Impact of Road Gradient on Electric Vehicle Energy Consumption in Real-World Driving

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Abstract. With serious concerns on environmental problems related to CO_2 emissions and energy crisis, special attention has recently been paid to Electric Vehicles (EVs). Specifically, an accurate estimation of energy consumption for EV is still a big issue. Therefore, quantifying the impact of various external factors on EV energy consumption, such as road topology, driver profile and traffic conditions is a necessity. In this paper, we review the energy consumption models for EVs. Then, we analyze the impact of the road gradient on EV energy consumption through a set of real world experimentations. The obtained results, allow us to better understand the impact of upward and downward gradient on both energy consumption and energy recuperation processes.

Keywords: Electric vehicle · Road gradient · Energy consumption models · Energy recuperation · Traffic simulation · Energy efficiency

1 Introduction

The growing interest in EVs has been highlighted by Intelligent Transport Systems (ITS) embedding Information and Communication Technologies (ICT) to promote smart navigation and eco-driving [18,20]. Indeed, reducing the EV energy consumption is a key issue for extending the use of EVs in the transportation field. In particular, realistic traffic simulations require a reliable energy consumption model to accurately estimate and hence reduce the EV energy consumption [10,25]. Usually, the EV energy consumption estimation process can be designed as illustrated in Fig. 1.

This process is used in traffic simulations to calculate the amount of EV energy consumed at each time step. The energy model requires four input data types that are related to various parameters such as: speed profile, road information, weather conditions and road traffic conditions. The speed profile and the vehicle specifications (e.g. weight, drag coefficient, etc.) can be extracted from

L. Barolli et al. (Eds.): AINA 2020, AISC 1151, pp. 393–404, 2020.
https://doi.org/10.1007/978-3-030-44041-1_36

EV sensors. The road information (e.g. road slope profile, GPS coordinates, road type, road length, etc.) can be obtained from the Shuttle Radar Topography Mission (SRTM) [2] and OpenStreetMap (OSM) data [5]. The ambient temperature can be extracted from the weather conditions report.

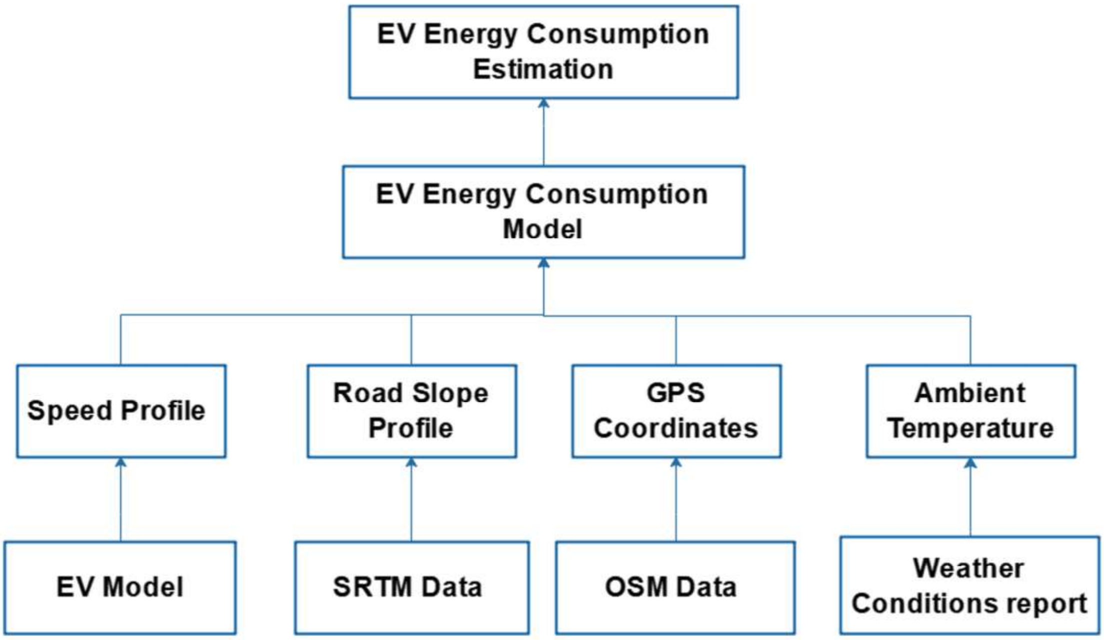

Fig. 1. The energy consumption estimation process.

