Analysis of the Battery Energy Estimation Model in SUMO Compared with Actual Analysis of Battery Energy Consumption

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Abstract — **Electric vehicles (EVs) are considered a key alternative transportation for improving energy efficiency and reducing CO2 emissions in the traffic sector. To promote the use of these vehicles a reliable, real-world close evaluation in terms of energy consumption and range is crucial. One of the most efficient and frequently adopted microscopic traffic simulation tools, simulation of urban mobility (SUMO), implements an energy estimation model that relies on vehicle and road characteristics. We conduct a comparative analysis of SUMO's estimated energy consumption and state of charge (SOC) of a simulated battery electric vehicle (BEV) and the energy consumption of an actual 2020 Toyota RAV4 Hybrid LE AWD. Results showed that the energy consumption model in SUMO delivers different results than the ones obtained from the real world driving experiments. These findings are discussed in this paper.**

Keywords – electric vehicles; battery energy consumption; microscopic traffic simulation.

I. Introduction

Transportation accounts for 23% of the global energy-related CO2 emissions. It continued to increase an average of 2.5% annually between 2010 and 2015 [1]. Electrification is considered one of the essential approaches to decrease CO2 emissions in the transport sector [2]. Therefore, the deployment of BEVs is an option for significantly reducing oil dependency and providing environmental and economic benefits [3]. Significant progress has been observed in recent years in the technological development of BEVs [4], [5]. The accurate energy consumption estimation of BEVs is a key performance index that is of interest to automakers and policy-makers, since this aspect of the technology positively contributes to a decrease of pollutants and helps conserve the environment [6]. However, recent research studies on the future market diffusion of BEVs raise various challenges related to energy consumption, charging station deployment, ECO driving activities, route planning, etc. [7].

Among the academic research studies on simulation tools for analyzing battery energy consumption, designing a realistic energy estimation model is reported to be challenging [8]. This challenge is mainly due to the scarcity of real-world measuring data, which make it difficult to build, evaluate and validate the energy consumption estimation models [9].

In this paper, we present the analysis of a set of driving data that was collected using a 2020 Toyota RAV4 Hybrid LE AWD (Fig. 1). The vehicle drove in Upper Austria and was equipped with different devices for testing automation [10], [11], simultaneously serving our purposes as a BEV for estimating energy consumption using the extracted data.

As the simulation platform Simulation of Urban Mobility (SUMO) includes an implemented energy estimation model that relies on vehicle and road characteristics [12], we generated in SUMO the driving route with the Toyota by considering the information extracted from the trip. We then compared the energy consumption from the trip with the estimated consumption from the energy model in SUMO.

The remaining parts of this paper are organized as follows: Section II describes the related works in literature; Section III presents the methodology; the results from the analysis of the defined scenarios are presented in Section IV, in Section V, the discussion and the perspective for future work bring the paper to a close.

II. Related Work

The problem of how to overcome the challenges related to the estimation of BEV energy consumption is drawing attention from the scientific community and the industry. In recent literature, several energy consumptions models have been presented and discussed to simulate a realistic and accurate BEV

Figure 1. Vehicle used to acquire the driving data, 2020 Toyota RAV4 Hybrid LE AWD

energy consumption [13], [14]. Often, BEV is considered as a complex system [15]. Therefore, the energy consumption model can be formulated according to the consumption and the recuperation parts.

The consumption part consists of the mechanical and electrical subsystems. Evaluating an energy estimation model of a BEV in a simulation environment requires adopting a set of real-world data and a set of comparisons between the obtained results with a real-life BEV [13]. In this section, we reviewed and summarized some related works and highlighted the gap in literature, to which we contribute with this paper.

Energy consumption models have been implemented in several works [16], [17]. The authors in [18] presented a method to study the influence of different factors ranging from environmental, to vehicle auxiliary devices on battery energy consumption. Relying on a simulation tool that was validated through experiments on a climatic 4 Wheel Drive (4WD) chassis dyno, the authors concluded that driver aggressiveness, based on mean positive acceleration, increased the consumption 40% at a velocity of 20 km/h and about 15% at 60 km/h.

