IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received March 19, 2021, accepted April 7, 2021, date of publication April 13, 2021, date of current version April 28, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3072979

Analyzing the Impact of Roadmap and Vehicle Features on Electric Vehicles Energy Consumption

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This work was supported in part by the Government of Aragón and the European Social Fund through the T40_20D Research Group, in part by the European Union's CONCORDA Project (Connected Corridor for Driving Automation, CEF Action) under Grant 2016-EU-TM-0327-S, in part by the European Union's Horizon 2020 projects: Fed4FIREplus under Agreement 723638, 5G-Blueprint under Agreement 952189, Interconnect under Agreement 857237 in part by the Ministerio de Ciencia, Innovación y Universidades, Programa Estatal de Investigación, Desarrollo e Innovación Orientada a los Retos de la Sociedad, Proyectos ICDCi 2018, Spain, under Grant RTI2018-096384-B-I00.

ABSTRACT Electric Vehicles (EVs) market penetration rate is continuously increasing due to several aspects such as pollution reduction initiatives, government incentives, cost reduction, and fuel cost increase, among others. In the vehicular field, researchers frequently use simulators to validate their proposals before implementing them in real world, while reducing costs and time. In this work, we use our ns-3 network simulator enhanced version to demonstrate the influence of the map layout and the vehicle features on the EVs consumption. In particular, we analyze the estimated consumption of EVs simulating two different scenarios: (i) a segment of the E313 highway, located in the north of Antwerp, Belgium and (ii) the downtown of the city of Antwerp with real vehicle models. According to the results obtained, we demonstrate that the mass of the vehicle is a key factor for energy consumption in urban scenarios, while in contrast, the Air Drag Coefficient (C_d) and the Front Surface Area (FSA) play a critical role in highway environments. The most popular and powerful simulations tools do no present combined features for mobility, realistic map-layouts and electric vehicles consumption. As ns-3 is one of the most used open source based simulators in research, we have enhanced it with a realistic energy consumption feature for electric vehicles, while maintaining its original design and structure, as well as its coding style guides. Our approach allows researchers to perform comprehensive studies including EVs mobility, energy consumption, and communications, while adding a negligible overhead.

INDEX TERMS Electric vehicles, vehicular networks, simulation, energy consumption, ns-3, SUMO.

I. INTRODUCTION

Automobile factoring has become one of the most important world-wide industries, not only at economic level but also in terms of research and development. Enhancing the safety of both in-vehicle and road users has been the first step of a series of developments in the automotive industry. Another consideration it is the ever-increasing number of vehicles present in our roads and the effects produced by this situation, such as traffic jams and pollution. In fact, according to a report by the European Union, the transportation sector is responsible for nearly 28% of the total carbon dioxide (CO_2) emissions, while the road transport is accountable for over 70% of the transport sector emissions [1].

Therefore, several advancements in order to mitigate the above mentioned undesirable situations have been proposed in the recent years [2]–[4], and the Electric Vehicle (EV)

The associate editor coordinating the review of this manuscript and approving it for publication was Razi Iqbal.

is foreseen as one of the most important players to reduce polluting emissions. Nowadays, EVs are the first alternative to internal combustion vehicles in order to reduce pollution issues in the transportation sector. EVs solve one of the most important environmental problems caused by traditional vehicles, the tailpipe emissions, specially in downtown areas where the pollution is localized at the same zone. As a matter of fact, Electric Vehicles have emerged as a feasible alternative to replace traditional internal combustion engine vehicles. Having into account their lack of tailpipe emissions, EVs can significantly reduce localized pollution, which is currently a critical issue in overpopulated urban areas [5]. Another key aspect regarding EVs is the battery charging, and therefore, research efforts have also significantly increased regarding this topic [6]–[8]. We consider that using wireless communications can greatly enhance EV charging processes enabling a great leap forward.

Research in Intelligent Transportation Systems (ITS), in general, and more specifically in Vehicular Networks, usually relies on simulation since it is a cost-effective alternative compared to the more costly real deploying of such systems when testing new opportunities and challenges. In addition, real-world testbeds also present scalability problems. When simulating vehicular environments, different issues must be addressed, such as mobility models, wireless communications, and vehicular fuel/energy consumption, among others. Moreover, considering real environments and scenarios, communications elements, and signaling impairments of wireless communications for vehicles, must be taken into account. According to this, and focusing on the study of Electric Vehicles global deployment, there is a lack of integrated simulation tools that consider ITS key factors such as mobility models, street map layouts, communication network technologies, along with fuel/electric consumption, all together within a holistic approach. We consider that a network simulator, in order to be a supportive tool for the research community, should definitely integrate the mapping of such real world considerations into the simulation principles, in order to empower researchers towards comprehensive studies including mobility, connectivity, and consumption aspects.

In the near future, all the vehicles will need to be wirelessly connected among them (V2V communications), and also to the infrastructure (V2I), for different purposes, such as autonomous driving, smart traffic management, accident avoidance, multimedia resources, etc., and hence, the use of accurate and comprehensive simulation environments will be crucial to better test new protocols and approaches, prior to make them real.

The insights and contributions of this work are the following:

- We include an Electric Vehicle (EV) consumption model to a widely used network simulator (i.e., ns-3) to ease the simulation of bot EVs consumption and vehicular network capabilities under different parameters and realistic scenarios.
- We present two realistic layouts (i.e., Urban and Highway-based) from real location in Antwerp, Belgium. This lets researchers to evaluate the consumption of EVs under different map conditions.
- We present the main features of the best-selling car models in Europe. In particular, we include the Maximum Battery Capacity, the vehicle mass, the Front Surface Area, and the Air Drag Coefficient.
- We analyze the influence of different EV models and their consumption in both layouts.
- We include detailed figures and results in order to demonstrate the effects of braking and acceleration depending on vehicle features.

The paper is organized as follows: Section II reviews some of the most relevant existing alternatives in the literature to estimate the energy demanded by EVs including the analytical and simulation tools used by different authors. In Section III, we describe the realistic vehicle features and the roadmap layouts used (i.e., urban and highway) in the simulations, the EV consumption model included in the ns-3 as well as the module that has been specially designed. In Section IV, we present the influence of the roadmap layout and the electric vehicle model on the energy consumption. Finally, Section V shows the main conclusions drawn from this work.

II. RELATED WORK

For several years, researchers have been proposing methods to accurately estimate the consumption of electric vehicles since driving range is a critical factor for EVs. Analyzing existing literature, we can identify two critical factors that determine the energy consumption: (i) the dynamic properties of the vehicles that are determined by the features of each vehicle model and (ii) the type of road on which vehicles circulate, since consumption varies considerably if the vehicle runs on urban or extra-urban ways.