In this context, this work is a part of CMCU project entitled "Urban Platform for Connected Electric Vehicles" (PUVEC) [13]. The main goal of this project is to elaborate a simulation platform for connected EVs. In particular, it aims at generating an energy-saving map (i.e. specifying energy-saving routes on the basis of energy consumption estimation to optimize battery consumption of connected EVs). Therefore, this energy-saving map depends mainly on the accuracy of estimating EV energy consumption in road traffic simulation tools.

The main contribution of the present work is to reveal the impact of the road gradient on EV energy consumption according to real world experimental data.

The rest of this paper is organized as follows: Sect. 2 describes previous works about EV energy consumption models and characterizes the influence of road gradient on the EV energy consumption. Section 3 presents the real world experimentation context by introducing a "data acquisition and processing system for EVs". This system is used for recording EV data and related- driving information. Additionally, this section highlights the impact of the road gradient through a set of experimental analyses. Finally, Sect. 4 concludes this work with suggestions for future work.

2 Related Work

Previous studies [1,3,19] present various energy consumption models to accurately estimate the energy consumption for EV in different scenarios and trajectories. Often, most studies in this field have considered the EV as a complex system [10]. The energy consumption model consists of two main parts: energy consumption and energy recuperation [16].

The energy consumption part can be mainly formulated according to two main subsystems: the electrical and mechanical subsystems [10].

The electrical subsystem can be divided into two components: the energy consumed by auxiliary systems (i.e. air conditioning, heating, ventilation, radio, etc.); and the additional electric losses which occur from the unstable power output of the electric motor due to the particularities of the dynamic system [17].

The mechanical subsystem is considered as a common core model for modeling the energy consumption part. It reflects the amount of electrical power taken from the battery of EV and transformed by the EV motor into mechanical energy at the wheels. Actually, it has been formulated using the fundamentals of vehicle dynamics theory [23]. The mechanical subsystem is formulated by the tractive force, which is referred to as the total sum of forces acting on the EV in motion, as described in Fig. 2. The tractive force represents mainly the acceleration resistance, rolling resistance, air resistance and road gradient resistance forces [10,21]. More specifically, the force commonly used to overcome road gradient resistance for predicting the amount of energy in terms of road gradient is given by Eq. 1.

$$F_{hc} = m \times g \times \sin\theta \tag{1}$$

Where: m [Kg] is the total vehicle mass; g [m/s²] is the gravitational acceleration and θ [°] is the road slope angle.

The road gradient induces a change in forces acting on EV, and hence influences its energy consumption. Indeed, positive values of θ correspond to uphill phases and negative values represent downhill phases. During uphill driving, the increase of the slope elevation causes an increase of the power dependent on the road gradient resistance force because of the sinusoidal component, which in

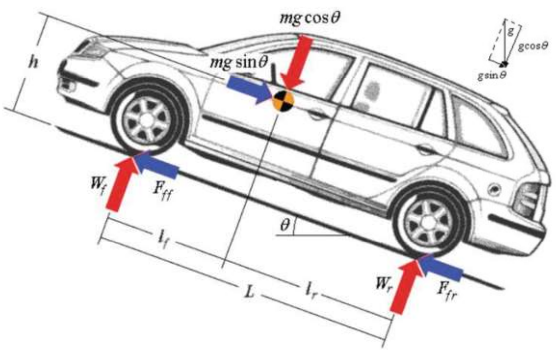

Fig. 2. Forces acting on an EV in motion on slope [14].

turn induces an increase of the total electric motor power consumption. Therefore, special attention should be paid to the road gradient impact. The lack of such information in traffic simulations may affect the reliability of the energy consumption model which in turn affects the accuracy of the total EV energy consumption estimation. For instance, simulation results presented in [14] show that incorporating road gradient profile makes the simulation more realistic, with a difference of 16.4 kWh compared to a simulation without road gradient profile.

$$\Delta E_{Totalconsumption}[t] = \Delta E_{consumed}[t] + \Delta E_{recuperated}[t] \tag{2}$$

$$\Delta E_{recuperated}[t] = \Delta E_{kinetic}[t] + \Delta E_{potential}[t] \tag{3}$$

Where: $E_{Totalconsumption}$ [Wh] is the total energy consumption, $E_{consumed}$ [Wh] is the instant energy consumption, $E_{recuperated}$ [Wh] is the instant energy recovered, $E_{kinetic}$ [Wh] is the kinetic energy and $E_{potential}$ [Wh] is the potential energy.