A vehicle simulation model for a BEV that is equipped with a single pedal control system is described in [19]. The authors implemented a set of simulations to predict and analyze the effects of different environmental factors and control parameters on energy consumption. The simulator was calibrated using experimental data related to vehicle energy flow and driving range. The results of the study suggested that vehicle speed, running time, and frequency distribution of the braking process influenced energy consumption, the value in a congested traffic scenario being 46.07 kWh.

In a further work, driving data from EV were analyzed to develop an analytical model of power estimation [20]. The data set was collected with one vehicle driving on the freeway. The reported results indicated that the energy consumption model appeared to work well and had potential as both a research tool and a resource for EV users.

Adopting a data collection system using controller area network (CAN) bus data logger from an actual functioning EV and proposing an estimation energy consumption model based on the fundamental theory of vehicle dynamics was the main focus of [21]. According to the authors, the proposed model can accurately estimate and calculate the energy consumption by integrating the power over the time of the trip.

SUMO can be used to estimate the energy consumption and required charging infrastructure for EV [22]. However, an accurate, direct evaluation of results with real driving data has not been performed.

We contribute with this work to the research in the field by comparing the actual energy consumption of a BEV (2020 Toyota RAV4 Hybrid LE AWD) operated in Upper Austria and the energy consumption estimation determined by SUMO.

III. METHODOLOGY

As previously mentioned in the introduction, we collected the battery and driving data from a 125 km trip from St Pölten to Linz in Austria. We then generated the corresponding map and route in SUMO to reproduce the acquired information and calculate the energy consumption. The energy consumption model in SUMO requires a prior simulation to be performed, after the simulation is run, it evaluates the vehicle's energetic state and computes energy variations in the content of similar vehicles. The changes in the vehicle’s energy state are calculated through the sum of the kinetic, potential, and rotational energy gain components from one discrete time step to the following step [22].

After having replicated the trip in SUMO with the corresponding data of the Toyota, including the battery specifications, we analyzed the energy consumption and state of charge (SOC) of the battery. We implemented the following scenarios in which the BEV traveled the same route of 125 km.

- Scenario 1: a real world driving test in which the BEV’s energy consumption was only affected by driving (no other devices that could increase the consumption were activated)
- Scenario 2: a simulated BEV

A. Data collection and analysis

The data collected during the trip referred to the i) location and trajectory of the vehicle and ii) the battery characteristics.

To log the relevant information, we relied on two devices. First, we used a CAN bus data logger through an ELM327 microcontroller [23], which is a personal computer to on-board diagnostics (PC-to-OBD) connector. To this end, we implemented the ELM327 to collect the battery data of the BEV while driving on the route. Through the second device, the global positioning system (GPS), we collected the BEV location data and trip trajectories. The trajectory data set (GPS data) was then synchronized with the data obtained from the ELM327 by adopting a nearest neighbor approach and relying on the timestamp recorded by each device.

As the ELM327 records data at a lower frequency than the GPS, we recorded the timestamps of the ELM327 with its data. We then added the GPS coordinates to each of the timestamps that were recorded before 0.1 seconds had elapsed and that were the closest in time. Using the synchronized data, we generated the route with the trip parameters in SUMO. The detailed characteristics of the Toyota used in Scenario 1, including the battery specifications, are presented in Table I.

The GPS and driving-related data, velocity, acceleration/deceleration and vehicle position are depicted in Table II. The steps of the simulation procedure are illustrated in Fig. 2.

To calculate the real world battery’s actual energy consumption in terms of battery power (W), we multiplied the voltage (V) by the current (A).

To obtain the energy consumption (kWh) of the battery, we multiplied the obtained power (W) by each time step in the whole trip.

