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Evaluation of the Energy Consumption Model Performance for Electric Vehicles in SUMO

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***Abstract*—In recent years, the diffusion of electric vehicles(EVs) is of great importance in the road transport and automotive sectors. Reducing electricity consumption and increasing battery autonomy are actually motivating vehicle manufacturers to focus their attention on the EV concept. The evaluation of EV performance through realistic scenarios in traffic simulations is still a key issue. In fact, the road traffic Simulator Simulation of Urban Mobility (SUMO) integrates an energy model for calculating the EV energy consumption. However, this model underestimates the energy consumption values in the real world. In this paper, we intend to investigate the energy consumption models existing in the literature. Then, we assess the performance of the existing energy model in SUMO through a set of simulation scenarios. Finally, we present the main requirements for a realistic, accurate and scalable energy model to estimate the instantaneous energy consumption for EVs.**

***Index Terms*—Electric vehicle, energy consumption model, vehicular networks, energy recuperation, traffic simulation, energy efficiency.**

I. Introduction

The automotive manufacturers have recently focused their attentions on EVs technology as a solution to the environmental problems especially fossil fuels crisis and greenhouse gas emissions [3] [39]. Actually, the energy consumption rate in the transport sector achieves around 30% of the total consumed energy in the world [5]. To this end, Intelligent transportation systems (ITS) aim at introducing the EV new automobile technologies to increase the energy efficiency [28] [13]. However, recent research studies on the future market diffusion of EVs raise various challenges related to: energy consumption estimation, charging station deployment, eco-driving activities, route planning, etc. [16] [40] [15] [27].

In this context, we are working on a Tunisian-french Joint Committee for University Cooperation (JCUC) research project entitled "Urban Platform for Connected Electric Vehicles"(PUVEC) [33]. The main goal is to elaborate an energy map that reflects the average real-time road energy consumption. Such a map will be used to propose innovative energy-oriented navigation services for connected EVs.
The related new services are mainly: (1)identifying the energy-saving path toward the vehicle's destination, (2) estimating the recharging needs according to the actual battery state and traffic conditions, (3) displaying the energy map that provides significant information about the required EV energy consumption on each lane, etc. A basic overview of the PUVEC architecture is depicted by Fig.1.

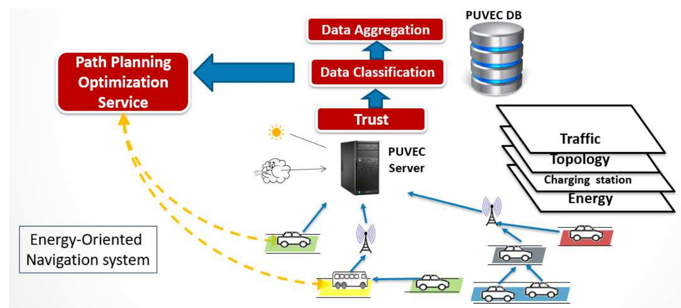

Fig. 1. PUVEC architecture.

EVs on the road send to the PUVEC server real time data (i.e. electrical consumption, vehicle ID, road ID, etc.). The collected data in the server are filtered (i.e. trust component), classified (i.e. data classification component) and merged (i.e. data aggregation component) to build the energy map using even complementary data such as traffic state, weather conditions, road topology, etc. The established map will be used to provide energy-oriented trip planning optimisation services to address and resolve EV energy issues (i.e. the lowest energy path, the nearest available charging station, etc.).

In this paper, we are interested on the EV energy consumption estimation issues that can be performed in the context of PUVEC. Obviously, realistic traffic simulations are required for such kind of project to assist humans in evaluating and reducing the EV energy consumption. Indeed, high-efficiency solution depends mainly on the reliability of traffic simulation tools especially the accuracy of its energy consumption model. SUMO is considered as the most reliable road traffic simulator [19] [18]. It is used for simulating various types of EVs, vehicular networks, charging stations infrastructure, microscopic and multi-modal traffic flow in road networks [17] [32] [8] [34] . SUMO currently integrates a simple energy consumption model for calculating EV energy consumption at each time step [20]. However, this model lacks accuracy and does not reflect real EV energy consumption.

