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# Power-based electric vehicle energy consumption model: Model development and validation

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## HIGHLIGHTS

- The study developed an instantaneous energy consumption model (VT-CPEM) for EVs.
- The model captures instantaneous braking energy regeneration.
- The model can be used for transportation modeling and vehicle applications (*e.g.* eco-routing).
- The proposed model can be easily calibrated using publically available EV data.
- Usages of air conditioning and heating systems reduce EV energy consumption by up to 10% and 24%, respectively.

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## ABSTRACT

The limited drive range (The maximum distance that an EV can travel.) of Electric Vehicles (EVs) is one of the major challenges that EV manufacturers are attempting to overcome. To this end, a simple, accurate, and efficient energy consumption model is needed to develop real-time eco-driving and eco-routing systems that can enhance the energy efficiency of EVs and thus extend their travel range. Although numerous publications have focused on the modeling of EV energy consumption levels, these studies are limited to measuring energy consumption of an EV's control algorithm, macro-project evaluations, or simplified well-to-wheels analyses. Consequently, this paper addresses this need by developing a simple EV energy model that computes an EV's instantaneous energy consumption using second-by-second vehicle speed, acceleration and roadway grade data as input variables. In doing so, the model estimates the instantaneous braking energy regeneration. The proposed model can be easily implemented in the following applications: in-vehicle, Smartphone eco-driving, eco-routing and transportation simulation software to quantify the network-wide energy consumption levels for a fleet of EVs. One of the main advantages of EVs is their ability to recover energy while braking using a regenerative braking system. State-of-the-art vehicle energy consumption models consider an average constant regenerative braking energy efficiency or regenerative braking factors that are mainly dependent on the vehicle's average speed. In an attempt to enhance EV energy consumption models, the proposed model computes the regenerative braking efficiency using the instantaneous vehicle operational variables. The proposed model accurately estimates the energy consumption, producing an average error of 5.9% relative to empirical data. The results also demonstrate that EVs can recover a higher amount of energy in an urban driving environment when compared to high speed highway driving using the proposed model. Moreover, the study also compared different electric vehicles and quantified the impact of auxiliary systems, including the air conditioning and heating systems, on vehicle energy consumption levels using the proposed energy model. The study demonstrated that the use of the heating and air conditioning system could significantly reduce the EV efficiency and travel range.

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## 1. Introduction

The transportation sector in 2014 accounted for approximately one third (27%) of the total world primary energy consumption [1]. Moreover, the transportation sector is the second-largest source of

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greenhouse gas emissions, and is responsible for 34% of the total $CO_2$ emissions. These emissions are produced principally from the combustion of fossil fuel, including gasoline, diesel, heavy oils, and jet fuel [2]. These days, personal mobility is *de facto* powered only by petroleum. Specifically, in 2014 petroleum accounted for 92% of the total transportation energy consumption [1,3].

Electric Vehicles (EVs) are expected to gain a significant market share in the near future. Extensive studies performed by the University of California, Berkeley predict that approximately 2.5 million EVs will be present on American roads by 2020 [4]. The introduction of EVs will significantly reduce vehicle fuel consumption and emission levels. In order to quantify the network-wide impacts of EVs, there is a need to develop simple and accurate EV energy consumption models. This study attempts to address this need by developing a simple EV energy consumption model that can be easily calibrated to specific vehicles and easily implemented in transportation simulation software and in-vehicle and Smartphone eco-driving and eco-routing applications. The proposed model captures instantaneous braking energy regeneration as a function of the vehicle deceleration level. Compared with conventional vehicles powered by Internal Combustion Engines (ICEs), the advantages of EVs include: (a) a greater energy efficiency achievable through the use of on-board electric devices, (b) braking energy recovery, (c) reducing emission levels, and (d) the possibility to obtain electricity input from renewable sources [5].

A regenerative braking system of EVs allows for the recovery of energy while braking. Specifically, the electric motor works as a generator by sending energy from the vehicle wheels to the electric motor that is then stored in the battery system. Previous studies found that EVs were much more efficient when driving on "inter mittent" urban routes when compared to uninterrupted freeways because the regenerative braking system is able to regenerate energy [6]. The opposite occurs in ICE vehicles where they exert additional energy in urban driving because of braking and thermal losses [7–9]. Empirical studies have demonstrated that EVs consume lower energy while driving on urban driving cycles [10] and are able to recover energy while braking [11].

### 1.1. Study objectives

The objective of this paper is to develop a simple, accurate, and efficient model, the Virginia Tech Comprehensive Power-based EV Energy consumption Model (VT-CPEM). The input variables to estimate the instantaneous energy consumption of EVs include the vehicle's instantaneous speed and acceleration levels. The proposed model also captures instantaneous braking energy regeneration as a function of the deceleration level. Due to the simplicity of the model structure, the proposed model can be easily integrated into more complex modeling frameworks including microscopic traffic simulation models and in-vehicle and Smartphone applications. The microscopic traffic simulation models that estimate the instantaneous energy consumption of EVs can be used to quantify the energy and environmental impacts of EVs on large and complex urban network environments including the impact of traffic signal control systems, highway ramp metering systems, and arterial and highway operational projects, which is required to capture the expected significant growth in the EV market share. The simple energy model is essential to assess the EV's energy impacts of new transportation technologies including connected vehicle (CV) and automated vehicle research and to develop sustainable transportation systems.

A major contribution of the study is the development of a simple, accurate, and efficient energy model for EVs that can be easily calibrated using publically available EV data without the need for field data collection.

### 1.2. Study contributions

This study compliments and extends existing EV energy consumption models in the following ways: (1) *this model is the first approach that uses the instantaneous regenerative braking energy efficiency as a function of the vehicle deceleration level to estimate the instantaneous energy consumption for EVs*. Some previous studies used an average regenerative braking energy efficiency [12] or a regenerative braking factor mainly dependent on the vehicle speed [13–15]. In particular, the proposed study attempted to capture the instantaneous regenerative braking energy using vehicle speed and acceleration input variables. The study utilizes the deceleration level to estimate the instantaneous regenerative braking energy efficiency. This efficiency is then used to compute the energy consumed by the vehicle. (2) *Applicability*. The proposed method can be easily implemented in microscopic traffic simulation models and in-vehicle and Smartphone eco-driving applications. The advantage of the proposed model is the ability to predict energy consumption levels using data that can be easily gathered using a Global Positioning System (GPS). Using speed measurements, vehicle accelerations can be computed. Differences in speed and acceleration distributions can significantly affect the instantaneous energy consumption level. Most energy models use average speed as an input variable and thus cannot distinguish between facilities that operate at the same average speed. However, a vehicle typically consumes significantly higher energy at a high-speed facility with multiple traffic signal controls than a low-speed facility where the vehicle travels at a constant speed if both trips have identical average speeds. The proposed approach can accurately estimate the energy consumption based on transient behavior. (3) *Validation using real reliable data*. Some electric vehicle models, such as the model presented in Doucette et al. (2011), were validated against aggregate energy consumption values reported by the vehicle manufacturers or the U.S. Environmental Protection Agency (U.S. EPA) [16]. This validation effort was limited due to the energy data availability of EVs. Model outputs in this paper are validated using experimental data on EV consumption levels that were collected by the Joint Research Centre (JRC) of the European Commission (2015) and by the Idaho National Laboratory (INL) in the AVTA program of the United States Department of Energy (U.S. DOE) (2013). (4) *Assessment of auxiliary system impacts on energy consumption levels*. The proposed model can estimate the impacts of auxiliary loads. The study quantified the impact of air the conditioning and heating systems on the EV performance.