TABLE I. PARAMETERS OF THE VEHICLE USED TO COLLECT THE DRIVING DATA

Parameters		Value
Physical specifications	Weight	2231.68 kg
	Length	4.6 m
	Max vehicle speed	120 km/h
	Acceleration	1.5 m/s^2
Battery characteristics	Maximum voltage	244.8 V
	Capacity	6.5 Ah
	Power	88 kW

The obtained energy consumption is derived from positive (propulsion) and negative (energy recovery through braking) power values of the traction battery. Thus, these negative values affect the power value as well. For the present analysis, which considers the impact of driving patterns such as speed and acceleration, this is disadvantageous. However, a separation of these effects was not technically possible. Therefore, in this work we multiplied the negative power values by 0.9 to correct for battery losses that occur when the battery is recharging. Battery losses depend on different parameters, and 10% is a value that has been considered for lithium-ion batteries in many works [24].

B. BEV traffic simulation implementation

To examine and evaluate the estimated energy consumption model in SUMO compared to actual, real world consumption, we generated the simulation of the vehicle we used to collect the data on the road by defining it through the data obtained from the GPS and ELM327 devices.

We first generated the traffic simulation network in SUMO by importing the corresponding *OpenStreetMap* (OSM) [25] based on the acquired GPS data. We then applied NETCONVERT [26] and POLYCONVERT [27] to process the network.

We set the parameters for the vehicle in SUMO according to the characteristics of our vehicle. In order to generate the corresponding vehicle class, *vClass* "passenger", we defined the vehicle types using the *vType* parameter. In addition, to specify the characteristics of the real BEV in the simulation, we set the parameter for the *vehicleMass* in SUMO. Finally, we added the route file. The route is depicted in Fig. 3. To model the battery characteristics, we adopted the electric vehicle model from SUMO [22] using generic vehicle parameters. To this end, we added the battery device [30] attribute with the *maximumBatteryCapacity* to the simulated Toyota in SUMO (Fig. 2).

In order to have a better overview of the traveled route, we additionally visualized the route's maximum speed limit, which is illustrated in Fig. 4.

TABLE II. INFORMATION COLLECTED THROUGH THE DEVICES INSTALLED IN THE VEHICLE

Parameters		Description
GPS	Time	unix timestamp (format: ISO 8601: 1970-01-01T00:00:00Z)
	Latitude	north -south geographic coordinates
	Longitude	east-west geographic coordinates
	Altitude	elevation above sea level (unit:meter)
ELM327	Acceleration	unit : meter per square second
	Motor revolution	unit: revolutions per minute
	Current	unit: ampere
	Voltage	unit: volt

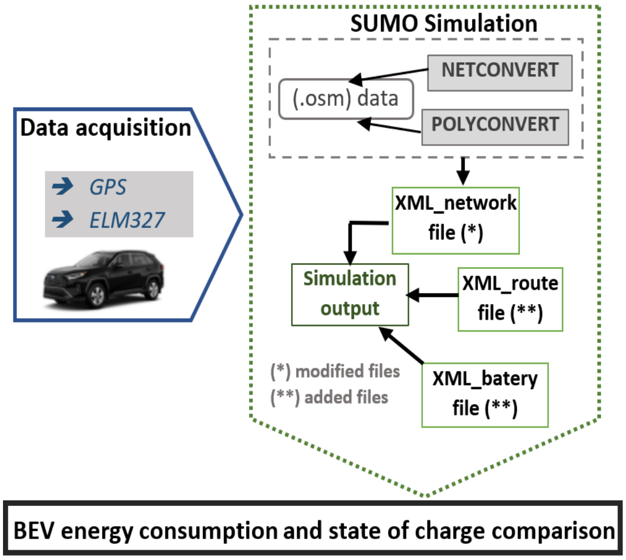

Figure 2. Simulation process (adapted from [28, 29])

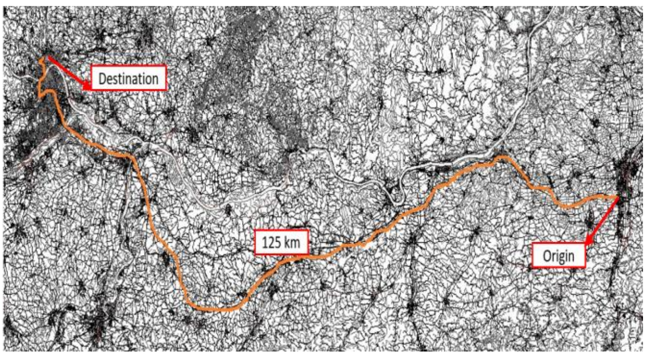

Figure 3. SUMO network showing the traveled route of 125 km from the origin (St. Pölten) to the destination (Linz)