The main contribution of the present investigation is to assess the performance of the existing energy model in SUMO among various simulation scenarios. We aim to compare the energy model outputs with real world experimental data, and further to specify the main requirements of a more realistic, accurate and scalable EV energy model.

This paper is organized as follows: section II discusses previous works related to EV energy models existing in the literature. In section III, we aim to prove the limits of the existing model implemented on SUMO compared to real world experimental data. We present in section IV the main requirements of a realistic, accurate and scalable energy model to be easy-to-integrate in SUMO. Section V presents conclusions and perspectives.

II. Related Work

In order to estimate the energy consumption of an EV, an energy model must be defined for traffic simulations and analysis [9] [7].
The aim of the present work is to specify the main requirements to elaborate a realistic, easy-implementable and scalable energy model ensuring realistic traffic simulations and producing valuable results. Indeed, a realistic energy model should simulate EV energy consumption more realistically [26]. An easy-implementable model can speed up the traffic simulation runtime. A scalable model can be applied on various types of EVs and under different road traffic conditions [43].

In literature, several energy consumption models have been elaborated and discussed to simulate a realistic and accurate EV energy consumption [20] [23] [42].
Often, EV is considered as a complex system [21] [4]. Therefore, the energy consumption model can be formulated according to the consumption and recuperation parts.

The consumption part consists of the mechanical and electrical subsystems.

The mechanical subsystem represent a common core model for the EV energy model, since it is considered as the most important part of the EV energy consumption model. It has been modeled using the vehicle dynamics equation [22]. Indeed, it has been specified using the tractive force F_{te} applied to wheels and insuring EV movement [23]. This force formula is presented by Eq.(6). This force represents the sum of forces acting on EV vehicle in motion as shown in Fig.2. These forces reflect acceleration resistance (F_{wa} and F_{wa}) , rolling resistance (F_{rr}), air resistance (F_{ad}) and road slope resistance (F_{hc}).

$$F_{te} = F_{rr} + F_{ad} + F_{hc} + F_{la} + F_{wa} \tag{1}$$

Where:

$$F_{rr} = \mu_{rr} \times m \times g \tag{2}$$

$$F_{ad} = \frac{1}{2} \times \rho \times A \times C_d \times v^2 \tag{3}$$

$$F_{hc} = g \times \sin \psi \tag{4}$$

$$F_{la} = m \times a \tag{5}$$

$$F_{wa} = I \times \frac{G^2}{\eta_g \times r^2} \times a \tag{6}$$

Where: m [Kg] is the total vehicle mass; v [m/s] is the vehicle speed; a [m/s^2] is the linear vehicle acceleration; g [m/s^2] is the gravitational acceleration; I[Kg.m^2] is the moment of inertia of internal rotating elements; ρ [Kg/ m^3] is the variable air density; C_d [%] is the air drag coefficient; A [%] is the vehicle front surface area; μ_{rr} [%] is the rolling resistance coefficient; G [%] is the gear ratio of the system, ψ [°] is the angle of slope; η_g [%] is the gear system efficiency; and r [m] is the tyre radius.

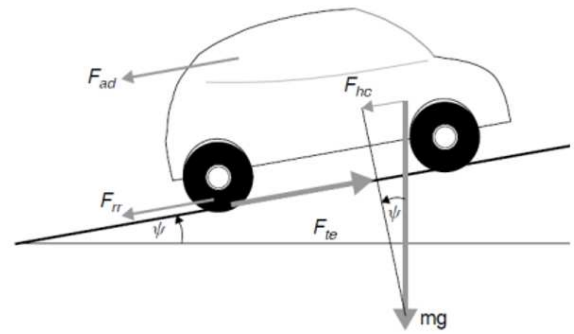

Fig. 2. Outside forces acting on a driving EV along a slope [23].

