore, the lack of wind shadow may also cause an increase in energy consumption when AVs keep greater headways.

In scenarios characterized by lower traffic volumes, the energy consumption of conventional, human-operated vehicles demonstrated a decline as the proportion of AVs increased. This phenomenon can be elucidated by a combination of factors,

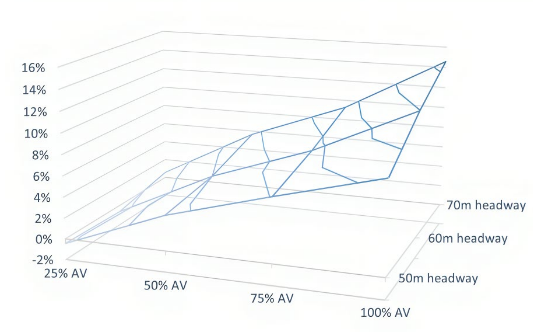

Figure 2. *Energy consumption relative to 0% AV case (traffic volume: 200 veh./h)*

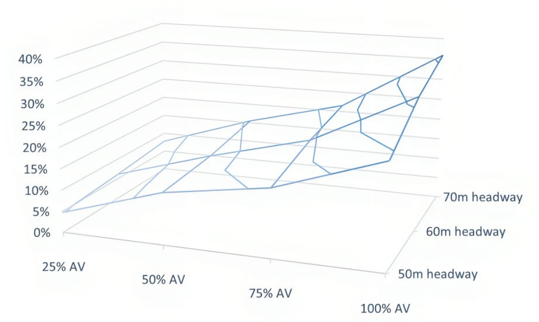

Figure 3. *Energy consumption relative to 0% AV case (traffic volume: 400 veh./h)*

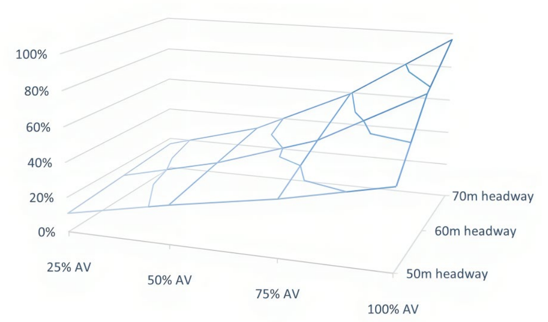

Figure 4. *Energy consumption relative to 0% AV case (traffic volume: 600 veh./h)*

including the speed limits followed by AVs and the behavior of pedestrians. The first factor results in a reduction of energy consumption as the number of speeding vehicles decreases. In the case of the second factor, due to the greater distances between vehicles, pedestrians tend to cross the road without requiring vehicles to come to a complete stop, which also results in reduced energy consumption. **Table 5** shows an example of such an alteration in energy consumption. With the increase of AV traffic rate, a noticeable decrease in energy consumption due to the adherence to speed limits was measured. Simultaneously, as the headway expands, a slight decrease in energy consumption was detected due to pedestrians transversing the road without the necessity of vehicles stopping at the pedestrian crossing. However, we have to admit that the rise in energy consumption was measured with the increased AV traffic.

Table 5. *Energy consumption per* ***not yielding*** *vehicle [KWh](200 veh./h)*

Headway/ AV ratio	***AV 0%***	***AV 25%***	***AV 50%***	***AV 75%***
50 m	0.1090	0.1143	0.1029	0.0973
60 m		0.1144	0.1025	0.0962
70 m		0.1141	0.1019	0.0955

While energy consumption increased, potential enhancements could be realized through vehicle-to-vehicle communication and pedestrian movement prediction. In both cases, electric vehicles could eliminate the necessity of forceful braking, rather applying regenerative braking and coasting mode. Moreover, it is imperative to note that while there may be a potential increase in energy consumption, the enhancement of traffic safety and pedestrians' sense of security is evident through the reduction in vehicle speeds and the provision of unconditional priority.

V. CONCLUSIONS

In this study, a simulation model was developed to measure alteration in energy consumption of conventional and autonomous vehicles in the vicinity of a pedestrian crossing. We calibrated the model to assess pedestrians' crossing decisions based on vehicle distance. Additionally, the method for calculation energy consumption was provided as an external input. Various scenarios were formulated to examine the impact of different autonomous vehicle traffic ratio, their maintained headways, and varying traffic volumes.

The results show that in case of low traffic, autonomous vehicles may have a slight advantage mainly on conventional vehicles' consumption. In part, this is achieved through the adherence of speed limits, and, on the other hand, by the maintained headways by autonomous vehicles which may result in pedestrians crossing without the stopping of vehicles. Considering low traffic (200 or 400 vehicle per hour), results showed a maximum decrease of 12.41% in energy consumption for not yielding, and 10.67% for yielding vehicles, compared to 0% AV traffic ratio.

However, with increased traffic, AV ratio and headways, the energy consumption increased significantly. Comparing with the 0% AV ratio, when reaching 100% AV traffic, the energy consumption rose by 35.92% and by 96.55% in case of 400 and 600 vehicles per hour traffic, respectively.

Further research is needed to examine the operational aspect of the following distance set for autonomous vehicles and its consequent influence on energy consumption. This requires generating and then analysing short-term data series involving only 2 vehicles.

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AUTHOR CONTRIBUTIONS

Sz. Szigeti: Conceptualization, Simulation, Measurements, Discussion.

D. Földes: Conceptualization, Discussion, Review and editing.

X. Ye: Energy modelling.

DISCLOSURE STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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