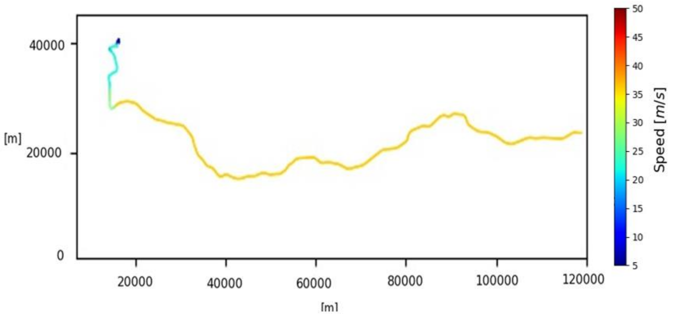

Figure 4. Visualization of the maximum speed limit during the trip in m/s

IV. Results

Results of this research are categorized into energy consumption and state of charge, presented in this section.

A. Energy consumption

The energy consumption development in the real-world scenario and its related speed profile are depicted in Fig. 5. Without any additional devices activated during the trip, the total accumulated energy consumption is associated with the mechanical part, resulting in a total of 82.853 kWh.

The driving speed is reflected in the battery energy consumption. At the end of the trip, when the vehicle is decelerating at the time of 3.300 s, due to the speed limit in the city (see Fig. 3 and Fig. 4), the cumulative battery energy consumption decreases (see Fig. 5, bottom).

The energy consumption in the SUMO scenario, calculated with the energy estimation model, is illustrated in Fig. 6. As it can be observed, the cumulative energy consumption is 11.9% lower (72.98 kWh) in Scenario 2 than this in the real-world driving conditions of Scenario 1 (actual driving BEV, 82.85 kWh).

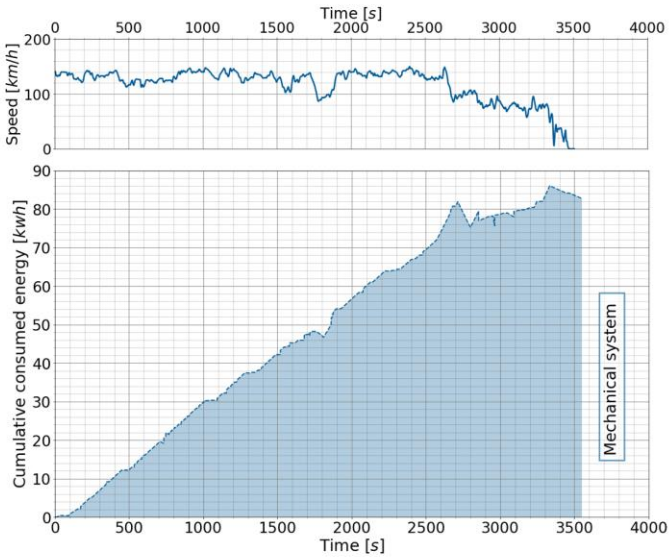

Figure 5. Speed profile (top) and cumulative energy consumption in the real world scenario (bottom)