For instance, Wu *et al.* [12] presented a system specially designed to gather EVs driving data, which was installed in an ad hoc EV conversion vehicle built by the authors themselves. Authors collected data over 5 months to analyze both driver behavior and EV performance. They demonstrated that EVs are more suitable and efficient for urban routes than for highways. Other authors such as Fiori *et al.* [13] also stated that EVs are more energy efficient in urban environments than in high speed highways because they can recover a higher amount of energy in the former ones. In their study, the authors proposed a model that computes the regenerative braking efficiency using the instantaneous vehicle operational variables. More specifically, their model accurately estimates the energy consumption, presenting an average error of only 5.9% compared to empirical data. However, they only validated their proposal using one single vehicle, in this particular case a Nissan leaf. Similarly, Yuan *et al.* [14] proposed a method for assessing EVs energy consumption under realistic driving conditions. The results showed that the

TABLE 1. Features of the electric vehicles used in our simulations [9]–[11].

Make	Model	MBC (kWh)	Mass (kg)	FSA (m^2)	C_d	Sales (%)	J_{int} (kg·m^2)	C_{rad}	C_{roll}	P_{const} W	η_{prop}	η_{recup}
Nissan	Leaf 2018	40.0	1,557	2.30	0.28	28.01	0.01	0.5	0.01	100	0.9	0.9
Renault	Zoe	41.0	1,468	0.75	0.29	27.01						
BMW	i3	33.0	1,195	2.38	0.29	17.60						
VW	e-Golf	35.8	1,540	1.97	0.31	15.23						
Tesla	Model S	72.5	2,250	2.34	0.24	11.97						

energy consumption parameters derived from their proposal accurately determine the energy consumption of electric vehicles under different driving conditions. Unfortunately, they only validated their proposal using one vehicle model, in particular a Nissan Leaf. Grubwinkler and Lienkamp [15] proposed modular approach to predict the energy consumption of electric vehicles considering the average propulsion energy, map attributes and speed profiles. Similarly, Yi and Bauer [16] also detailed an energy consumption model, that took into account tractive effort components, regenerative braking, and parasitic power uses.

As it can be observed, all the proposals merge in the proposed critical factors, however all of them have been tested under singular conditions, or with single models such as Nissan Leaf due to the high costs needed to validate the proposals in this field.

Simulation is a key factor when researchers aim to validate their proposals in vehicular research areas where a real implementation may require considerable high costs and amount of resources. Mets *et al.* [17] designed their own framework to model and simulate both the communication and power networks, and hence validate proposals addressing the future Smart Grid. Anderson *et al.* [18] proposed an open-source simulation framework that allows researchers to design and model smart grid-oriented solutions. More specifically, GridSpice integrates useful electric power simulation tools, and enables electric networks modeling, comprising the energy generation, distribution, transmission, as well as electricity markets. However, this simulator does not provide any communication capabilities which are required by ITS.

Other authors such as Sarker *et al.* [19] needed to use three different tools (ns-3, MatLab, and the Simulation of Urban MObility (SUMO) [20]) to validate a system designed to balance the Battery State of Charge (BSoC) at Wireless Power Transfer (WTP) lanes. In particular, the authors required all those tools because there was not any simulator able to estimate EVs consumption including realistic layout features at the time authors performed their research. More recently, Torres-Sanz *et al.* [21] implemented a simulator able to model and predict the EVs energy demand which relies on Vehicular Networks. However, this approach does not consider realistic mobility and map layouts. Now, with our module, ns-3 is able to consider the features of each vehicle model involved in the simulation and realistic layouts, while maintaining the communication capabilities offered by ns-3 simulator.

Closest to our work, Chen *et al.* [22] presented a SystemC-AMS-based framework for modeling EV consumption. Their solution simultaneously models both the physical and mechanical evolution, along with energy flows and environmental issues. However, unlike our work, the authors only assessed their proposal using one vehicle in the market (a Tesla Model 3). In addition, their proposed framework is not able to simulate vehicular communications. Baek *et al.* [23] proposed a methodology able to predict and enhance the EV operation range. More specifically, their approach allows using different accuracy and complexity trade-offs, including the route, the vehicle, and the battery, as well as considering the decoupling between motor and battery power. Similarly to the previous work, the authors evaluated their approach using a Tesla Model S alone, although they used a real route obtained from Google Maps.

Although the ns-3 simulator is one of the most used communications oriented simulator, in its current version it does not allow to estimate the consumption of vehicles, either EVs or those based on internal combustion engines. Taking into account this, along with the necessity of having an integrated simulation tool able to accurately model vehicles mobility, realistic maps, communication network technologies, and electric consumption, in a holistic manner, in this paper, we have presented our implementation and validation of a ns-3 module which will allow researchers to perform comprehensive studies including transportation, networking, and consumption features.

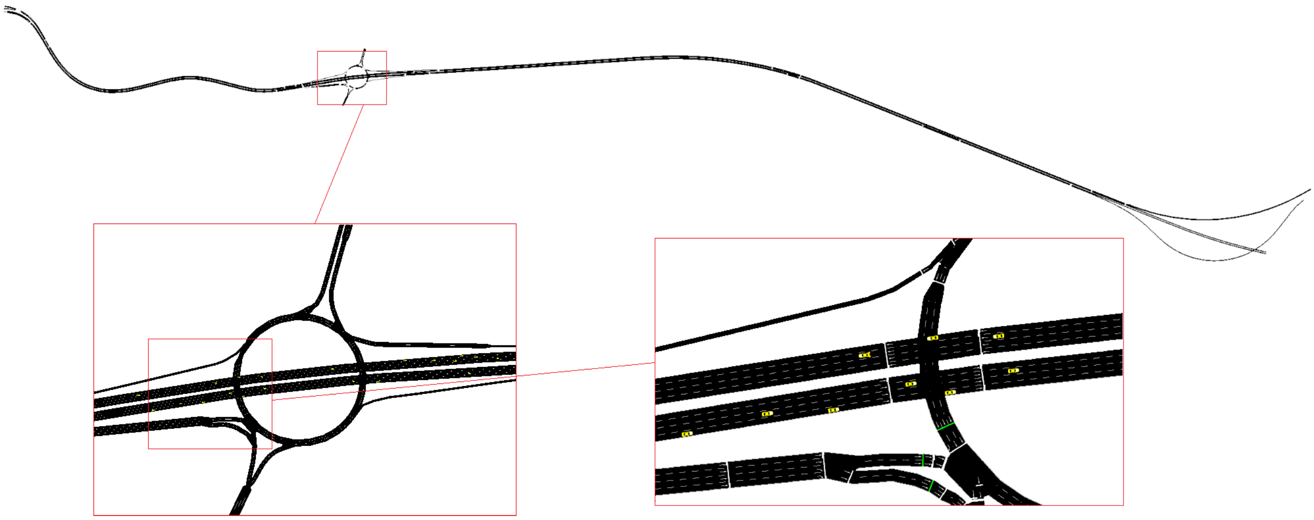
III. SIMULATING REALISTIC EVs FEATURES IN DIFFERENT MAP LAYOUTS

In this section, we present the realistic vehicle features of the model used in our simulations and the layouts of the scenarios used to analyze the consumption of EVs. In addition, we introduce the mathematical model and so the parameters required to accurately estimate the energy consumed by each vehicle. Finally, we also detail the modifications included at the ns-3 simulator, in order to estimate the energy consumption by each vehicle depending on its features and the roadmap layout where the vehicle is traveling.