The remainder of the paper is organized as follows: The next section presents an overview of the *state-of-the art* vehicle energy consumption studies. Section 3 describes the CPEM model development, while in Section 4 the instantaneous regenerative braking energy efficiency module is reported. Section 5 describes the model validation effort. In Section 6 the results are reported. In particular, the energy consumption of the Nissan Leaf, the comparison between the Nissan Leaf and the Nissan Versa (using the CPEM and the VT-CPFM, respectively), the comparison of the Nissan Leaf with the BMW i3 and the Tesla Model S and the impact of auxiliary systems are reported. Conclusions and future work are summarized in Section 7.

## 2. Literature review

Vehicle energy consumption models can be divided into two categories: forward models and backward models. Models that compute the tractive contribution required at the wheels and "work backward" towards the engine are called "backward models". Alternatively, models that start from the engine and work with transmitted and reflected torque are called "forward models".

In the case of forward models, realistic modeling is achieved by capturing driver input. Forward models are widely used in the industry to identify component interactions that affect energy consumption levels and vehicle performance. These models, however, are characterized by slow execution times. While in the case of backward models, reliable evaluation of vehicle energy consumption is achieved based on drive cycle and vehicle characteristic data. These models can be implemented in a Matlab/Simulink environment and allow for integration in more complex frameworks. These models are characterized by fast execution times and are faster than forward models [17].

Depending on the level of detail required for each component, the vehicle model may be steady-state, quasi-steady, or dynamic. The main advantage of employing a steady-state model or a quasi-steady model is fast computation times, while the disadvantage is inaccuracy for dynamic simulation [17].

In this paper a quasi-steady backward approach is used because these models are fast in terms of simulation time and allow for the flexibility needed to simulate a large number of driving cycles. Moreover, these models are easily integrated in more complex modeling frameworks such as Intelligent Transportation System (ITS) applications.

In particular, this work focuses on the second-by-second energy consumption evaluation of EVs but in the available literature several models have been developed to evaluate the fuel consumption of conventional vehicles and hybrid vehicles. In particular, some of the same authors of this paper developed a second-by-second fuel consumption model, the Virginia Tech Comprehensive Power-based Fuel consumption Model (VT-CPFM), for conventional vehicles [18–20] and for diesel and hybrid bus [21]. Moreover, some authors such as Gadsden et al. (2011) [22], Kumar et al. (2006) [23], Liukkonen et al. (2010) [24] and Vagg et al. (2013) [25] studied the modeling of Hybrid Vehicle. Other works are instead focused on Plug-in Hybrid Electric Vehicles as in Hilshey et al. (2015) [26].

In the available literature to evaluate the energy consumption of a plug-in electric vehicle different solutions are adopted such as: (1) the use of a medium consumption values provided, for example by: the automakers or previous experimental studies; (2) the use of widespread consumption vehicle simulators such as: the Advanced VehIcle SimulatOR (ADVISOR) developed by the National Renewable Energy Laboratory (NREL); and Autonomie, the vehicle model developed by the Argonne National Laboratory (ANL); or (3) the development of *ad hoc* energy consumption vehicle models [16,27].

The use of an average value of energy consumption [Wh/km] is an approximation that does not allow for the capturing of real consumption of the electric vehicle and the differences of consumption among different driving cycles. Also, the average values are not able to reflect differences in energy consumption that results from travel on a high-speed facility with several stops and travel along a low speed arterial without signalization of stops if both trips have identical average speeds. Foley et al. (2012) adopted this solution in their work that attempted to analyze the impacts of electric vehicle charging for electricity market operations using an average value of energy consumption from experimental analysis [28] provided by Markel et al. (2009) [29]. Hilshey (2015) in his study used a constant value of the energy consumption [kW h/km] in the evaluation of the impact of the PEVs charging to the electric power grid [26]. This last analysis is in fact the goal of the study.

Among the most widespread vehicle simulators is ADVISOR, which was developed by NREL; and Autonomie the vehicle model developed by ANL. ADVISOR has a quasi-steady backward-forward approximation approach. The input to the model are the vehicle characteristics and the drive cycles and the output are the fuel/energy consumption and the emissions [30]. While, Autonomie is a forward looking model. Consequently, a drive cycle (vehicle speed versus time profile) is required to compute power/torque demand to a virtual driver [31]. Those simulators cannot be integrated with ITS applications due to their complexity and the high execution time compared with *ad hoc* models. Lewis et al. (2012) and (2014) utilized this approach to evaluate the Life Cycle Greenhouse Gas Emissions from a Lightweight Plug-in Hybrid Electric Vehicle in a regional context and for diverse powertrain vehicles using the software Autonomie [32,33]. Also, Lee et al. (2014) used Autonomie for the analysis of the Ford Focus Electric in their study [34]. While for example Levinson et al. (2011) used ADVISOR to evaluate the potential benefits of solar reflective car shells [35].

A number of models have been developed to estimate plug-in EV energy consumption levels. For example, Muratori et al. (2013) proposed a model centered on the estimation of the total primary energy consumption associated with personal transportation in the U.S. including different vehicle types to evaluate the impact of plug-in electric vehicles on the electric power grid at the distribution level. In particular, three main modeling steps were introduced: modeling of the behavior of drivers, generating realistic driving profiles, and simulating energy consumption of different vehicle types [27]. Wu et al. (2015) in their study first present a system which can collect in-use EV data and vehicle driving data. Approximately 5 months of EV data were collected and these data were used to analyze both EV performance and driver behavior. The analysis showed that EVs are more efficient when driving on in-city routes than driving on freeway routes. Further investigation of EV driver route choice behavior indicated that the EV users tried to balance the trade-off between travel time and energy consumption. Additionally, the study analyzed the relationships among the EV's power, the vehicle's velocity, acceleration, and the roadway grade. Based on the analysis results, an analytical EV power estimation model is developed [9]. Hayes et al. (2011) developed simplified EV models to quantify the impact of battery degradation with time and vehicle HVAC loads on the total vehicle energy consumption. The models were compared with published manufacturer specifications under various route and driving conditions, and for various driving cycles [36]. Fleurbaey (2012, 2013) developed a plugin hybrid electric vehicle model to evaluate the performance of different hybrid Rechargeable Energy Storage Systems (RESSs). In particular a combination of an Electrical Double Layer Capacitor (EDLC) system with an energy-optimized battery was analyzed to quantify the influence of the EDLC system on the power performance, cycle life, energy efficiency and all-electric driving range [12]. Doucette et al. (2011) proposed a model to compute the $CO_2$ emissions from EV and Plug-in Hybrid Electric Vehicles (PHEVs), and compared the results to published values for $CO_2$ emissions from conventional Internal Combustion Engine (ICE) vehicles. Amongst the results it was estimated that with a highly $CO_2$ intense power generation mix, such as in China, PHEVs had the potential to be responsible for fewer tank-to-wheels $CO_2$ emissions over their entire range than a similar electric or conventional vehicle. The results also showed that high $CO_2$ intensive countries need to pursue a major de-carbonization of their power generation in order to fully take advantage of the ability of EVs and PHEVs to reduce $CO_2$ emissions from the transportation sector [16].

Shibata et al. (2015) [37] and Abousleiman et al. (2015) [38] in their papers evaluate the energy consumption of an EV considering a constant regenerative braking efficiency. While for example Hayes et al. (2014), in their paper on the energy consumption model based on EPA coast-down parameters, assumed that all the available regenerative energy is returned to the battery as long as the regenerative power level is 20 kW or less [39]. Kollmeyer et al. (2011) in their work on a specific analysis of a Corbin Sparrow electric vehicle to evaluate the data of the electric motor used the map of the torque as function of the current obtained based on experimental results on the vehicle tested [40]. Halmeaho et al. (2015) developed an analysis focused on an Electric City Bus Energy Flow Model but in this study the magnitude of the regenerative braking is limited due to the effective powertrain capacity, traction and eventually the bus stability [41]. A detailed analysis of this parameter is not reported and as such this study cannot be compared with electric vehicle analysis.