The explicit method considers that the dissipated energy is totally recovered. However, a small part of the dissipated energy is converted to a heat energy that is dissipated into the atmosphere [10,22]. Therefore, this approach lacks accuracy and remains unable to provide an accurate assessment of energy consumption in traffic simulations. The implicit method is based on an estimation approach through a constant regenerative braking efficiency factor specified by the EV manufacturer [4,6,24]. In this case, The average energy recuperated can be expressed as:

$$\Delta E_{recuperated}[t] = \eta_{recup} \times \Delta E_{consumed}[t] \tag{4}$$

Where: $\eta_{recup}[\%]$ is the regenerative braking efficiency factor.

Recent studies [9,24,26] have expressed this factor according to two main approach. The first one presents the regenerative braking efficiency factor as a constant value provided by the EV constructor [9,10] or through a set of experimentation results [24]. The second approach considers that this factor is computed as a function of deceleration level, EV weight, speed, etc. [3,26,27]. For instance, the regenerative braking efficiency factor formula corresponds to [3]:

$$\eta_{recup}[t] = \left(e^{\left(\frac{0.0411}{|a[t]|}\right)}\right)^{-1} \tag{5}$$

Where: a $[m.s^{-2}]$ is the instantaneous acceleration.

In addition, several research studies focus on incorporating the road gradient information in such formula due to its valuable impact on the energy recuperation. For instance, the study in [14] has shown that including the road gradient information in traffic simulations may increase the energy recuperation by up to 1.6 kWh as compared to a simulation without road gradient profile. Obviously, it is crucial to integrate the road slope parameter in the energy consumption model to simulate a realistic EV energy consumption [12]. In brief, the diagram depicted in Fig. 3 outlines the energy consumption model main subsystems and their related parameters.

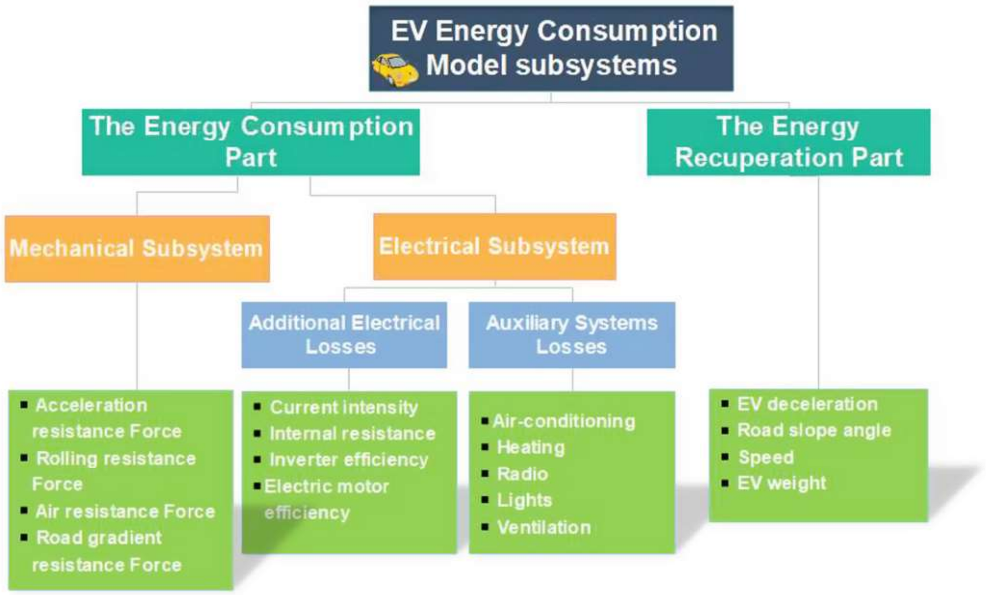

Fig. 3. EV energy model components.

In the next section, we investigate the impact of the road gradient factor on energy recuperation and hence on the total EV energy consumption through a set of real world experimental results.

3 Experimentation Results

Real-world exploratory experimentations are required to better understand and accurately modelize the EV energy consumption in traffic simulation tools.

In this section, we first introduce the context of our experimentation. Then, we discuss in detail the real world experimentation results to understand the impact of the road gradient parameter on the EV energy consumption and recuperation processes.