A. REALISTIC VEHICLE FEATURES

The energy consumed by one electric vehicle can be calculated by adding its potential, kinetic, and rotational energy gain components from one discrete time step to the following, while subtracting the losses caused by different resistance components [24]. To perform these calculations, it is

(a)



(b)

FIGURE 1. **Antwerp E313 highway segment used in our simulations: (a) OpenStreetMap view and (b) detail of the simulation.**

necessary to determine several factors for each model in order to increase the realism of the energy estimation.

In Table 1, we present the vehicle features that we consider in the simulations. In particular, we included the Maximum Battery Capacity (MBC) for each model, the vehicle mass, the Front Surface Area (FSA), and also the Air Drag Coefficient (C_d) since they are key features to estimate the energy consumption of the vehicles [10]. Additionally, and with the aim of increasing the realism of the simulations, we consider the 2018 top-selling vehicle models in Europe in our simulations, according to the data provided by EVVolumes.com [9]. In other words, we would select 280 Nissan Leaf, 270 Renault Zoe, 176 BMW i3, 154 VW e-Golf, and 120 Tesla Model S, when simulating a total of 1,000 vehicles. We consider this point absolutely essential to obtain accurate and representative simulation results since each model presents significant differences compared to the rest of vehicles (e.g., the BMW i3 has a mass of slightly more than half of the Tesla Model S). These differences are supposed to highly affect the energy consumption, and so must be considered.

Finally, the consumption model also considers other parameters, such as the moment of inertia (J_{int}), the radial drag coefficient (C_{rad}), the rolling resistance coefficient (C_{roll}), the constant power intake (P_{const}), the propulsion efficiency (η_{prop}), and the recuperation efficiency (η_{recup}). For all these parameters, we have used the default values for passenger cars already defined by SUMO, an open source, highly portable, microscopic and continuous traffic simulator developed by the Institute of Transportation Systems at the German Aerospace Center [20]. SUMO has been well-validated and it is widely used by researchers in areas such as traffic engineering and transport management.

Additionally, our simulations also consider realistic mobility features, such as lane changing rules, car following models, speed limit rules, and overtaking restrictions.

B. ROADMAP LAYOUTS

In the vehicular industry it is well-known that combustion vehicles offer different fuel consumption at different layouts. In fact, standards such as Worldwide harmonized Light vehicles Test Procedure (WLTP) [25] divide the test into two separate parts: urban and extra-urban scenarios. To perform the impact of a highway roadmap, we decide to include one of the segments of the European Connected

Corridor [26]. We selected the Antwerp E313 highway, since the SmartHighway testbed [27] is deployed in such highway. This recently built testbed is one of a kind, since it provides Cellular vehicle-to-everything (CV2X) communications in such relevant real scenario (see Figure 1). We used SUMO to extract the primary structure of the highway. More specifically, we selected a 12-kilometer-long highway segment with 4 lanes per direction in most of the scenario. As for the vehicles, we introduced different flows from East to West and from West to East, respectively.

Different environments lead to different behaviors in the movement of vehicles. In order to observe these differences, and to comply with the above mentioned test procedure, a simulation has also been carried out in an urban environment, considering the area covered by the Citylab Smart City testbed [28], which provides several wireless technologies for users and also for vehicles. Specifically, we simulated EVs energy consumption in the downtown of Antwerp on an area of about 5 km^2. As on the highway, SUMO has been used to extract the geometry of the region and to obtain the mobility of 1,000 electric vehicles for one hour. The electric vehicle models have been the same as for the previous scenario. Figure 2 shows the area used in OpenStreetMap and the geometry in SUMO.

C. NS-3: ELECTRIC VEHICLES MODEL

In this subsection we present the consumption model used in our simulations, which allows the simulation of EV energy consumption. The model is based on the model included in the SUMO traffic simulator, which was proposed by Kurczveil *et al.* [29], and also validated in our previous work [30].

In order to estimate vehicles energy consumption, it is necessary to determine the energy of each vehicle. This can be obtained by adding the kinetic energy, the potential energy, and the rotational energy, while subtracting the energy lost by the vehicle components. The following equation shows how the model estimates the energy of a vehicle at an instant k:

$$\begin{aligned} E_{veh}[k] &= E_{kin}[k] + E_{pot}[k] + E_{rot}[k] \\ &= \frac{m}{2} \cdot v^2[k] + mgh[k] + \frac{J_{int}}{2} \cdot v^2[k] \end{aligned} \tag{1}$$

where m is the mass of vehicle, v is the velocity, g is the gravity acceleration, h is the altitude, and J_{int} represents the moment of inertia.

After calculating the vehicle energy, we calculate the energy either consumed or restored between an instant k and $k+1$, and include the energy loss:

$$\Delta E_{cons}[k+1] = E_{veh}[k] - E_{veh}[k+1] + \Delta E_{loss}[k] \tag{2}$$

To estimate the total energy loss, we accumulate the energy lost by the resistance of the air, the resistance with the ground, the resistance of curve, and the constant energy consumed by each vehicle (see Equation 3).

$$\begin{aligned} \Delta E_{loss}[k] = \Delta E_{air}[k] + \Delta E_{roll}[k] \\ + \Delta E_{curve}[k] + \Delta E_{const}[k] \end{aligned} \tag{3}$$

The different parameters of this equation can be calculated as follows:

$$\begin{aligned} \Delta E_{air}[k] &= \frac{1}{2}\rho_{air} \cdot FSA_{veh} \cdot C_d \cdot v^2[k] \cdot |\Delta s[k]| \\ \Delta E_{roll}[k] &= c_{roll} \cdot m \cdot g \cdot |\Delta s[k]| \\ \Delta E_{curve}[k] &= c_{rad} \cdot \frac{mv^2[k]}{r[k]} \cdot |\Delta s[k]| \\ \Delta E_{const}[k] &= P_{const} \cdot \Delta t \end{aligned} \tag{4}$$

where ρ_{air} is the air density in the simulated scenario, FSA_{veh} is the front surface area of each vehicle, C_d represents the vehicle air drag coefficient, $s[k]$ is the distance covered by each vehicle, c_{roll} refers to the rolling resistance coefficient, c_{rad} is the radial drag coefficient, and P_{const} is the constant power intake.