Some works available in the open literature are focused on the impact of the residential applications on the electric power grid as in [42–44]. Of them just a few include also the impact of EVs, and in this analysis usually a constant value of the energy consumption [kW h/km] is considered as in [44].

Though there have been numerous studies on the modeling of EV energy consumption, these studies were of limited application. For example, they either focused on measuring energy consumption of an EV's control strategy, macro-project evaluations, or simplified well-to-wheels analyses. None of these models were developed in a manner that would allow them to be applied without collecting vehicle-specific data while at the same time accurately model vehicle transient behavior, model energy regeneration at a microscopic level, and are simple enough to be incorporated within traffic simulation software or Smartphone applications. The proposed model was developed address this urgent need.

Moreover, as shown in this literature review section it is important to highlight that in this paper for the first time a relationship that relates the energy recovery efficiency with the deceleration level is introduced.

## 3. Modeling: proposed CPEM framework

The Comprehensive Power-based EV Energy consumption Model (CPEM) is a quasi-steady backward highly-resolved power-based model. Specifically, the input required by the model are the following: the instantaneous speed and the EV characteristics. The output of the model are the following: the energy consumption (EC) [kW h/km] by the vehicle for a specific drive cycle, the instantaneous power consumed [kW], and the state of charge (SOC) of the electric battery [%].

The following formulation is used to develop the model. As this is a backward model, initially, the power at the wheels is computed using Eq. (1).

$$P_{Wheels}(t) = \left( ma(t) + mg \cdot \cos(\theta) \cdot \frac{C_r}{1000}(c_1 v(t) + c_2) + \frac{1}{2}\rho_{Air} A_f C_D v^2(t) + mg \cdot \sin(\theta) \right) \cdot v(t) \quad (1)$$

The proposed model is general and is applied to the Nissan Leaf for illustration purposes. Here $m$ is the vehicle mass ($m$ = 1521[2] [kg] for the Nissan Leaf), $a(t) = dv(t)/dt$ is the acceleration of the vehicle in [m/s$^2$] ($a(t)$ takes negative values when the vehicle decelerates), $g = 9.8066$ [m/s$^2$] is the gravitational acceleration, $\theta$ is the road grade, $C_r = 1.75$, $c_1 = 0.0328$ and $c_2 = 4.575$ are the rolling resistance parameters that vary as a function of the road surface type, road condition, and vehicle tire type. The typical values of vehicle coefficients are reported in Rakha et al. (2001). $\rho_{Air}$ = 1.2256[3] [kg/m$^3$] is the air mass density, $A_f = 2.3316$ [m$^2$] is the frontal area of the vehicle, and $C_D = 0.28$ is the aerodynamic drag coefficient of the vehicle and $v(t)$ is the vehicle speed in [m/s] [45–47].

[2] Curb weight of the Nissan Leaf. In the validation process to validate the data collected by JRC a mass of 1595 [kg] has been used while for the INL data a value of 1640 [kg] has been considered. This because during the tests performed by the JRC and INL a different weight of the driver and of the equipment were involved.

[3] Density of air at sea level at 15 °C (59 °F).

The power at the electric motor ($P_{Electric\ motor}(t)$) is computed, given the power at the wheels, considering the driveline efficiency $\eta_{Driveline} = 92\%$ [20] and, assuming that the efficiency of the electric motor is $\eta_{Electric\ Motor} = 91\%$. This is a reasonable assumption according to [48], in fact, the efficiency of the electric motor of the Nissan Leaf is reported to be between 85% and 95%. Also, in this range, 91% is the value that minimizes the average error between the empirical data and the estimated energy consumption values.

While the vehicle is in traction mode the energy flows from the motor to the wheels. In this case the power at the electric motor is higher than the power at the wheels and the power at the wheels is assumed to be positive. Alternatively, in the regenerative braking mode, energy flows from the wheels to the motor. In this case, the power at the electric motor is lower than the power at the wheels and the power is assumed to be negative.

While decelerating the electric power is negative and the regenerative braking energy efficiency ($\eta_{rb}$) is computed when $P_{Electric\ motor}(t) < 0$ using Eq. (2).

$$P_{Electric\ motor}(t) < 0 \rightarrow P_{Electric\ motor\_neg}(t) = P_{Electric\ motor}(t) \cdot \eta_{rb}(t) \quad (2)$$

The details on how the $\eta_{RB}(t)$ is estimated is presented later in the paper. Using this model it is possible also to estimate the final battery state-of-charge (SOC) [%] using Eq. (3).

$$SOC_{Final}(t) = SOC_0 - \sum_{i=1}^{N} \Delta SOC_{(i)}(t) \quad (3)$$

$$\Delta SOC_{(i)}(t) = SOC_{(i-1)}(t) - \frac{P_{Electric\ motor\_net_{(i)}}(t)}{3600 \cdot \mathrm{Capacity_{Battery}}} \quad (4)$$

Here $P_{Electric\ motor\_net_{(i)}}(t)$ is the electric power consumed considering a battery efficiency of $\eta_{Battery} = 90\%$ [49]. In addition, the power consumed by the auxiliary systems ($P_{Auxiliary}$ = 700 [W] [50]) is considered. $\mathrm{Capacity_{Battery}}$ is the capacity of the battery in [Wh]. The operation range of SOC is between 20% and 95% to guarantee the safety of the battery system [51], in particular the initial SOC is assumed to be $SOC_0 = 95\%$.

Given the SOC it is possible to compute the energy consumption (EC) in [kW h/km] using Eq. (5).

$$EC\left[\frac{\mathrm{kW\ h}}{\mathrm{km}}\right] = \frac{1}{3,600,000} \cdot \int_o^t P_{Electric\ motor_{net}}(t)dt \cdot \frac{1}{d} \quad (5)$$

Here $d$ is the distance in [km]. The parameters related to the specific electric vehicle used are reported in [47] where all the characteristics of the electric vehicle used are shown.

## 4. Regenerative braking energy efficiency as a function of vehicle deceleration

The purpose of this analysis is to identify a relationship to compute the portion of the total braking energy available for recovering ($\eta_{rb}$) in Plug-in Electric Vehicles (PEVs).This relationship is general and applies to any drive cycle.

The regenerative braking energy efficiency ($\eta_{rb}$) is defined in Eq. (6).

$$\eta_{rb}[\%] = \frac{E_{Recoverable}[\mathrm{kW\ h}]}{E_{Available}[\mathrm{kW\ h}]} \quad (6)$$

Here $E_{Recoverable}$ [kW h] is the energy recovered during braking and $E_{Available}$ [kW h] is the maximum energy available to be recovered during braking, computed using Eq. (7).

$$E_{Available}[\mathrm{kW\ h}] = \int_0^t P^{(-)}_{Wheels}(t)dt \quad (7)$$

Here $P^{(-)}_{Wheels}(t)$ is the negative portion of the power at the wheels, $P_{Wheels}$ in [kW]. The power at the wheels is computed as shown in the "Modeling Section" of the paper.

The power at the wheels is positive ($P_{Wheels}(t) > 0$) in traction mode (energy flows from the motor to the wheels), in this case the braking power is zero. $P_{Wheels}(t)$ is negative ($P_{Wheels}(t) < 0$) when the vehicle is braking. In this phase the kinetic energy of the vehicle is dissipated by the braking system, and the driving power is zero. This portion of the power ($P^{(-)}_{Wheels}(t)$) is recoverable using regenerative braking strategies. To compute the energy available in the braking mode only the negative power at the wheels is considered.

This analysis is based on data on the regenerative braking energy efficiency ($\eta_{rb}$) computed by Gao et al. (2007) [52]. The authors report regenerative braking energy efficiency values ($\hat{\eta}_{rb}$) for five drive cycles, as shown in the second column of Table 1. The average values of the regenerative braking efficiency reported by Gao et al. (2007) [52] for those five drive cycles are used to derive the relationship sought.