3.1 The Context of Exploratory Experimentation

3.1.1 Data Acquisition and Processing System

A data Acquisition and processing system is developed in this research to record real world EV driving data (i.e. speed, acceleration/deceleration, brake pedal pressure, GPS coordinates, instant energy consumption, instant energy recuperation, and driving range). Data acquisition and analysis serve as a solid foundation for our research. This system was installed in the 2015 Renault Zoe EV which is our test vehicle. The test vehicle was equipped with a variety of Electronic Control Units (ECUs) controllers which communicate with each other over a Controller Area Network (CAN) bus. ECUs are interfaced with multiple sensors for collecting EV-related data. The CAN bus protocol is considered as the most common protocol for in-vehicle network [7]. A basic overview of the system architecture is illustrated in Fig. 4.

In practice, we integrated in our test EV the Peak-System's PCAN-USB device for collecting data from each ECU through CAN bus. This device is connected to our test vehicle with DB9-OBD2 cable on one side and connected to a laptop computer with USB cable on the other side. The RTMaps [11] software platform was installed in the laptop computer. RTMaps is used to efficiently process and display, in real-time, multiple data flows. Finally, the processed data are transmitted for storage to a remote Database server.

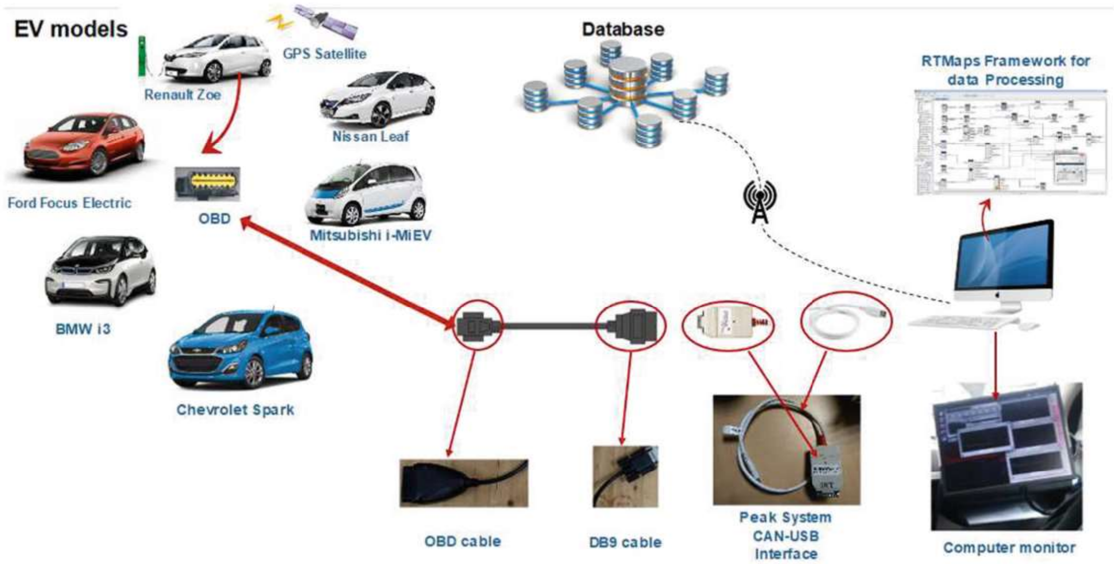

Fig. 4. EV data acquisition and processing system architecture.

Table 1 enumerates the collected data.

Table 1. Description of data collected during real world experimentation.

Experimental output data	Description
Energy consumption-related parameters	Instantaneous energy consumption [kWh]
	Instantaneous energy recuperation [kWh]
	Energy available in the battery [kWh]
	Available charging power [kWh]
	Vehicle autonomy [km]
	Instantaneous auxiliaries consumption[kW]
Route profile-related parameters	Latitude coordinate [m]
	Longitude coordinate [m]
	Altitude coordinate [m]
Driver profile-related parameters	Instantaneous speed of driving [Km/h]
	Instantaneous acceleration [m.s^{-2}]
	Instantaneous brake pedal pressure [%]
Weather conditions-related parameters	External temperature degree [°C]
EV-related parameters	Auxiliary systems status [ON/OFF]
	Maximum loading capacity [kW]

3.1.2 Route Profile

A particular test route profile was selected in this research to reflect a typical daily driving behavior as illustrated in Fig. 5. The test route starts and ends at University street Saint-Etienne-du-Rouvray, France, with a complete driving distance of 20.7 Km. The test route was selected to better cover the road topography impact with a wide variety of discrete road slope values as shown in Fig. 6. The test vehicle was equipped with a GPS system to collect road data, characterizing the selected driving route. The Road slope profile was elaborated from the following GPS coordinates: latitude coordinate φ [m], longitude coordinate λ [m] and altitude coordinate ψ [m].