All the previous works are generally based on the tractive force F_{te} formula, but with notable differences which affects the energy model accuracy and makes it more complex to implement. For example, Maia et al.(2011) [23] have employed the angle of road slope, while Kurczveil et al.(2014) [20] have considered the elevation component in the evaluation of the acceleration resistance forces applied on the EV. In addition, Cauwer et al.(2015) [9] and Shibata et al. (2015) [38] have employed alongside with the vehicle mass, the fictive mass of rolling inertia to estimate the acceleration resistance force. Similarly, in the works of Abousleiman et al.(2015) [1] and Wang et al.(2015) [41] the air resistance force have been modeled with the wind velocity. They have also integrated the average mass of the vehicle and passengers to calculate the rolling resistance force.

The electric subsystem modeling is a controversial issue. It can be formulated by two parts: the first part is mainly presented by the energy consumed by auxiliary systems (i.e. air-conditioning, heating, radio, lights, etc.). The second part represents the additional electric loss occur from the instable power flowing from/into the EV battery due to the particularities of the dynamic system [31].

Regarding auxiliary consumption estimation, two different approaches have been defined: the first approach consists in formulating the auxiliary consumption part as a constant charge provided by the vehicle manufacturer as shown in [23], [20] and [12]. The second approach, presented by Cauwer et al. (2015) [9], expressed this energy as a function of the ambient temperature due to its impact on the energy consumed by auxiliary systems.

The additional electric loss subsystem has been modeled using into two different approaches : the first approach is based

on detailed mathematical model. Indeed, it is an accurate estimation of the physical characteristics of electrical-components [23], [42](e.g. the current intensity, open circuit voltage from the battery, the internal Resistance, etc.).
The second approach is a sophisticated estimation based on constant efficiency percentage (e.g. inverter efficiency, battery efficiency, electric motor efficiency, etc.) [38] [12].

As for the recuperation part, the regenerative braking system makes the electric motor act as a generator by transforming of the kinetic energy at the wheels to electrical energy to be stored in the battery during deceleration and/or driving downhill phases [12]. Despite the potential impact of the regenerative braking process on the EV energy consumption, the studies presented in [23], [9] and [42] did not take account of this process. However, the results of other researcher's investigations have introduced the energy recuperation part according to two different methods: the first method is an estimation approach based mainly on a constant regenerative braking efficiency factor provided by the EV manufacturer [20] [38]. The second method is an explicit based mainly on modeling this process by an instantaneous braking energy regeneration formula [12]. This formula depends mainly on the deceleration level and hence easy to incorporate in the EV energy model.

In brief, the diagram depicted by Fig.3 illustrates the main subsystems required for modeling a realistic, accurate and scalable energy consumption model.

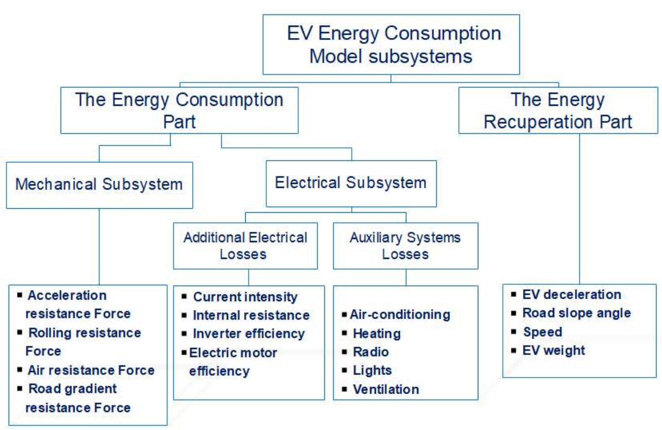

Fig. 3. EV energy model main subsystems.