In this study the regenerative braking energy efficiency $\eta_{rb}$ is assumed to be a function of the negative acceleration of the vehicle ($a^{(-)}$). In particular, the shape of $\eta_{rb}$ is assumed to be exponential based on an experimental analysis developed on the regenerative braking behavior on the Chevy Volt [53]. The implicit assumption in this model is that the shape of the energy efficiency is the same for all electric vehicles. In calibrating the function that relates $\eta_{rb}$ with $a^{(-)}$, the Least Squared Optimization Method is adopted. The relationship is validated against the data reported by Gao et al. (2007) [52]. This method finds the optimum model coefficients that minimizes the difference between the empirical values of the regenerative braking energy efficiency ($\hat{\eta}_{rb}$) and the calculated values ($\bar{\eta}_{rb}$) for the five drive cycles reported earlier.

### 4.1. Least Square Optimization Method

The Least Squared Method is a standard approach to the approximate solution of overdetermined systems, *i.e.,* sets of equations in which there are more equations than unknowns. "Least squares" means that the overall solution minimizes the sum of the squares of the errors made in the results of every single equation. The most important application is in data fitting. The best fit in the least-squares sense minimizes the sum of squared residuals, a residual being the difference between an observed value and the fitted value provided by a model.

The general formulation to find the optimum set of model parameters can be cast using Eq. (8).

$$\min_x f(x) = \sum_{i=1}^{N} (\widehat{x}_i - x_i)^2. \tag{8}$$

In this model $f(x) = \eta_{rb}(a^{(-)})$, $N = 5$, is the number of drive cycles, $a^{(-)}$ is the deceleration in [m/s$^2$], $\widehat{x}_i = \hat{\eta}_{rb}$ contains the real values of the average regenerative braking energy efficiency reported in Table 1 and $x_i = \bar{\eta}_{rb}$ contains the calculated values of the average regenerative braking energy efficiency $\bar{\eta}_{rb}$ for the same drive cycles ($\bar{\eta}_{rb}$ is computed as the arithmetic average of the $\eta_{rb}(a^{(-)})$).

### 4.2. Proposed exponential regenerative energy efficiency relationship

The relationship between $\eta_{rb}$ and $a^{(-)}$ is assumed to be exponential, based on empirical data on regenerative braking energy efficiency of a Chevy Volt vehicle [53]. The Least Square Method is used to calibrate the alpha[4] parameter in the exponential relationship, as illustrated in Fig. 1.

[4] This study assumes that the alpha parameter is the same for all EVs.

**Table 1**
Average empirical regenerative braking energy efficiencies [52], modeled average regenerative braking energy efficiencies and corresponding errors.

| | $\hat{\eta}_{rb}$ [%] | $\bar{\eta}_{rb}$ [%] | $\varepsilon$ [%] |
|---|---|---|---|
| FTP75 | 89.69 | 81.64 | −8.97 |
| LA92 | 82.95 | 89.41 | 7.79 |
| US06 | 86.55 | 83.76 | −3.22 |
| New York | 76.16 | 83.48 | 9.61 |
| ECE15 | 95.75 | 94.48 | −1.33 |

$$\eta_{rb} = \left[ e^{\left(\frac{\alpha}{|a^{(-)}|}\right)} \right]^{-1} \tag{9}$$

After calibrating the model, the regenerative energy efficiency at any instant $t$ ($\eta_{rb}(t)$) is computed as a function of the instantaneous acceleration using Eq. (10).

$$\eta_{rb}(t) = \begin{cases} \left[ e^{\left(\frac{0.0411}{|a(t)|}\right)} \right]^{-1} & \forall a(t) < 0 \\ 0 & \forall a(t) \geqslant 0 \end{cases} \tag{10}$$

The average energy efficiency for the entire drive cycle $\bar{\eta}_{rb}$ is then computed by averaging over all instants $t$ over the entire trip for which the vehicle is decelerating and reported in the third column of Table 1. In Table 1 the parameter $\varepsilon$ [%] is the error between the values of efficiencies reported in the literature ($\hat{\eta}_{rb}$) [52] and the drive cycle average estimated using the proposed model ($\bar{\eta}_{rb}$). The average error over all four drive cycles was 6.2%.

## 5. Model validation

The Nissan Leaf EV was used for validation of the CPEM model for two reasons. First, it is easy to collect data on this vehicle because it is one of the most popular EVs available on the market. Second, this vehicle has been tested by a few research centers and thus experimental data on the energy consumption of this vehicle are available. The vehicle characteristics can be found in [47].

The validation effort used data collected by the Joint Research Centre (JRC) of the European Commission [45] and by the DOE's Advanced Vehicle Testing Activity (AVTA) of the Idaho Nation Laboratory (INL) [46]. The JRC data are related to the following driving cycles: the New European Driving Cycle (NEDC) [54,55], the World-wide harmonized Light-duty Test Cycle (WLTC) and the World-wide harmonized Motorcycle emission Test Cycle (WLMC). The New European Driving Cycle (NEDC) for passenger cars is the current legislative cycle used to determine whether a new Light Duty Vehicle (LDV) model meets EU environmental regulations. The United Nations Economic Commission for Europe (UNECE), in an attempt to develop a global test procedure, developed two test cycles, namely: the WLTC for LDVs [56] and the WLMC for two wheelers.

The AVTA data include the following driving cycles: the EPA Urban Dynamometer Driving Schedule (UDDS), the Highway Fuel Economy Driving Schedule (HWFET) and the US06 or high acceleration aggressive driving schedule that is often identified as the "Supplemental FTP" driving schedule [57]. The speed profiles of all driving cycles used to validate the model are illustrated Fig. 2.

In Fig. 3 the speed, power and SOC profiles for the WMTC driving cycle are shown. As illustrated in Fig. 3(a), when the vehicle decelerates, the electric power is negative. In this mode of operation, the energy flows from the wheels to the motor and charges the batteries, thus in these phases the SOC increases. During braking events the energy available to be recovered is computed using Eq. (11).