The distance traveled d (m) between two consecutive GPS coordinates is a function of the two first parameters (i.e. latitude and longitude) using the Haversine formula [15] (Eq. 6).

$$d = R * 2 * \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\varphi}{2}\right) + \cos\varphi_1 * \cos\varphi_2 * \sin^2\left(\frac{\Delta\lambda}{2}\right)}\right) \tag{6}$$

Where R is the Earth's radius.

The road gradient θ was calculated from the altitude parameter and the traveled distance d[m] as shown in Eq. 7.

Fig. 5. Test EV route.

Fig. 6. Road slope profile of the test EV route.

$$\theta = \arctan\left(\frac{\Delta\psi}{\Delta d}\right) \tag{7}$$

Moreover, the test route contains diversified road types covering arterial roads, local roads, expressways and motorways. Obviously, a driver profile may be characterized in such particular conditions. Therefore, the speed profile depends mainly on several driving parts (urban areas must assume the speed limit of 50 km/h, major arterial roads are used for a speed limit of 80 km/h, expressways with a speed limit of 100 km/h and several parts of motorways with speed limit of 130 km/h). Accordingly, a preselected driving profile was established in the experimentation taking account of these road type specifications.

3.2 Experimentation Evaluation

The related real-world data was collected and then processed by dividing the selected route into sections of 10 m. Then, we have calculated the average of required values of parameters (i.e. road gradient, energy consumption, energy recuperation, etc.) at each section. The main goal is to provide accurate calculations of the road gradient parameters. Additionally, a 95% confidence interval is ensured for these results.

In this sub-section, we assess the impact of the road gradient on both energy consumption and energy recovery for EVs.

3.2.1 Impact of Road Gradient on EV Energy Consumption

Figure 7 illustrates the evolution of energy consumption with regard to the road slope variation. Experimental results show that EV consumes more energy on uphill roads (i.e. positive values of road slopes) than downhill roads (i.e. negative values of road slopes). For instance, when the road gradient is equal to 8%, the average consumed energy is around 81 Wh, while it is about 8Wh, when the road gradient is about −8%. Indeed, the hill climbing force F_{hc} aforementioned, applied to EV for overcoming road gradient resistance increases the energy consumption at uphill roads. In fact, the increase of the slope elevation makes this force act to decelerate the EV and hence to increase the total EV energy consumption [8]. Therefore, this force has a valuable impact while estimating the EV energy consumption in regards to the road slope [8].

A part from some gradients, for which not enough data could be collected, confidence intervals remain quite acceptable.

3.2.2 Impact of Road Gradient on EV Energy Recuperation

Figure 8 illustrates the energy recovery evolution in regards with the road gradient variation. Experimental results show that the EV recovers more energy on downhill roads than on uphill roads. For example, when the road slope is equal to −7%, the average recovered energy is around 35 Wh, while the average recovered energy quickly reaches 0 Wh when the uphill slope is higher than 8%. Indeed, EV drivers are supposed to brake more frequently at extreme downhill slope [8]. Furthermore, during downhill driving, the decrease of the slope elevation makes the road gradient resistance force act to accelerate the EV and hence to recover more energy and to reduce the total of EV energy consumption [8].