The existing EV energy model implemented in SUMO is proposed by Kurczveil et al.(2014) [20]. They present a simple model to improve the runtime of calculating the EV energy consumption calculations. Indeed, their model is principally based on modeling the mechanical subsystem. They oversimplified the electrical subsystem by introducing a constant efficiency parameter for propulsion provided by the EV constructor. This parameter represents the additional electric loss that come out of the battery and are dissipated while accelerating the vehicle. In addition, they represented the energy loss by auxiliary systems by a constant power provided by the vehicle manufacturer. Regarding the recuperation part, Kurczveil et al.(2014) [20] proposed a constant regenerative braking efficiency factor provided by the vehicle manufacturer. However, they did not proposed this parameter by an explicit formula.

To sum up, these simplifications seem to make their energy model lacks accuracy and underestimate the real world energy consumption. Special attention towards incorporating a realistic, accurate and scalable EV energy model should be paid to improve the energy consumption estimation in road traffic simulators. Indeed, Fiori et al.(2016) [12] propose a simple, accurate and efficient energy model for EVs which is known as the Virginia Tech Comprehensive Power-based EV Energy consumption Model (VT-CPEM). Their main contribution is modeling the regenerative braking concept by an explicit formula depending on the EV deceleration at each simulation time step. They compared their results to real experimentations data [10] [2] [30] and proved that their model is close to reality.

In the next section, we evaluate the performance of the existing energy model implemented in SUMO [20] by establishing a comparison between energy model SUMO outputs, VT-CPEM model [12] outputs and real word experimental data [30].

III. SIMULATION SETUP AND RESULTS

The simulation phase is required to reduce the design and development costs. The aim of such simulation environments is to work at a much faster processing than any real environment, and hence to improve the performance of EVs and to increase its driving range. Accordingly, the integration of a reliable and realistic energy model in traffic simulations is an important task to calculate realistic EV energy consumption.

In this section, we aim to assess the existing energy consumption model in SUMO [20] through a set of simulation scenarios. Therefore, we identified the required parameters for a realistic simulation process as shown in Fig.4. Indeed, we have specified as inputs the data related to a speed profile of a standardized driving cycle and a description of an EV model parameters (i.e. data inputs component). Then, the selected data are incorporated in the simulator SUMO [8] to perform a realistic simulation scenario (i.e. data processing component). The obtained results especially the instantaneous energy consumption (i.e. data outputs component) are used for evaluating the related energy consumption model.

The main goal of this section is to compare these results with the VT-CPEM model results [12] and, as well with real world experimentation results [2] [30]. In fact, we incorporated in SUMO the same input parameters used for validating the VT-CPEM model [12], since they have achieved significant results. Then, we show the impact of the ambient temperature on the energy consumed by the auxiliary system and even on the total EV energy consumption.

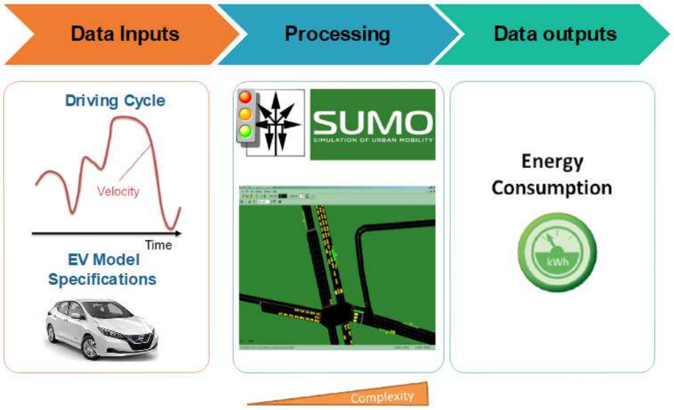

Fig. 4. Simulation Process.

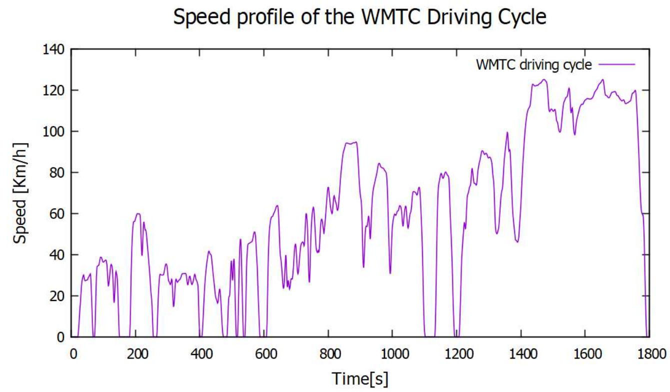

Fig. 5. WMTC driving cycle.