If the variation of the vehicle energy between instants k and $k+1$ is positive or negative, it will be multiplied by a propulsion or recovery factor, which is determined by how the batteries charge or discharge. The level of vehicle battery at an instant $k+1$ is calculated by the following equation:

$$E_{bat}[k+1] = \begin{Bmatrix} E_{bat}[k] - \Delta E_{cons}[k] \cdot n_{prop} \;\; if \;\; \Delta E_{bat} < 1 \\ E_{bat}[k] - \Delta E_{cons}[k] \cdot n_{recov} \;\; if \;\; \Delta E_{bat} > 1 \end{Bmatrix} \tag{5}$$

In the previous equation, n_{prop} refers to the propulsion factor, and the constant recovery factor is represented by n_{recov}.

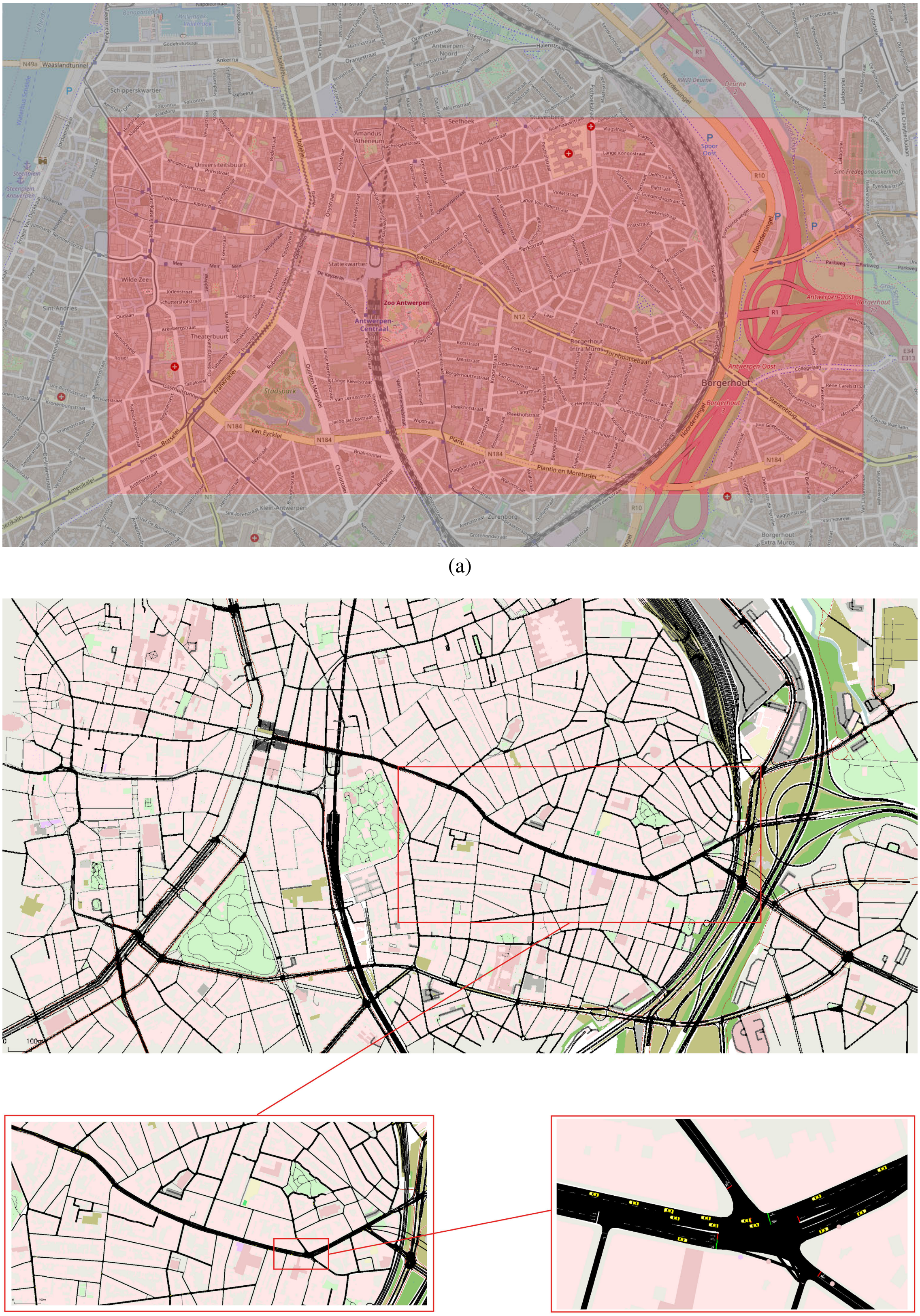
As can be observed, the model includes several parameters determined by the roadmap and the specific features of each vehicle model.

D. ENABLING EV CONSUMPTION SIMULATION IN NS-3

In this section, we present the implementation of the consumption model at ns-3 in order to allow researchers to perform accurate simulations to estimate EV energy consumption including realistic vehicular features and realistic roadmaps. In addition, vehicular communications could be tested using the original functionalities of ns-3.

The ns-3 is a discrete-event simulator for communication networks mainly used for educational and research purposes [31]. The last release of simulator is the ns-3.30, which has more than 40 modules developed in C++ addressing different simulation scenarios. The development is constant and has an active community of developers, mainly composed of researchers from several universities. In fact, a consortium of different organizations around the maintenance and development of the simulator was established [32]. The initial agreement establishing and specifying the operation of the ns-3 Consortium was made between the University of Washington and INRIA.

The ns-3 is composed of standard modules, and each module integrates the following components: (i) a model class responsible for the calculations, (ii) a helper class that implements the necessary methods to carry out a simulation (read data from a file, create the model, etc.), and (iii) an



(a)

(b)

FIGURE 2. **Antwerp urban environment used in our simulations: (a) OpenStreetMap view and (b) detail of the simulation.**

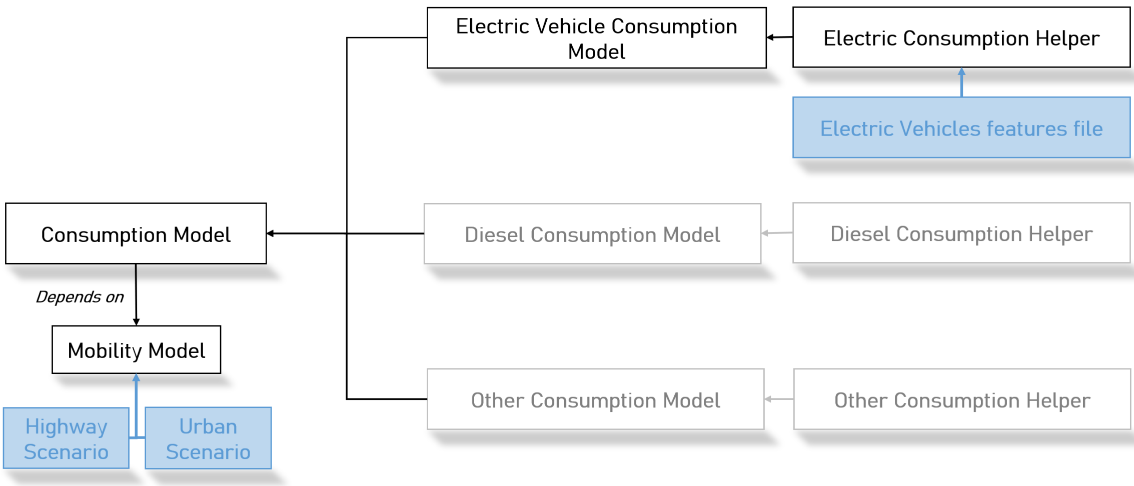


FIGURE 3. Software structure following the ns-3 code guidelines including files needed for the simulation (in blue).

