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Method for evaluating the real-world driving energy consumptions of electric vehicles

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ABSTRACT

Energy consumption directly determines the environmental benefits and driving range of electric vehicles. The energy consumptions of vehicles are generally evaluated using standardized driving cycle tests; however, the results from standardized driving cycle tests deviate from the results characterizing real driving and present opportunities for cheating. The evaluation of the real-world driving energy consumptions of electric vehicles is becoming a requirement in proposed vehicle regulations. In this paper, a method for evaluating the energy consumption characteristics of electric vehicles under real-world driving conditions is proposed. A simplified analytical function for estimating the energy consumption of an electric vehicle is derived. Using regression analysis, the effects of driving conditions are decoupled, and the independent energy consumption characteristics are obtained. Simulation and experimental data are used to validate the proposed method. The results show that the independent energy consumption characteristics obtained by the proposed method perfectly represent the energy consumptions of electric vehicles under different driving conditions. Therefore, the proposed method represents a possible alternative mechanism for extending the scope of energy consumption evaluations of electric vehicles, providing a basis for the comprehensive assessment of the environmental benefits of electric vehicles.

1. Introduction

Global electric vehicle ownership reached 1 million in 2015 [1], and surpassed 2 million in 2016 [2]. The number of electric vehicles is expected to continue to grow substantially. It is pointed out that the development of electric vehicles has been determined to be the national strategy for solving energy and environmental problems in China [3], but the evaluation of electric vehicles is still controversial. Reference [4] addressed that the promotion of EVs make sense only if it is ensured that a major share of electricity they use is generated from renewable sources, because the final goal is not just to increase the number of EVs but to reduce emissions. Similar discussion is given in Ref. [5], by using life cycle analysis combined with a Monte Carlo stochastic simulation, it shows that there is a huge uncertainty in the GHG emissions reduction potential with transport electrification. Real-world usable driving range is another barrier affect the adoption of EVs, because it affects the user experience [6] but cannot be accurately estimated currently. These issues are all highly dependent on the energy consumption rates of EVs. However, the tested energy consumption rates might not properly represent real-world energy consumptions and presents opportunities for cheating. After the Volkswagen diesel emissions cheating scandal, the widening gap between results in standardized tests and the real world is attracting more public concern [7]. Therefore, a challenging problem of evaluating the real-world driving energy consumption is presented.

Generally, a constant energy consumption rate used for EV evaluation is obtained under standardized driving cycles (NEDC, FTP75, WLTC, etc.) from laboratory testing or simulation [8]. Compared with real driving tests, standardized driving cycle tests conducted in the laboratory are insufficient. Traffic can be significantly different for different routes and locations during peak and lull periods; therefore, the test results from standardized driving cycles are usually inconsistent with the results obtained during real-world driving. The tested energy consumptions of EVs on predefined routes with various drivers in Sheffield (UK) showed that the differences between driving manners can produce up to

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Nomenclature

Abbreviations

Coef.	Coefficient
CV	Conventional vehicle
EPA	Environmental protection agency
EV	Electric vehicle
GHG	Green house gas
HVAC	Heating, ventilation and air-Conditioning
Prob.	Probability
RSS	Residual sum of squares
SOC	State of charge
Std. Err	Standard error

Standardized Driving Cycles

FTP75	Federal test procedure 75
HWFET	Highway fuel economy test cycle
NEDC	New European driving cycle
UDDS	Urban dynamometer driving schedule
US06	US06 supplemental federal test procedure
WLTC	Worldwide harmonized light vehicle test cycle
WMTC	World motorcycle test cycle