A. Parameters identification in the simulation of EVs

We aim in this subsection to introduce a set of simulation input parameters in order to generate instantaneous energy consumption output. These parameters are often used in the validation process of any energy model.

In this case, we incorporated the data inputs aforementioned in SUMO for the validation process to analyze and compare the related simulation outputs with VT-CPEM model outputs [12] and even with real world data collected by the Joint Research Centre (JRC) of the European Commission [10] [30]. Thereafter, we will compare the State Of Charge(SOC) profile of our simulation output with the SOC profile result related to the VT-CPEM model [12] since it has provided significant results compared with the real world JRC data [10]. Finally, we compare our results with real world experimentation data [10] [2].

1) Driving Cycle: The vehicle driving cycles are necessary to simulate realistic traffic scenarios.
A driving cycle is known also as a speed profile which reflects a set of vehicle speed values in terms of time. This process is used to decrease the on-road tests'cost [29]. Many standard driving cycles are required in traffic simulations for assessing EVs performance [37] [14]. Among these, two categories of driving cycles might be characterized : the European [37], and the American [14]driving cycles.
In practice, we integrated in SUMO the European driving cycle: World-wide harmonized Motorcycle emission Test Cycle (WMTC) as illustrated in Fig.5.

2) EV model parameters: Regarding the EV model parameters, we have incorporated in SUMO the EV model parameters used for validating the VT-CPEM model [12],and hence used in real world JRC experimentations [10]. Accordingly, we have selected the Nissan Leaf EV model [10] [29] due to its popularity and, thus, to the availability of its technical specifications and related experimental data results [36] [10].

B. Analysis of Simulation results

We aim in this subsection to evaluate the differences in the SOC outputs of the energy model implemented in SUMO [20], the VT-CPEM model [12], and real world JRC experimental results [10]. Indeed, We conducted a set of simulation scenarios to assess the performance of the existing EV energy model in SUMO [20]. We have integrated in SUMO the Nissan Leaf parameters with the WMTC driving cycle. Then, we have elaborated through the simulation outputs, the SOC profile graphs as shown in Fig.6.
In particular, we have combined the SOC profile graphs related to (1) the VT-CPEM model (violet line), (2) the existing energy model available in SUMO (blue line) and (3) the Real world JRC Experimental data (green line) together.

- *SUMO SOC output Vs Real JRC SOC profile:* Fig.6 shows that the SOC profile graph of the existing energy model in SUMO is significantly higher than the real SOC profile related to JRC data. In particular, the SOC percentage difference grew significantly from 3% to 11% between 1200s and 1800s. In brief, there is a significant gap between simulated SOC and real SOC. The existing energy model in SUMO requires some improvements to be more realistic.
- *VT-CPEM SOC output Vs Real JRC SOC profile:* Fig.6 illustrates the SOC profiles results for both VT-CPEM model and the SOC profile related to the JRC data. In particular, the SOC profile graphs show that the VT-CPEM model is close to the reality with an average error of 0.33%.