TABLE 2. Simulation times (in seconds) when varying the number of vehicles.

Number of nodes	100	200	400	800	1000	1600	2000
Parsing (Mobility)	3.92	7.85	16.04	32.49	40.78	66.63	83.99
Parsing (Mobility + EVs)	3.92	7.87	16.06	32.50	40.85	66.78	84.90
Execution (Mobility)	0.02	0.03	0.06	0.12	0.14	0.23	0.30
Execution (Mobility + EVs)	0.04	0.09	0.17	0.34	0.42	0.67	0.84
Total (Mobility)	3.94	7.88	16.10	32.61	40.92	66.86	84.29
Total (Mobility + Evs)	3.96	7.96	16.23	32.84	41.27	67.45	85.74

example script of one simulation using the module that serves as a reference for users who want to use such module.

In our work, we have implemented a new ns-3 module, designed for including the simulation of the energy consumption of EVs. The class design of the module implemented is depicted in Figure 3. As can be observed, the ElectricConsumptionHelper uses the electric consumption model for each vehicle (ElectricVehicleConsumptionModel), which inherits from the abstract class (ConsumptionModel). This design allows the addition of new consumption models, and thus enabling the simulation of different types of vehicles in a simple manner. Notice that we have carefully designed the model to enable the addition of new consumption models for different vehicle engines (diesel, gasoline, etc.), that could be useful for those researchers interested in compare combustion vehicles and electric vehicles under similar environments.

The functionality of the implemented module could be summarized as follows. The user will execute the simulation script including: (i) a file with the mobility trace of each vehicle, and (ii) a XML file with the specific attributes of each EV. The XML file that specifies the physical attributes of each electric vehicle is arranged in a similar way to the one used by SUMO since the same parameters are used to simulate consumption. Each simulation node has an electric vehicle assigned with the parameters that the user specifies in the file.

The mobility traces will be in Tcl format which is compatible with the ns-3 mobility module. Furthermore, each time that the vehicles energy consumed is updated during the simulation, an event to access to all the variables of the consumption model is generated, and thus enabling the statistics compilation either using the standard output or a file.

In order to measure the overhead produced by the new module, we simulated the EV energy consumption when varying the number of EVs ranging from 100 to 2,000, using an Intel® Core^{TM} i7-4790K with 16 GB RAM.

Table 2 shows the time required to parse the mobility and EV configuration files, as well as the time needed to execute the mobility and consumption simulation. For instance, the time required for simulating 1,000 vehicles is of 40.92 seconds (40.78 s. for parsing the mobility and EV trace files, and 0.14 s. for executing the EVs consumption estimation). However, this total time slightly increases (+0.35 s.) when including the EV energy consumption. More specifically, it requires a total time of 41.27 s., 40.85 s. for parsing mobility and EV trace files, and 0.42 s. for executing the EVs consumption estimation. Therefore, results presented in Table 2 confirm that the simulator scales properly when highly increasing the number of vehicles simulated, and thus allowing researchers to perform full EV consumption and vehicular communication simulations, while considering realistic scenarios.

Finally, it is worth noting that to accelerate and improve the workflow when performing simulations with the module implemented in ns-3, we have developed a script which is capable to generate the file with the specifications of the electric vehicle models. The script uses the parameters indicated by the user to generate a file with a number