Symbols

α	Road grade angle [°]
$\mathbf{D}_{\mathrm{exp}}$	Dynamometer testing results dataset
$\mathbf{D}_{\mathrm{sim}}$	Simulation result dataset
η_{bat}	Battery efficiency [−]
η_{g2b}	Grid to battery efficiency, including the AC-DC converter and battery [−]
η_{mot}	Electric motor efficiency, including the electric motor and the inverter [−]
η_{pow}	Powertrain efficiency, including the driveline, electric motor and battery [−]
η_{regen}	Brake regeneration efficiency [−]
η_{trans}	Driveline efficiency [−]
ρ	Air density [kg/m^3]
A	Target coefficient A [N]
A_f	Frontal area [m^2]
B	Target coefficient B [N/(m/s)]
C	Target coefficient C [N/(m/s)^2]
C_d	Aerodynamic drag coefficient[-]
C_e	Energy consumption of electric vehicle [Wh/km]
E_{ac}^{loss}	Air conditioning losses
E_{aero}^{loss}	Aerodynamic losses [Wh]
E_{bat}^{loss}	Battery losses [Wh]
E_{brk}	Braking energy [Wh]
E_{brk}^{loss}	Braking losses [Wh]
E_{ch}^{loss}	Charging losses [Wh]
E_{dec}	Kinetic energy losses during deceleration [Wh]
E_{drv}^{loss}	Driveline losses [Wh]
E_{grid}	Total energy consumed from grid [Wh]
E_{load}^{loss}	Load losses, including aerodynamic and rolling friction losses [Wh]
E_{mot}^{loss}	Electric motor losses [Wh]
E_{roll}^{loss}	Rolling friction losses [Wh]
E_{start}^{loss}	Cold start losses
f_0	Rolling friction coefficient [−]
F_{load}	Load force [N]
g	Gravity acceleration [m/s^2]
i	Index of the discrete samples [−]
K_r	Coefficient used to change the intensity of regenerative braking [−]
m	Equivalent vehicle mass, with rotating parts and passengers [kg]
N	Number of observations [−]
n	Number of samples in a cycle [−]
P_{ac}	Air conditioning power
t_s	Sample period [s]
T_{amb}	Ambient temperature
v	Vehicle speed [km/h]

30% differences in energy consumption even on the same route [9]. The driving ranges under conditions relevant to highway driving show a significant deviation from the driving ranges published by EV manufacturers; in Ref. [10], the simulated driving ranges at a speed of 110 km/h under different scenarios are only 19%–27% of the range under NEDC. Reference [11] indicated that the measured energy consumption differences of EVs at the grid for different standardized driving cycles (NEDC, WLTC and WMTC) were up to 25%, and the differences for different phases in a driving cycle were up to 89%. Therefore, an evaluation method that can more comprehensively represent the real driving energy consumptions of EVs is required.

Simulation models, such as AVL CRUISE and AUTONOMIE [12], are used to describe the energy consumption characteristics of EVs; however, a large number of parameters are needed in these models. A neural network has been used to describe the energy consumption characteristics of EVs under real-world driving conditions [13]. The disadvantage of neural networks is that the data processing is complex, and the universality of the results is difficult to prove. The difficulty in evaluating the real driving energy consumption is that real-world driving conditions vary all the time and are not repeatable; therefore, the energy consumptions under different driving conditions cannot be directly compared. Principal component analysis has been used to obtain key driving condition factors affecting the energy consumptions of vehicles [14], but the principal components were only used for clustering the driving conditions; further energy consumption relationships have not been discussed. In Ref. [15], the energy consumptions of electric buses are estimated by fitting the coefficients of average driving speed; however, the impact of acceleration and deceleration cannot be considered. A computationally efficient simulation model for estimating the energy consumptions of EVs is proposed in Ref. [16]. By using normalization factors, the nonlinear characteristics are simplified, but normalization factors needed to be calculated from detailed vehicle parameters. Reference [17] finds that infrastructure, traffic, topography and climate are four factors significantly influencing the energy consumptions of EVs, and these factors can be used for rough estimation. More accurate energy consumption estimation of EVs by properly constructed driving condition factors is proposed in Ref. [18], but more vehicle parameters are needed. By analyzing the big data from real-world driving, the non-linear effects of driving speed, acceleration and temperature on the energy consumptions of EVs are discussed in Ref. [19], the findings of which are macroscopic, and cannot be applied to the evaluation of a specific EV model. In Ref. [20], a data-driven estimation method for electric vehicle energy consumption under real-world traffic