These results show that the SOC profile graph of VT-CPEM model [12] is closer to the real world SOC profile ; While there is a significant difference between the SOC profile output of SUMO and the real SOC profile. In fact, this difference is due to two main reasons: The first reason is related to the energy model design. Indeed, Kurczveil et al. [20] have introduced a set of simplifications to their energy model. They focused mainly on modeling the mechanical subsystem. However, they have oversimplified the electrical subsystem. Likewise, they presented the energy consumed by EV auxiliary system as a

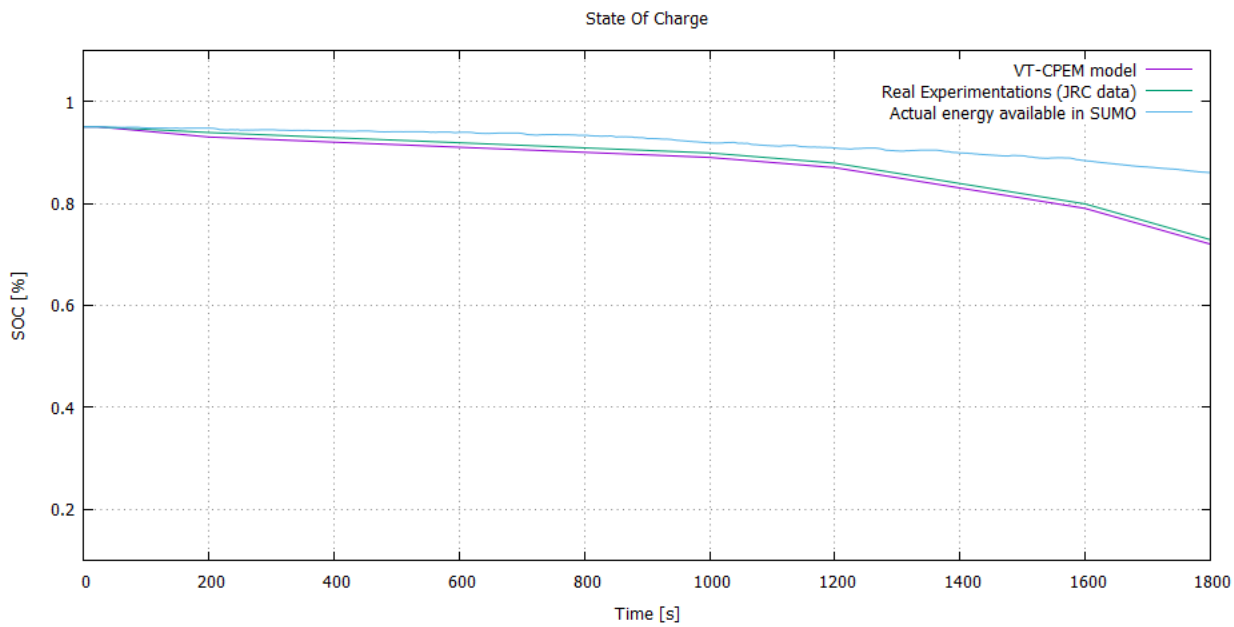

Fig. 6. Combination of the SOC profile graphs related to (1)the VT-CPEM model, (2) The SUMO energy model and (3) the Real world JRC experimental results.

constant provided by the vehicle constructor. Moreover, they did not model the recuperation part by an explicit formula. They just presented a constant regenerative braking efficiency factor provided by the vehicle constructor. The second reason is related to the model validation process. In fact, they carried out their simulations using only one type of EV. Moreover, their energy model has just been tested with the New European Driving Cycle (NEDC) [24]. However, many research studies proved that the NDEC driving cycle does not reflect real-world driving conditions. It was replaced by the Worldwide Harmonized Light Vehicles Test Procedure (WLTP) driving cycle [24]. The WLTP presents a set of test procedures including the WMTC and the World-wide harmonized Light duty Test Cycle (WLTC) driving cycles [25].

1) Impact of modeling the energy recuperation part: With the aim to evaluate the current energy model integrated in SUMO with various driving cycles, we have included three American Driving Cycles and the two most recent European Driving Cycles (WMTC and WLTC) in SUMO to explore more results. The American Driving Cycles are [14]:

- The EPA Urban Dynamometer Driving Schedule (UDDS) which provides a typical speed profile that reflect city driving conditions;
- The Highway Fuel Economy Driving Schedule (HWFET) which as well, representing highway driving;
- The high acceleration aggressive driving schedule that is often identified as the "Supplemental 368 FTP" driving schedule (US06) which reflects aggressive driving.