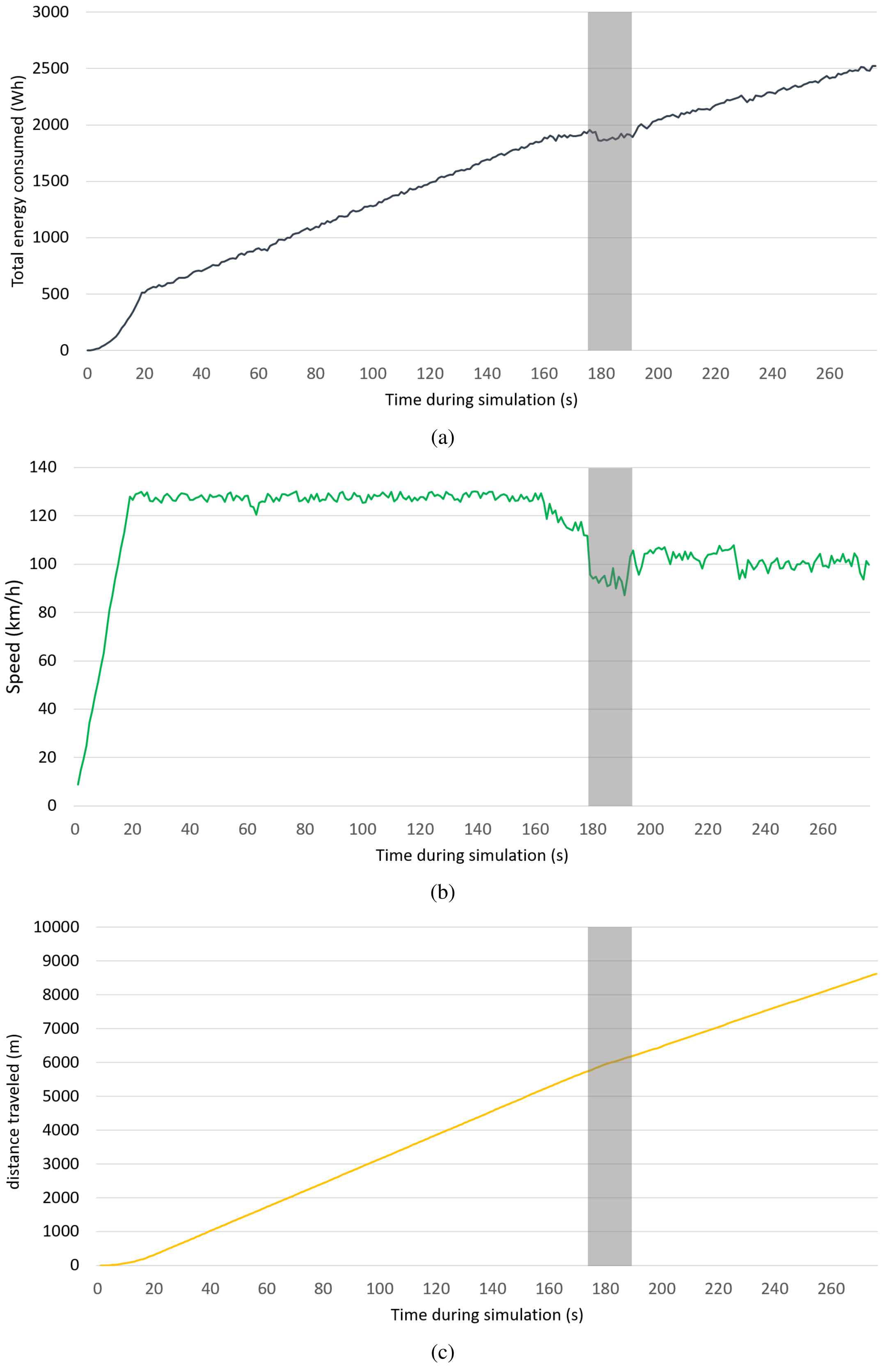


FIGURE 4. **Example of a single EV traveling on a highway layout: (a) energy consumed during the simulation, (b) speed of the selected vehicle, and (c) distance traveled.**

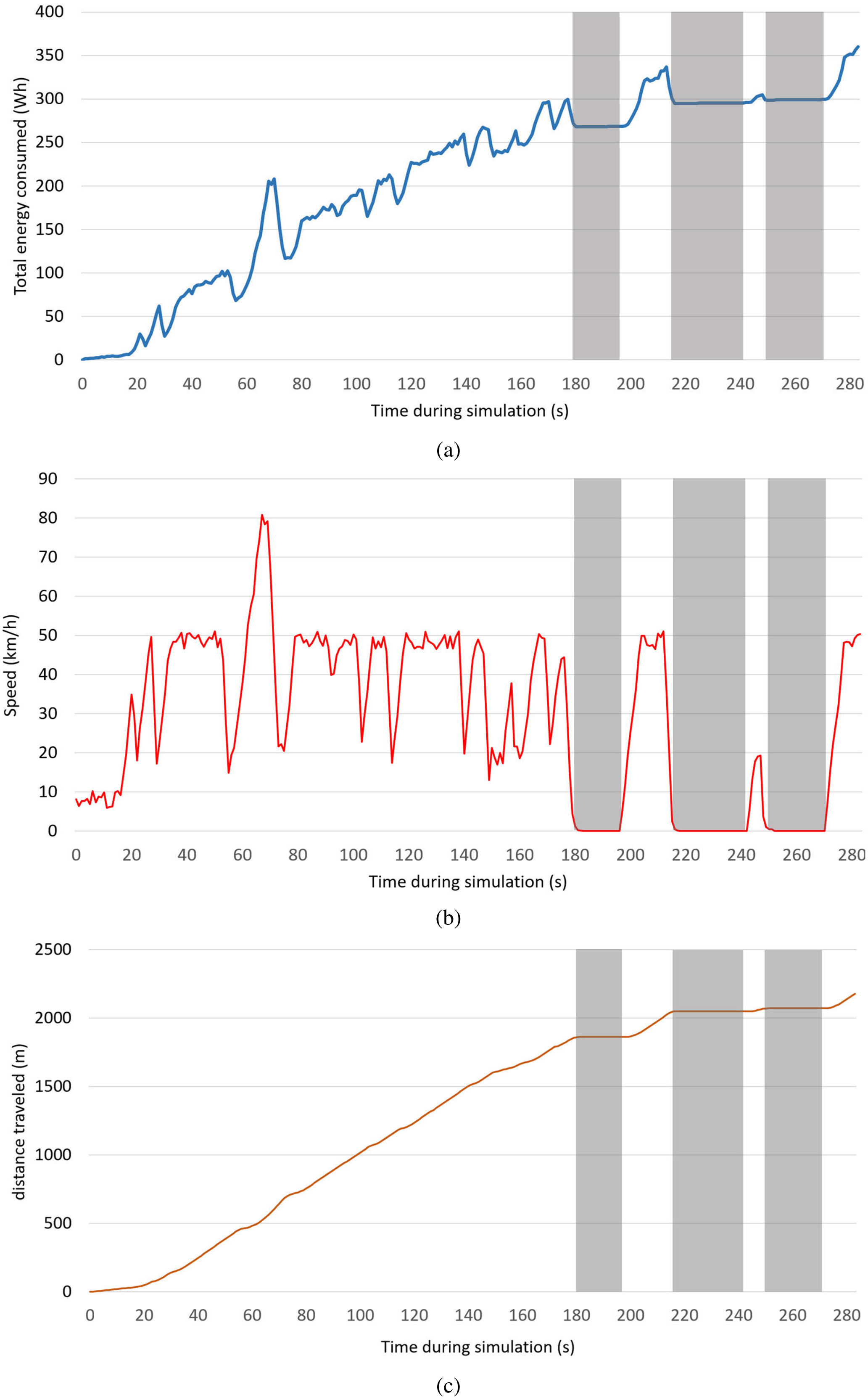


FIGURE 5. Example of a single EV traveling on a urban layout: (a) energy consumed during the simulation, (b) speed of the selected vehicle, and (c) distance traveled.