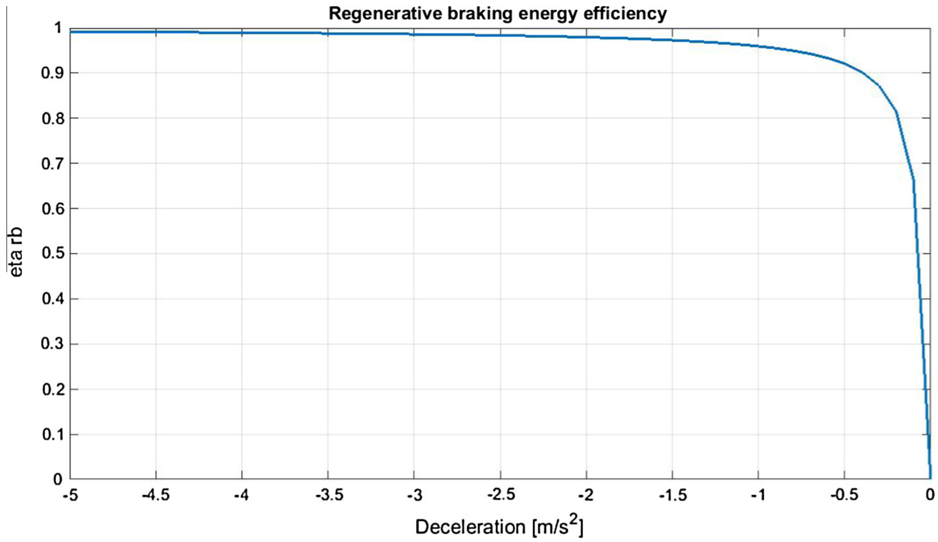



**Fig. 1.** Variation in the instantaneous regenerative braking efficiency as a function of the deceleration level.

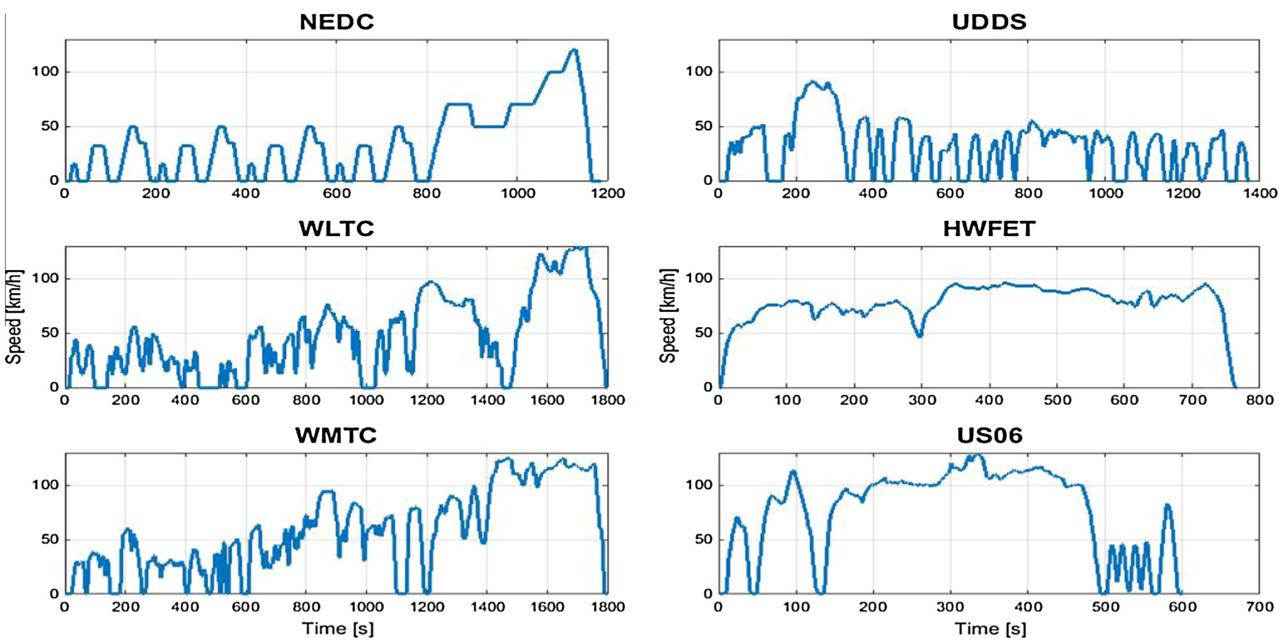



**Fig. 2.** Driving cycles used for model validation.

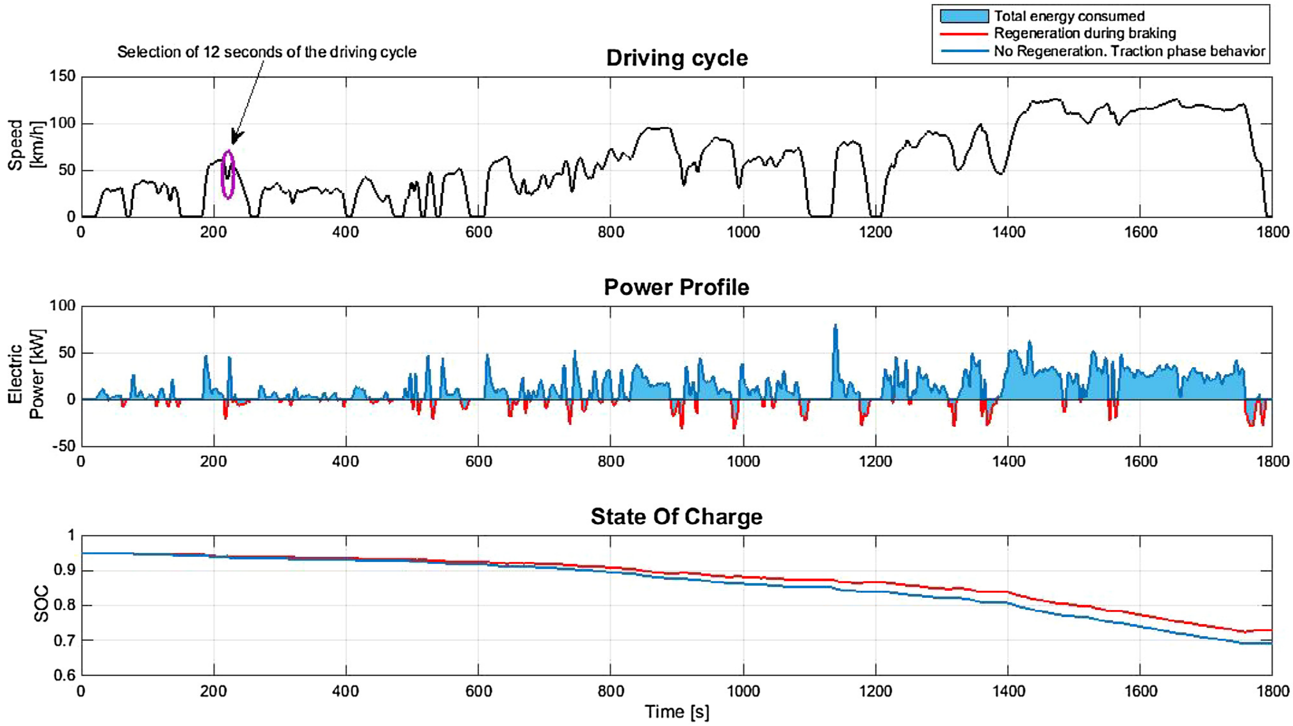
$$E_{Recoverable}[\text{kW h}] = \eta_{rb} \cdot E_{Available}[\text{kW h}] \quad (11)$$

Here $E_{Available}$ is the total energy available to be recovered while braking in [kW h] and $\eta_{rb}$ is the regenerative braking energy efficiency.

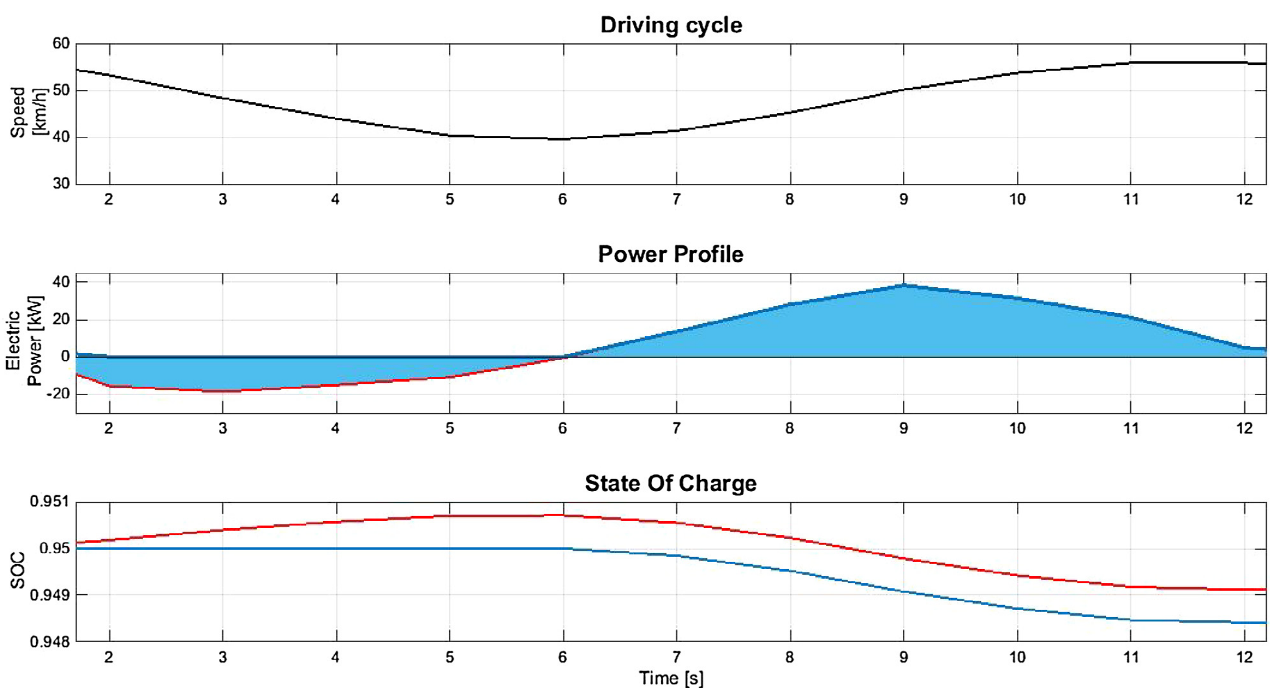
Moreover, in Fig. 3(a) the light blue area represents the energy consumed for the driving cycle. In particular, the portion of the area delimited by the blue line (positive quarter of the electric power graph) represents the case without energy regeneration during braking, while the red line (negative quarter of the electric power graph) shows the results considering the energy regeneration.