Table I depicts the total SOC percentage provided by the real world JRC experimentatal data, the energy model of SUMO and the VT-CPEM energy model.

The real world experimentation data related to the European Driving Cycles are provided by the JRC experimentation data [10]. Likewise, the real experimentation data related to American Driving Cycles are provided by the DOE's Advanced Vehicle Testing Activity (AVTA) of the Idaho Nation Laboratory (INL) [2]. The simulation scenarios were carried out at the ambient temperature of 25°C and when the auxiliary systems are switched off.

TABLE I
EVALUATION OF THE ESTIMATED BATTERY SOC PERCENTAGE.

Battey SoC [%]		Real Experimentatal data	VT-CPEM model Results	Error[%] VT-CPEM Vs Real Experiments	SUMO energy Model	Error[%] SUMO Vs Real Experiments
American Driving Cycles	UDDS	89,1	88,17	1,12	91,8	3,03
	HWFET	84,96	84,92	0,047	8,6	3,1
	US06	84,2	83,4	0,95	89,0	5,7
European Driving Cycles	WMTC	72,9	73,03	0,17	81,0	11,1
	WLTC	77,7	78,54	1,08	83,9	7,97

Table I shows that the energy model implemented in SUMO [20] does not accurately estimate the EV energy consumption compared with the real world experimental data. Indeed, the average errors rate related to SOC. percentages of the current energy model in SUMO is higher than the average errors rate related to SOC percentages provided by VT-CPEM model [12]. For instance, The total average errors produced by VT-CPEM model is of about 0.6% compared to experimental results. However, SUMO model produces a wrong estimation under the same conditions with an average error of 6.18%. Consequently, the simulation results show the limits of the EV energy model implemented in SUMO. Accordingly, the VT-CPEM model [12] is closer to the reality due to the explicit formula the model the recuperation part aforementioned. Obviously, it is crucial to incorporate such formula in the SUMO energy model to provide more accurate results.

In the next section, we show the impact of the ambient temperature on the EV energy consumption through a set of simulation scenarios.

2) Impact of the ambient temperature on the EV energy consumption : The existing energy model in SUMO [20] includes a constant power to reflect auxiliary systems power consumption. This parameter depends on the EV model and is provided by the EV manufacturer. However, it does not take account of modeling the auxiliary loads in terms of the external ambient temperature parameter. Accordingly, recent research studies [12] [9] [38] [40] show the impact of the ambient temperature on the energy consumed by auxiliary systems (i.e. especially the air conditioning and heating systems) and even on the total EV energy consumption. For instance, the National Renewable Energy Laboratory (NERL) study estimated a reduction of the EV range by 38% due to auxiliaries loads in terms of ambient temperature [40] [11]. Therefore, special attention should be paid towards the impact of such factor.

In this subsection, we carried out three different scenarios. First, the energy consumed by auxiliary systems in SUMO is set at 700 W [12]. Then, based on the data reported by [11] and [3], we aim to analyze the impact of the outside temperature on the EV battery SOC of the Nissan Leaf EV as illustrated in TableII. We consider the following ambient temperature degrees of: 25°C, 35°C and -7°C.

TABLE II
IMPACT OF THE AMBIENT TEMPERATURE ON THE EV ENERGY CONSUMPTION.

Battey SoC [%]		SUMO energy Model	Real Exper-imen-tatal results at 25°C	Real Exper-imen-tatal results at 35°C	Real Exper-imen-tatal results at -7°C
American Driving Cycles	UDDS	91,8	87,9	87,4	86
	HWFET	87,6	84,7	84,4	83
	US06	89,0	83,3	83,0	82
European Driving Cycles	WMTC	81,0	72,7	71,8	69
	WLTC	83,9	78,2	77,4	75

The experimental results show that the SOC percentage at each driving cycle varies in regards to the ambient temperature; while the energy model implemented in SUMO [20] provides the same results regardless the variations in temperature degrees. Consequently, the existing energy model in SUMO becomes unreliable for assessing EV performance.