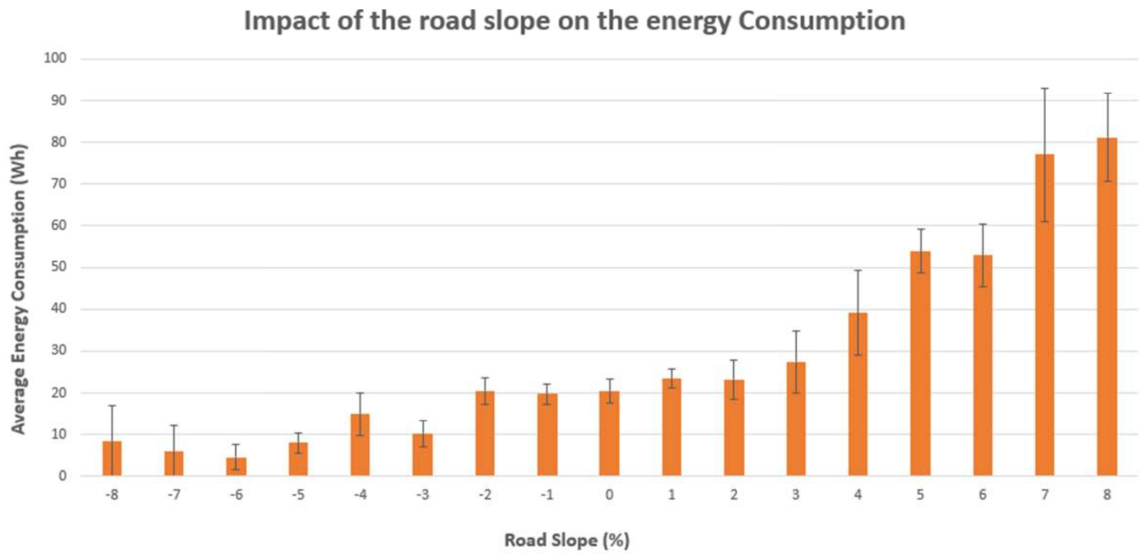

Fig. 7. Road slope impact on EV energy consumption.

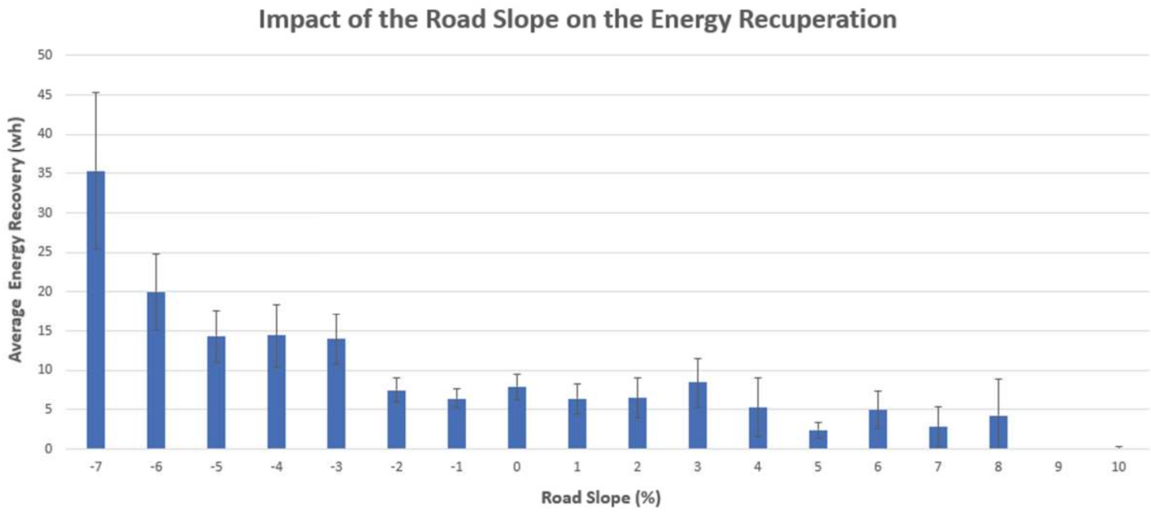

Fig. 8. Road slope impact on EV energy recuperation.

4 Conclusion

Realistic road traffic simulations require an accurate and reliable energy consumption model for EVs. Therefore, it is crucial to characterize different EV subsystems and various factors that influence its energy consumption. This paper discusses and reviews recent attempts regarding the EV energy model subsystems. The conducted theoretical analysis revealed the valuable impact of the road slope factor on the energy consumption and energy recuperation processes.

The main goal of this work, was hence to check, through real world experimentation, the real extent of this impact in both energy consumption and energy recuperation stages. Accordingly, we conducted a set of real-world exploratory experiments in different road topologies. A data acquisition and processing system is identified in this research to record various EV data and related-driving information. Experimental analyses have specified the importance of the road slope factor in the estimation accuracy of energy consumption for EVs.

Further research is recommended to investigate the impact of other external factors on EV energy consumption such as driver profile (i.e. speed, acceleration, etc.) and road traffic conditions on the EV energy consumption. Therefore, a further study on incorporating additional parameters in EV energy models of road traffic simulators is required.

Acknowledgements. This work was supported by the PHC Utique program of the French Ministry of Foreign Affairs and Ministry of higher education and research and the Tunisian Ministry of higher education and scientific research in the CMCU project number 16G1404.

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