As expected, the SOC increases while the vehicle is braking (red line) and produces a higher SOC compared to the no recovery case (blue line). The ability to recover energy during braking reduces the overall energy consumption, and thus the final SOC level is higher.

Fig. 3(b) shows the results of an example introduced to highlight the advantage of the energy recovery during braking events. A segment of 12 s of the WMTC cycle is analyzed for this purpose. The final SOC level without considering the regeneration is 94.91% while considering it is 94.84%. Consequently, when regeneration is considered, an increase of 0.07% in the final level of SOC is observed for these 12 s of the WTMC cycle. Moreover, if regeneration is not considered, net energy consumption is 39.4 [Wh] over 177.5 m, an energy efficiency of 222.1 [Wh/km]. When accounting for regenerative breaking, 17.5 [Wh] of energy is recaptured, resulting in a net energy consumption of 21.9 [Wh] and an energy efficiency of 123.3 [Wh/km]. The total energy consumption is computed by subtracting the energy recovered due to the use of regenerative braking from the energy used during traction, as a result the total energy consumed decreases.




(a) WMTC driving cycle: speed, electric power and state of charge profiles on the entire cycle.




(b) WMTC driving cycle: speed, electric power and state of charge profiles on selected 12 seconds of the cycle.

**Fig. 3.** WMTC driving cycle: speed, electric power and state of charge profiles.

## 6. Results

### 6.1. Energy consumption

Table 2 reports the energy consumption in [Wh/km] and [Wh/mile] available by the JRC and by DOE's AVTA, and the energy consumption evaluated using the VT-CPEM model. In the last column of the table the error relative to the JRC and DOE's AVTA values is reported. The results indicate that the proposed model accurately estimates the energy consumption with an average error of 5.86% compared to the field data.

Moreover, the consumption for the low speed range ($v(t) \leqslant 60$ km/h) in the following driving cycles is analyzed: NEDC, WLTC and WMTC. Table 3 provides the characteristics and the consumptions in [Wh/km] for the low and high speed range cycles.

**Table 2**
Validation results.

| | AVTA/JRC data | | VT-CPEM model | | Error [%] |
|---|---|---|---|---|---|
| | [Wh/miles] | [Wh/km] | [Wh/miles] | [Wh/km] | |
| Nissan Leaf | | | | | |
| *AVTA* | | | | | |
| UDDS | 201.4 | 125.1 | 233.8 | 145.3 | 16.11 |
| HWFET | 240.8 | 149.6 | 241.7 | 150.2 | 0.38 |
| US06 | 321.6 | 199.8 | 347.9 | 216.2 | 8.19 |
| *JRC* | | | | | |
| NEDC | 252.7 | 156.9 | 239.0 | 148.5 | −5.35 |
| WLTC | 287.3 | 178.4 | 273.3 | 169.8 | −4.82 |
| WMTC | 294.5 | 182.9 | 293.4 | 182.3 | −0.33 |

The average error, computed as the difference between the field data and the estimated consumption values, for the low speed range is 11.87%, while for the high speed range is 3.2%. The average error related to the low speed range results are higher than the error related to the high speed range. It is important to note, as shown in Table 3, that the traveled distance for the low speed range of every driving cycle analyzed are significantly lower when compared with the traveled distance for the high speed range. These distances are the "weights" in the evaluation of the error related to the average consumption on the entire driving cycle. For this reason the average error on the entire six driving cycles analyzed is 5.86%, thus lower than 11.87%.

### *6.2. Comparison with a conventional vehicle: Nissan Leaf vs. Nissan Versa*

To evaluate the advantages of using electric vehicles with respect to conventional ones a comparison on 16 driving cycles between the results of energy consumption obtained using the CPEM and those using the VT-CPFM by Rakha et al. (2011) [20], on a similar gasoline vehicle, is reported. The results evaluated for the Nissan Versa in the VT-CPFM are used for comparison and shown in Fig. 4.

The results show that the on-board consumption of EVs are significantly lower than the consumption of similar conventional vehicles. This result is attributed to a number of factors including the higher energy efficiency through the use of on-board electric devices and the ability of electric vehicles to recover energy while braking. This analysis, known in the literature as tank-to-wheels (TTW) analysis, considers only energy use and emissions associated with vehicle operation activities, neglecting the energy use and emissions associated with fuel production. In the general framework the TTW is part of a more global and complex analysis named the well-to-wheels (WTW) analysis. In the WTW analysis the energy use and emissions associated with fuel production activities are evaluated using an analysis named well-to-tank (WTT), while the energy use and emissions associated with the vehicle operation activities are evaluated using the TTW analysis [58]. The WTT component of the WTW analysis is significantly higher for electricity than for gasoline. For this reason, the WTW analysis shows different results and a lower gap between the energy consumption of an electric and a conventional vehicle. Generally, the WTW analysis is influenced by many factors such as the efficiency of the energy production, transportation and distribution processes in the specific country and the specific energy carrier (*e.g.* electricity, gasoline, etc.) considered.

Fig. 4 shows that the EVs consume on average 82.5% less TTW energy than conventional vehicles. The highest difference is observed for the LA92 driving cycle (average speed 39.6 [km/h]) with a gap of 90.9%, while the driving cycle with the lowest difference is the High Speed (average speed 102 [km/h]) with a gap of 70.1%. This highlights how the electric vehicles in the urban driving cycles, especially if characterized by non-aggressive braking, have lower energy consumption relative to the high speed driving cycles.

Also, it is possible to observe that the estimated energy consumption for the conventional vehicle in some cycles are very similar, such as for the Fwy G and the Local cycles the consumption is 948.5 [Wh/m] and 1032.4 [Wh/km], respectively. Analyzing the same driving cycles, the estimated energy consumption for the electric vehicle is, on the contrary, different: 161.9 [Wh/km] and 136.4 [Wh/km], respectively. This difference is due to the energy recovered during braking in the electric vehicle, the total energy recovered for these two driving cycles is 75.5 [Wh/km] and 102.7 [Wh/km], respectively. This is because in the Local cycle a higher amount of energy is recovered during braking, thus this cycle is characterized by a lower energy consumption in comparison to the Fwy G cycle. The same situation occurs for the High Speed and Fwy E cycles, the estimated consumption for the conventional vehicle in these cases is 628.6 [Wh/km] and 607.5 [Wh/km], respectively, while the estimated consumption for the electric vehicle in these two driving cycles is 188.1 [Wh/km] and 121.4 [Wh/km], the amount of energy recovered is 73.6 [Wh/km] for the High Speed and 170.2 [Wh/km] for the Fwy E cycle.