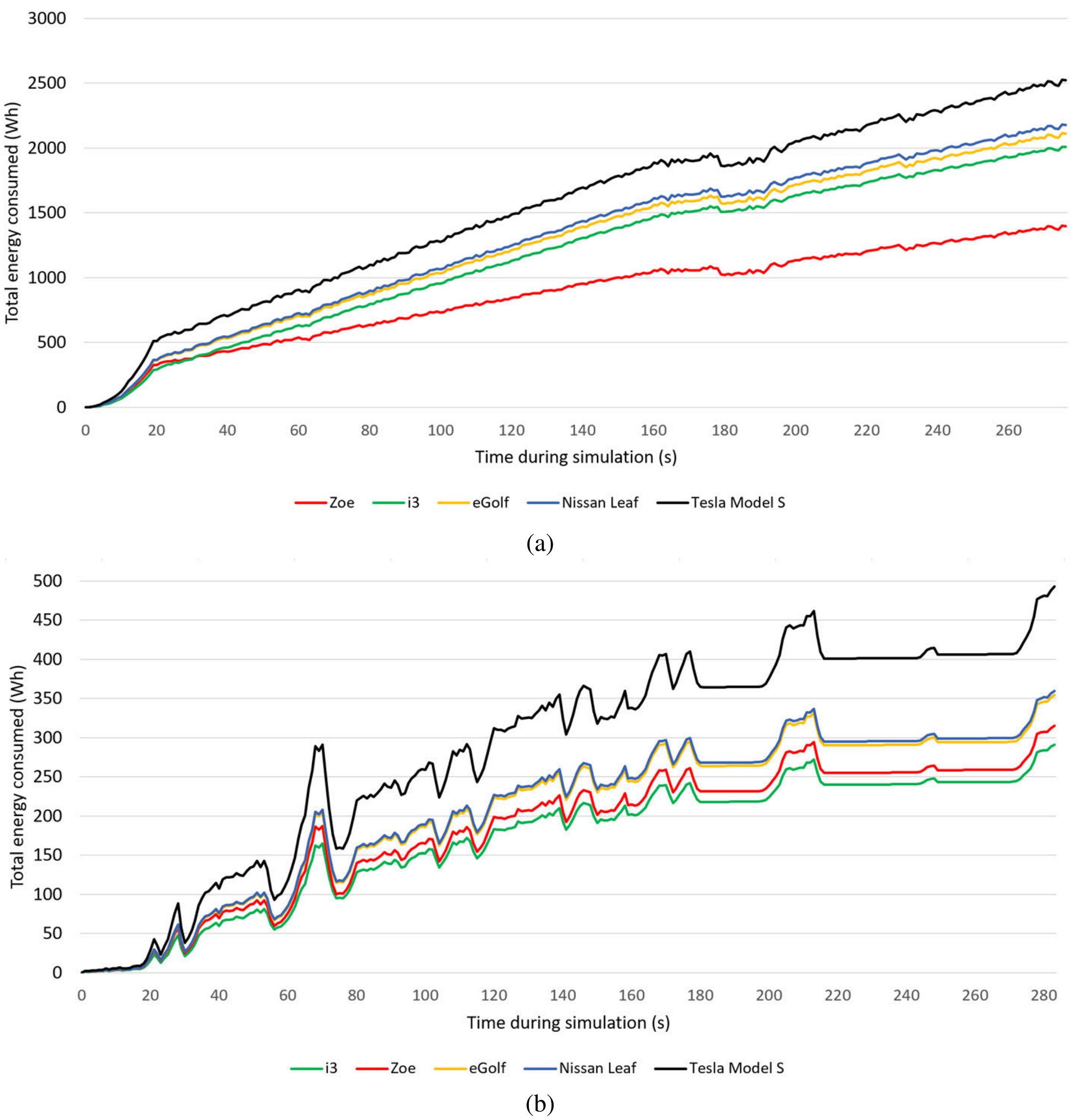


FIGURE 6. **Comparison of different EV models consumption at: (a) Highway layout and (b) Urban layout.**

of vehicles determined according to the model specified. At the moment, the script has the attributes for the Nissan Leaf, Renault Zoe, BMW i3, Volkswagen eGolf, and Tesla Model S. All the sources and files used are available online at: http://init.unizar.es/software/ns3evs/.

IV. RESULTS: EV CONSUMPTION EVALUATION

When evaluating the consumption of electric vehicles it is necessary to take into account two key factors that affect energy consumption; the first of them is the layout in which the vehicles travel; and the second one is the features of the different vehicle models.

A. LAYOUT INFLUENCE

With the aim of measuring the influence of the map layout in the EVs consumption, we have carefully analyzed the consumption results of one vehicle traveling on both the E313 Antwerp highway and the Antwerp downtown (see Figures 4 and 5). We choose these two quite different layout scenarios to clearly demonstrate the differences in terms of energy consumption, speed, and distance covered by a vehicle.

Regarding the highway layout, Figure 4a shows the accumulated energy consumption trend during the single vehicle simulation. In particular, we can observe that initially, the energy consumption increases rapidly since the vehicle accelerates sharply to reach the road speed limit. Later, there are smooth energy recoveries, represented as consumption drops, that take place when the vehicle decelerates (something quite rare when traveling on a highway). For example, in second 177, we can see an energy recovery since the vehicle meets a heavy vehicle traveling at 90 km/h and, not

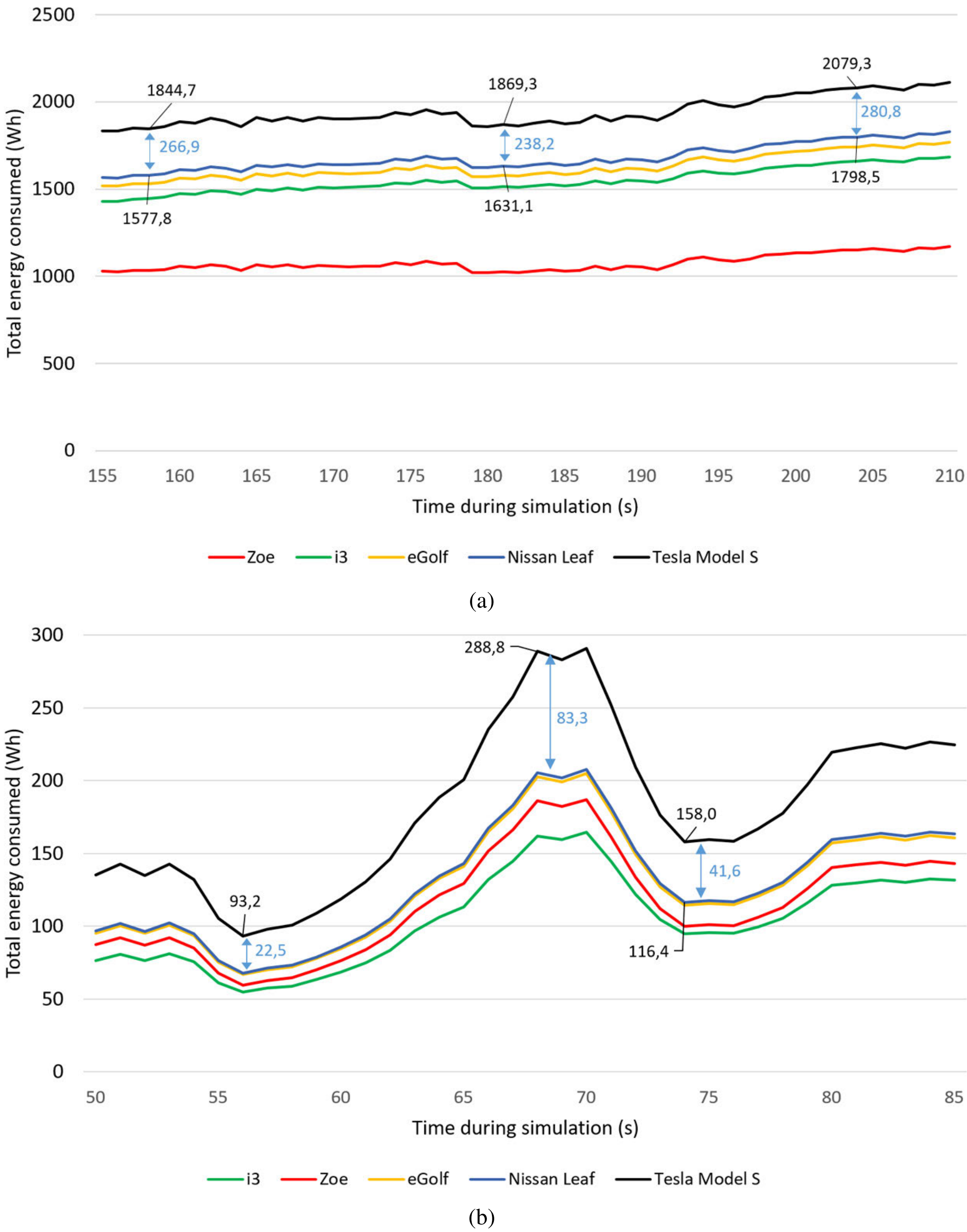


FIGURE 7. Details of different EV models consumption at: (a) Highway layout and (b) Urban layout.