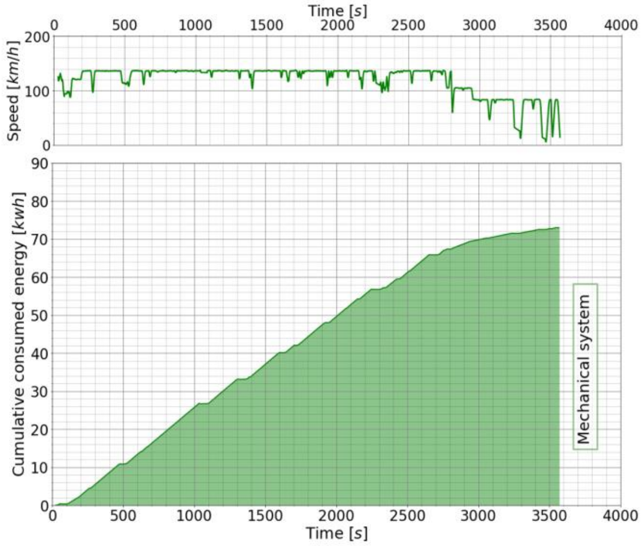

Figure 6. Speed profile (top) and cumulative energy consumption in the simulated scenario (bottom)

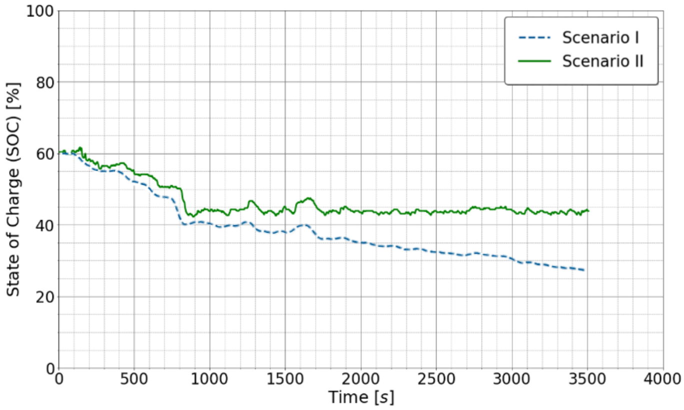

Figure 7. Comparison between SOC in the real driving Scenario I and the simulated Scenario II

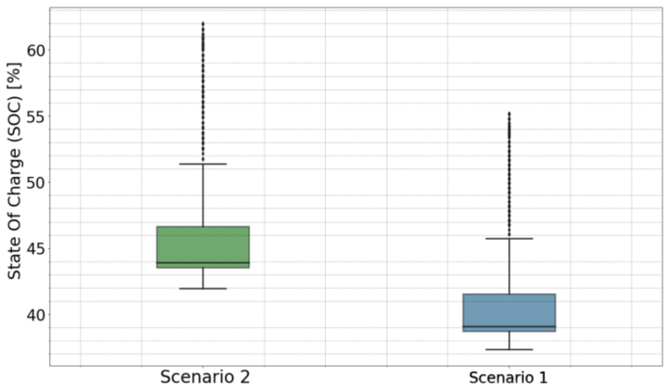

Figure 8. Data from each of the scenarios related to the state of charge

B. State of charge

Results from analyzing the SOC results and comparing Scenario 1 and Scenario 2 showed that the values obtained in the simulation, were about 11% higher than in real world conditions (Fig. 7 and Fig. 8).

This means that the level of charged energy in the simulation environment was higher than in the real vehicle, these results in line with the lower energy consumption of the simulated vehicle obtained from the previous energy consumption analysis.

I. Conclusion and Future Work

In this paper, we evaluated the accuracy of the energy estimation model in SUMO. We conducted a real world experiment by driving a BEV on Austrian roads between St. Pölten and Linz. We extracted the data from the battery of the driven BEV and calculated the energy consumption of the battery and SOC. The data was analyzed and implemented in SUMO to simulate the exact BEV with the same characteristics as the actual BEV.

After a comparative analysis between the obtained results from the simulation and the actual BEV, we concluded that the consumption estimation resulting from the SUMO platform was lower than the real consumed energy on the road. This difference was in line with the level of charged energy in the simulation environment, which according to the results was higher than in the real vehicle.

The reason for this discrepancy in the results can be attributed to the SUMO generalized model that is implemented with a constant parameter for propulsion efficiency. The model works with a constant value for regenerative braking and it does not consider in an accurate way the effect of acceleration on the battery consumption.

In future work we aim to improve the current energy estimation model in SUMO by conducting more real world experiments and use the obtained results to increase the model accuracy under different scenarios, as well as consider other devices that consume energy in the vehicle.

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