Also, in Fig. 5 the EV ranges available for each driving cycle analyzed, with and without considering the energy recovered during braking, are reported.

Fig. 5 highlights the fact that the lower the energy consumption [Wh/km], the higher the EV range is. In particular, considering the consumption with recovery during braking, the driving cycle with the lower consumption is the Fwy F with an energy consumption of 121 [Wh/km] and an EV range of 148.8 [km] and that one with the higher energy consumption is the Area cycle with an energy consumption of 209 [Wh/km] and an EV range of 85.8 [km]. The same consideration counts for the case where the recovery during braking is not considered. Fig. 5 demonstrates that the driving cycle where there is a high difference in the EV range are those with a higher amount of energy recovered during braking. The ST01 is the cycle characterized by the higher difference between the EV range with and without considering the energy recovered during braking 137.8 and 98.1, respectively. The Fwy AC is the cycle resulting in the lowest difference, namely 117.3 vs. 115, respectively.

### *6.3. Comparison of the Nissan Leaf with two electric vehicles: BMW i3 and Tesla model S*

To evaluate the differences in the energy consumption of diverse electric vehicles a comparison of the Nissan Leaf with the BMW i3 and the Tesla model S is conducted. In particular, the BMW i3 and the Tesla model S have been chosen for this comparison because they are among the most popular in terms of sales in the recent years. Also, according to EPA Size Class definition [59] they represent two different segments with the Nissan Leaf a mid-sized vehicle, a subcompact car and a large car, respectively. The characteristics of the BMW i3 and Tesla model S are reported in [60,61], respectively.

In Fig. 6 the results of the comparison, on 16 driving cycles, for the Nissan Leaf, BMW i3 and Tesla model S are reported. In this comparison the same 16 driving cycles used to compare the Nissan Leaf with the Nissan versa are considered.

The vehicle with the lowest energy consumption is the BMW i3, on average this vehicle consumes 7.9% less energy compared to the Nissan Leaf. While the electric vehicle with the highest energy consumption is the Tesla model S, on average this vehicle consumes 22.9% more energy than the Nissan Leaf except in the Fwy D cycle where this vehicle consumes 2.8% less energy compared to the

**Table 3**
Driving cycle characteristics and Nissan Leaf energy consumption levels.

| | Distance [km] | Duration [s] | Avg. speed [km/h] | Max speed [km/h] | AVTA/JRC [Wh/km] | VT-CPEM [Wh/km] | Error [%] |
|---|---|---|---|---|---|---|---|
| WLTC low speed | 3.09 | 589 | 18.89 | 56.5 | 158 | 140.6 | −11.01 |
| WMTC low speed | 4.06 | 600 | 24.4 | 60 | 169 | 142.4 | −15.74 |
| NEDC low speed | 4.06 | 780 | 18.35 | 50 | 144.3 | 131.5 | −8.87 |
| WLTC high speed | 20.17 | 1211 | 59.95 | 131.3 | 181.78 | 174.3 | −4.11 |
| WMTC high speed | 24.84 | 1200 | 74.55 | 125.3 | 185.31 | 188.9 | 1.94 |
| NEDC high speed | 6.95 | 400 | 62.44 | 120 | 164.1 | 158.3 | −3.53 |
| WLTC | 23.26 | 1800 | 46.5 | 131.3 | 178.4 | 169.8 | −4.82 |
| WMTC | 28.9 | 1800 | 57.83 | 125.3 | 182.9 | 182.3 | −0.33 |
| NEDC | 11.01 | 1180 | 33.21 | 120 | 156.9 | 148.5 | −5.35 |

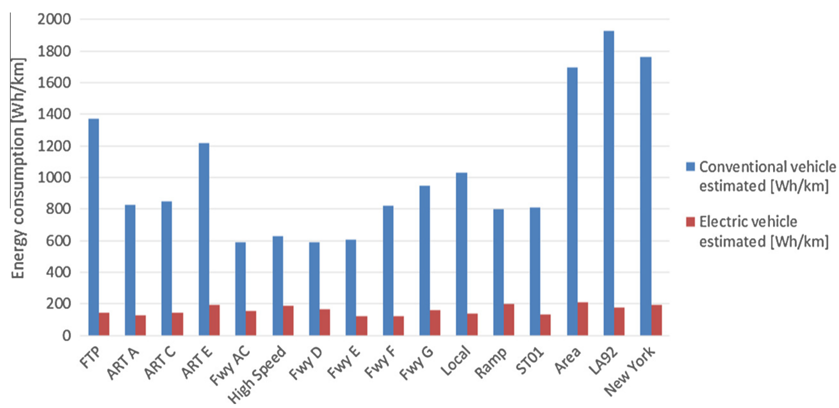



**Fig. 4.** Comparison between the energy consumption estimated values of Nissan Leaf (In this computation the vehicle mass of the Nissan Leaf has been assumed to be 1595 [kg], this value includes the vehicle curb weight and the weight of one driver on-board.) and of the Nissan Versa.

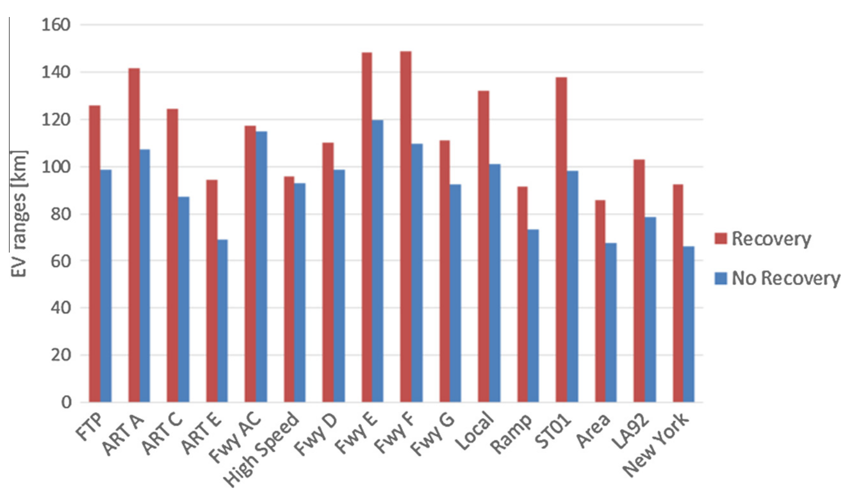



**Fig. 5.** EV ranges of the Nissan Leaf on the 16 driving cycles analyzed with and without the energy recovered during braking.

Nissan Leaf. This is because a higher amount of energy is recovered during braking by the Tesla model S in this specific drive cycle. In fact, the higher weight of the Tesla model S allows for more energy recovery and thus the State of Charge of the Tesla model S is always higher than that of the Nissan Leaf.

The driving cycle characterized by the higher consumptions, for all the three electric vehicles, is the Area; while that one with the lower consumptions is the Fwy F for the Nissan Leaf and the BMW i3, and the Fwy E for the Tesla model S.

This example is given to demonstrate that the proposed model can be used to easily estimate the energy consumption for any EV using public data. Specifically, in this study the same driveline, battery and electric motor efficiency, reported in the "Modeling" section, are used.

### 6.4. Evaluation of the impact of the auxiliary systems

Electric vehicles, as with conventional ones, have a number of auxiliary systems. Some of them, such as the power steering and power brakes, have a minor impact on the vehicle energy consumption and range. However, the heating and air conditioning systems can have a dramatic impact on the energy consumption and range of electric vehicles [62].