being able to overtake it, the vehicle has to slow down to adjust its speed. This energy recovery due to a sudden speed reduction is confirmed by Figure 4b, that depicts the vehicle deceleration from 130 km/h to 90 km/h. Conversely, Figure 4c shows the distance traveled by the vehicle along the whole simulation time. Overall, the aggregated consumption at the end of the simulation is of 2.5 kWh, and the distance traveled is of almost 9 kilometers.

As for the urban layout, Figure 5 shows the results obtained by the same vehicle when traveling in the Antwerp downtown. As shown, results are pretty different. In particular, speed limit is significantly lower, and city traffic makes the vehicle to perform a large number of braking maneuvers. Figure 5a confirms this point since it shows continuous energy recoveries during the journey. Moreover the vehicle has a negligible consumption when it is stopped at traffic lights (e.g., from second 217 to 243).

Figure 5b verifies the large number of speed variations over time (due to accelerations, braking maneuvers, or traffic lights). As usual in a urban scenario, the vehicle speed

TABLE 3. Consumption, distance traveled, and efficiency in urban and highway environments.

Make	Model	Number of vehicles	Consumption (kWh)		Distance (km)		Average Consumption (Wh/km)	
			Urban	Highway	Urban	Highway	Urban	Highway
Nissan	Leaf 2018	280	123.56	545.97	1,752	4,028	70.52	135.53
Renault	Zoe	270	104.69	358.58	1,639	3,890	63.86	92.17
BMW	i3	176	67.247	313.712	1,092	2,536	61.56	123.66
VW	e-Golf	154	67.72	287.97	965	2,226	71.18	129.33
Tesla	Model S	120	63.02	258.75	725	1,721	86.87	150.28
	Total	1,000	427.25	1,764.99	6,149	14,346	69.47	123.05

is mostly less than 50 km/h, except on a fast track where it achieves 80 km/h. Finally, Figure 5c shows the distance traveled by the vehicle. Overall, during the 5 minutes of simulation, the vehicle consumed a total of 359.81 Wh, and covered 2 km.

B. VEHICLE MODEL INFLUENCE

Similarly to conventional combustion vehicles, the consumption of each of the EV models is determined by the particular characteristics of the vehicle. To confirm this point, Figure 6 shows the consumption of a vehicle, according to the parameters of the different models presented previously in Table 1, when performing the same mobility trace. As shown, when the simulation progresses, some differences among the vehicles appear, in terms of cumulative consumption. The vehicle that has the highest consumption in the highway environment is the Tesla Model S, resulting in 2.52 kWh compared to 1.40 kWh consumed by the Renault Zoe, which presents a more efficient operation in this layout (−44.45%). This is due to the fact that at high speeds, both the Front Surface Area and the Air Drag Coefficient play a determining role.

In contrast, if we analyze the data related to urban consumption, the most efficient vehicle, in this case, is the BMW i3 (with only 290.68 kWh consumed). Hence, the vehicle mass demonstrates to be a key feature for energy consumption in urban scenarios. This fact is confirmed since the one with the highest consumption is the Tesla Model S (resulting in 492.55 kWh, a 69.45% higher than the BMW i3).

Figures 7a and 7b show a detailed portion of 55 and 35 seconds from Figures 6a and 6b, respectively. More specifically, Figure 7a details data from second 155 to 210 and Figure reffig:simuModelb focus on second 50 to 85. As can be seen, the differences between some models in terms of cumulative consumption increase, especially in accelerations. In particular, we can find observe how vehicles with similar mass and FSA present quite similar progression compared with to Tesla Model S. However, note that these differences slightly increase or decrease in accelerations and decelerations, respectively. This fact is essentially due to heavier Tesla Model S consumes more energy in accelerations, but it also regenerates a large amount of energy in braking maneuvers.

In the case of the urban environment, the differences are even more significant (in relative terms) since the number of accelerations and decelerations is much greater. Figure 7b shows how the difference between the energy consumed by Tesla Model S and Nissan Leaf, at second 56 is of 22.5 Wh. Only thirteen seconds later (i.e., at second 69), and after a sharp acceleration, the difference increases to 83.3 Wh. (+270,22%), and finally, after a braking occurs (in second 74), the difference is reduced again to 41.6 Wh (+84.89%). Overall, this example demonstrates that the energy consumption differences between EV models which present diverse features become higher, especially in urban layouts due to the intrinsic characteristics of urban traffic.

Table 3 presents the results obtained in terms of aggregate consumption, total distances traveled, and average consumption in both urban and highway environments. The data is segmented by each vehicle model present in the simulation. We can observe how electric vehicles show a better efficiency in urban environments, due to the slower speeds and energy recovered in braking. In addition, we corroborate that the average consumption of EV is very close to the data publicly offered by car manufacturers, especially in the highway layout.

V. CONCLUSION

Transportation systems are constantly improving, and so simulation emerges as a suitable solution to allow researchers to quickly and easily validate their proposals, while reducing the amount of time and funds required to do so, especially compared to the implementation of real testbeds. Moreover, EVs constitute a valuable alternative to traditional combustion-based vehicles since they offer many advantages, especially in terms of energy cost, pollutant emissions, maintenance, and efficiency.

In this work, we have analyzed the performance of EVs at different realistic layouts of Antwerp, Belgium, including urban and highway environments. We have also enhanced the ns-3 simulator by adding a well-validated consumption model able to estimate the amount of energy that any EV would require according to its mobility and specific features (i.e., mass, battery capacity, etc.) with a significant reduced overhead, almost negligible. As future work, we aim to perform a comprehensive analysis which combines vehicular communications and EVs' mobility patterns using our ns-3 enhanced version. We consider that new approaches regarding the reduction of EVs' energy required will be possible by exploiting vehicular communications.

ACKNOWLEDGMENT

The views expressed are those of the authors and do not necessarily represent the project. The Commission is not liable for any use that may be made of any of the information contained therein.

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