To sum up the effects of the ambient temperature, the current energy consumption model in SUMO [20] underestimates the battery SOC percentage in the real world. Therefore, proposing a set of improvements that must be applied on this model becomes a necessity.
In the next section, we present these improvements based on the analysis of previous results.

IV. FOLLOW-UP RECOMMENDATIONS

The main objective of this section is to present the main requirements of a realistic, accurate and scalable energy model for the EV energy consumption estimation. These requirements are based on our literature review and, as well on the analysis of simulation results as mentioned in the previous section.

SUMO [6] is considered today as one of the most reliable traffic simulators used especially for vehicular networks and, hence, for various EVs simulation scenarios. However, the current energy consumption model of SUMO [20] lacks accuracy, as we explained in the previous section. Actually, an efficient model must be easy to implement, and provide an accurate estimation of EV energy consumption. To achieve such requirements, a realistic energy model should be conceived by taking account of the following subsystems modeling :

- *More accurate auxiliary consumption modeling:* The experimentations presented in [12] showed through a set of simulation results that the power consumption might increase by up to 32% depending on the external ambient temperature. Therefore, an energy model should include an explicit formula of the power consumed by the auxiliary systems in terms of the external temperature degree to specify the impact of such factor on the EV energy consumption.
  The energy consumed by auxiliary systems formula as a function of time Δt as shown in Eq.(7) [35]:
  $$\Delta E_{Aux,T} = E_{Aux,const} \times \Delta t + \beta \times |20 - T| \times aux \times \Delta t \quad (7)$$
  Where: $E_{Aux,const}$ [w] is the minimum base energy consumed by these auxiliary systems: radio, light system, etc. at 20°C [35]; T: Ambient temperature in °C; β: regression coefficient mapping HVAC consumption to ambient temperature which was estimated by [9];
  aux = $\frac{Duration\, of\, auxiliaries\, switched\, on}{Total\, duration\, of\, trip}$ [9].

- *Explicit method for modeling the energy recuperation part:* an efficient energy model should incorporate an accurate energy recuperation model. It should also be easy to inject in the SUMO energy model formula while maintaining a reasonable complexity level.
  The regenerative braking efficiency factor injected in the VT-CPEM model [38], might be a significant support due

to the valuable provided results. In fact, the regenerative braking efficiency factor formula corresponds to [35]:

$$\eta_{recup}[t] = \left(e^{\left(\frac{0.0411}{|a[t]|}\right)}\right)^{-1} \quad (8)$$

Where: $\eta_{recup}[\%]$ is the regenerative braking efficiency factor; a $[m.s^{-2}]$ is the instantaneous acceleration.

V. Conclusion

In this paper, we presented a literature review of the existing energy consumption models for EVs. Based on the conducted theoretical analysis, we specified the different energy consumption modeling parts that should be considered while establishing an accurate energy model for EVs. Then, we identified the the required input parameters that should be integrated in SUMO (i.e. EV model specifications, the appropriate driving cycle, etc.) for assessing the energy model performance. To perform this evaluation, we incorporated the experimentation parameters used for validating the VT-CPEM model in the Simulator SUMO. Then, we have compared our simulation outputs with first the VT-CPEM model outputs and then with the real world JRC experimentation data.

The analysis of the simulation results show that the VT-CPEM model is closer to the reality than the existing energy model in SUMO [20]. In fact, the reliability of the VT-CPEM is due to the explicit formula of the regenerative braking efficiency factor. Then, we showed the potential impact of the ambient temperature especially on the energy consumed by the auxiliary systems and even on the total EV energy consumption.
Consequently, we proposed, through the theoretical and simulation analysis, a set of improvements that should be applied in the SUMO EV energy model with regard to its scalability, simplicity, and accuracy.

Based on the simulation results and deduced recommendations, the next work is to specify and integrate the proposed improvements in the SUMO energy model [20]. The main goal is to validate the improved energy model using real world experimentations at different travel conditions and road types.

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