The impact of auxiliary systems on the energy consumption of a vehicle is a topic that is of significant interest in recent years. Moreover, the evaluation of this impact is very important in computing the EV range. Specifically, the higher the impact of the auxiliary system load has, the higher is the energy consumption [Wh/km] and the lower is the available distance that can be

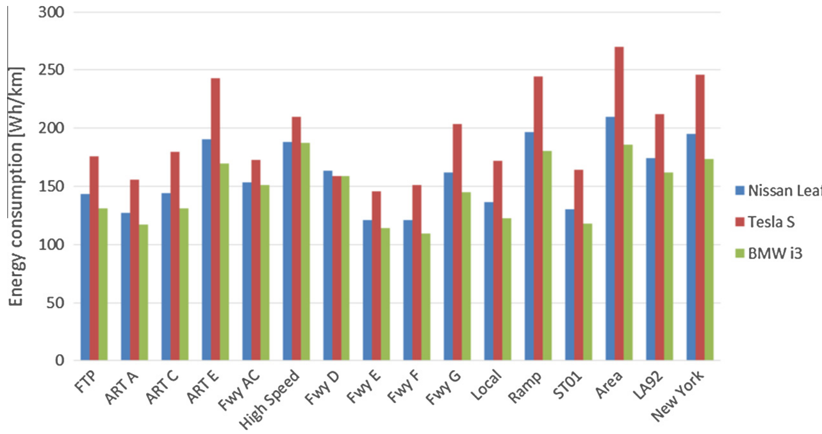



**Fig. 6.** Comparison between the energy consumption estimated values of Nissan Leaf, BMW i3 and Tesla model S.

**Table 4**
Impact of auxiliary systems load on the consumption at: 25 °C, 35 °C and −5 °C.

| Consumption | 700 W | 850 W [25 °C] | | 1200 W [35 °C] | | 2200 W [−5 °C] | |
|---|---|---|---|---|---|---|---|
| | [Wh/km] | [Wh/km] | Increase from 700 W [%] | [Wh/km] | Increase from 700 W [%] | [Wh/km] | Increase from 700 W [%] |
| UDDS | 145 | 150 | 3 | 161 | 11 | 192 | 32 |
| HWFET | 150 | 153 | 2 | 158 | 5 | 175 | 16 |
| US06 | 216 | 218 | 1 | 223 | 3 | 238 | 10 |
| NEDC | 149 | 153 | 3 | 163 | 9 | 190 | 28 |
| WLTC | 170 | 173 | 2 | 181 | 7 | 204 | 20 |
| WMTC | 182 | 185 | 2 | 192 | 5 | 211 | 16 |

**Table 5**
Impacts on the EV range by various auxiliary systems loads.

| EV range | 700 W | 850 W [25 °C] | | 1200 W [35 °C] | | 2200 W [−5 °C] | |
|---|---|---|---|---|---|---|---|
| | [km] | [km] | Decrease from 700 W [%] | [km] | Decrease from 700 W [%] | [km] | Decrease from 700 W [%] |
| UDDS | 124 | 120 | −3 | 112 | −10 | 94 | −24 |
| HWFET | 120 | 118 | −2 | 114 | −5 | 103 | −14 |
| US06 | 83 | 82 | −1 | 81 | −3 | 76 | −9 |
| NEDC | 121 | 118 | −3 | 111 | −9 | 95 | −22 |
| WLTC | 106 | 104 | −2 | 99 | −6 | 88 | −17 |
| WMTC | 99 | 97 | −2 | 94 | −5 | 85 | −14 |

driven using the electric vehicle [62–66]. A study by the National Renewable Energy Laboratory (NREL) concluded that a reduction on the EV range of up to 38% was possible [64]. The study investigated the impact of the auxiliary systems on the Nissan Leaf using data collected from a previous study [63]. Specifically, the data were collected on 7375 trips using Nissan Leaf vehicles with outside temperatures recorded. The total auxiliary system load considered includes: cabin heater and fan, component heaters (*ie.* battery heater), headlights, power steering, radio etc. A comfort temperature range between 15 and 24 °C in the cabin was set.

In the VT-CPEM model, a base auxiliary system load of 700 [W] is considered. In this section, three different scenarios are analyzed and compared with the case of a base auxiliary load of 700 [W]. In particular, the outside temperatures of: 25 °C, 35 °C and −5 °C are considered. On the basis of the data reported by [63], the total auxiliary system loads are 850 [W], 1200 [W ] and 2200 [W], respectively. Table 4 demonstrates the results of the impact of the auxiliary load on the energy consumption for 25 °C, 35 °C and −5 °C ambient temperatures.

The simulation results indicate that the UDDS is the most affected drive cycle by the auxiliary load on the energy consumption, with an energy consumption increase of 32% when the outside temperature is −5 °C. On the contrary, the US06 cycle is the least affected driving cycle by the heating system usage with a 10% increase in the energy consumption. These two cycles are also those with the highest and the lowest energy consumption levels, respectively. This result demonstrates that generally the higher the energy consumption [Wh/km], the lower is the impact of the auxiliary systems. These systems, in fact, represent a constant additional load for the vehicle. Also the study demonstrated that the absolute temperature differences from the base condition, between 15 and 24 °C, might correlate to the higher energy consumption of 35 °C and −5 °C ambient temperatures. The table demonstrates that a 20 °C difference (−5 °C) consumes 20.3% more energy and a 10 °C difference utilizes 6.7% more energy.

Table 5 also summarizes the impacts on the EV range for various auxiliary system loads for an outside temperature of 25 °C, 35 °C and −5 °C. Table 5 demonstrates that EV drivers should consider EV range reduction of up to 24% when the temperature difference between the inside cabin and the ambient temperature is approximately 30 °C.

## 7. Conclusions and recommendations for further research

The VT-CPEM model was developed in this paper. The model computes the instantaneous energy consumption of EVs using the instantaneous power exerted. Specifically, the speed profile (instantaneous vehicle speed and acceleration level) are utilized as input variables. This model compliments backward vehicle simulators available in the open literature by modeling the instantaneous regenerative braking energy efficiency as a function of the deceleration level. Furthermore, the proposed model can be easily integrated within microscopic traffic simulation software and in-vehicle and Smartphone eco-driving and eco-routing applications given its very simple formulation. The proposed model accurately estimates the energy consumption, producing an average error of 5.9% relative to empirical data. Moreover, the study found that the tank-to-wheels energy consumption for the electric vehicle (Nissan Leaf) is 82.5% lower than that of its conventional vehicle counterpart (Nissan Versa). The maximum difference is observed for the LA92 drive cycle with a difference of 90.9% and the minimum difference is observed for the High Speed cycle with a difference of 70.1%. These results demonstrate that in urban driving cycles there is the possibility to recover more energy due to the presence of several non-aggressive braking episodes in the drive cycle. The study confirmed that the EV energy advantage in urban driving could significantly impact people's route choices and further shake the foundation of conventional theories of traffic assignment [9].

Furthermore, the study compared the Nissan Leaf with two other different electric vehicles, the BMW i3 and the Tesla model S to evaluate the variation in energy consumption across different EVs. Results show that BMW i3 presents a reduction in the energy consumption in the range of 7.9%, on average, while Tesla model S is characterized by an increase in the energy consumption in the range of 22.9% on average, when compared with the Nissan Leaf.

The study also evaluated the impact of the auxiliary system load on the energy consumption of EVs. In particular, the auxiliary energy usages of both heating and air conditioning systems at outside temperatures of 25 °C, 35 °C and −5 °C were investigated. The simulation results demonstrated an increase in EV energy consumption by up to 32% depending on the ambient temperature. Furthermore, the study demonstrated that the EV range could be reduced by up to 24% when a heating system is operated and the ambient temperature is −5 °C and the in-cabin temperature is set at 24 °C.

Further research is recommended to evaluate and expand the proposed model using field collected data on electric vehicles. The research team plan to collect real-world energy consumption data on EVs in the near future. In addition, a further study on a complete well-to-wheels analysis is needed considering diverse scenarios of main energy sources to produce electricity including coal, nuclear, and other renewable energy sources to compute the total energy consumption and emissions related to the use of electric vehicles relative to conventional vehicles.

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