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A computationally efficient simulation model for estimating energy consumption of electric vehicles in the context of route planning applications

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ABSTRACT

The fact that electric vehicles (EVs) are characterized by relatively short driving range not only signifies the importance of routing applications to compute energy efficient or optimal paths, but also underlines the necessity for realistic simulation models to estimate the energy consumption of EVs. To this end, the present paper introduces an accurate yet computationally efficient energy consumption model for EVs, based on generic high-level specifications and technical characteristics. The proposed model employs a dynamic approach to simulate the energy recuperation capability of the EV and takes into account motor overload conditions to represent the vehicle performance over highly demanding route sections. To validate the simulation model developed in this work, its output over nine typical driving cycles is compared to that of the Future Automotive Systems Technology Simulator (FASTSim), which is a simulation tool tested on the basis of real-world data from existing vehicles. The validation results show that the mean absolute error (MAE) of cumulative energy consumption is less than 45 W h on average, while the computation time to perform each driving cycle is of the order of tens of milliseconds, indicating that the developed model strikes a reasonable balance between efficacy of representation and computational efficiency. Comprehensive simulation results are presented in order to exemplify the key features of the model and analyze its output under specific highly aggressive driving cycles for road gradients ranging from −6% to 6%, in support of its usability as a practical solution for estimating the energy consumption in EV routing applications.

1. Introduction

Electric vehicles (EVs) are typically viewed as a promising pathway to decarbonize the transportation sector in the long-term, given that the electrification of passenger vehicles bears the potential to reduce carbon emissions and dependence on fossil fuels, as well as to increase the efficiency of vehicle operation (Wu et al., 2015). In support of this, comparative studies based on field measurements show that on average the EVs are more energy efficient than hybrid vehicles and internal combustion engine vehicles (Howey et al., 2011; Lorf et al., 2013). In this context, EVs have received wide attention over the last

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years due to their distinctive advantages (Yao et al., 2013), while main drivers of their market uptake include the government support both on the demand and supply side, the release of new EV models by the automotive industry, as well as the growing interest from the side of the consumers. However, the figures of global EV sales reveal not only that the market size is small, but also that the gradually increasing EV global stock is the result of the adoption in a small number of countries. It is indicative that the share of EVs rose from 0.02% of total passenger cars in 2012 (IEA, 2013) to 0.08% in 2014 (IEA, 2015), with over 95% of the global EV stock accumulated in the sixteen participating countries of the Electric Vehicle Initiative (EVI), indicating that EV cost and uncertainties on performance are among the main barriers to EV worldwide adoption.

Despite the advances in battery technologies, EVs are still characterized by low cruising range (autonomy), a fact that has led to significant research efforts on developing routing applications to compute energy efficient or optimal paths under realistic constraints (Baum et al., 2013, 2014; Schneider et al., 2014; Yang et al., 2015). As a general rule, EV routing algorithms typically assign a representative consumption value (cost) to each segment (arc) of the road network in order to compute energy-optimal paths, while various techniques can be employed to handle negative arc costs due to energy recuperation (Baum et al., 2013). The latter comprises a key feature that contributes to the higher energy efficiency of EVs by using the electric motor to convert the kinetic energy to electrical energy and recharge the battery, for instance, during braking or driving downhill (Wu et al., 2015).

From the modeling perspective, the ability of EVs to recuperate and store energy is often approximated by a constant regeneration factor in the relevant literature of energy consumption models for EVs (Campanari et al., 2009; Li et al., 2015; Muneer et al., 2015; Smith, 2010; Travesset-Baro et al., 2015; Van Sterkenburg et al., 2011), while other published works are based on a speed-dependent regenerative braking factor expressing the percentage of the total braking energy that can be recovered by the motor (Yang et al., 2013; Zhang and Yao, 2015). For the same purpose, speed-dependent recuperation moments and engine's rotational speed are employed by Schellenberg et al. (2014). Moreover, a different approach is presented in the work of Fiori et al. (2016) for the development of the Comprehensive Power-based EV Energy consumption Model (CPEM), where the regenerative energy efficiency is computed as a function of the instantaneous deceleration of the vehicle. However, all the aforementioned models assume a constant value either for the efficiency of the electric motor (regardless of its load) or the energy regeneration factor, or both.

In addition to the energy consumption models for battery EVs reported above, existing vehicle simulation tools that support this type of EVs include: (i) the AVL CRUISE which comprises a software package for vehicle system and driveline analysis based on an object-orientated physical model approach (AVL, 2016), (ii) the AUTONOMIE which combines a driver model, an environment model, an optional vehicle controller, and the vehicle propulsion architecture in a forward-facing simulation approach (ANL, 2016), (iii) the ADvanced VehIcle SimulatOR (ADVISOR) which combines a backward/forward facing simulation approach (NREL, 2003), and (iv) the Future Automotive Systems Technology Simulator (FASTSim) which is a high-level vehicle powertrain model (NREL, 2014). However, vehicle modeling with these tools is typically a data-intensive process, which requires highly-detailed and potentially confidential manufacturer data with respect to vehicle characteristics as input parameters, while simulation execution is computationally expensive, in particular for routing applications.

The purpose of the present work is to support the algorithmic approaches for energy-efficient routing of EVs developed in the frame of the MOVESMART project, which aims at providing time-dependent route planning and renewable personal mobility services in large-scale urban traffic networks by exploiting a traffic prediction mechanism based on historical and crowd-sourced traffic data (MOVESMART, 2016). In this context, this paper focuses on the development and validation of a battery EV simulation model, which can be combined with pre-defined real-world driving cycles (speed profiles) in order to extract energy consumption factors for various EV configurations under different traffic conditions and road topologies, following a similar approach to the Handbook Emission Factors for Road Transport (HBEFA) that provides fuel consumption and emission factors for different categories and types of conventional vehicles with internal combustion engines (INFRAS, 2015). In the frame of the MOVESMART project, the challenge is to develop a computationally efficient yet accurate energy consumption model that can differentiate between the various EV configurations, serving as the basis for enabling the end user to receive route suggestions optimized for the preferences and EV characteristics defined in the user profile, given the traffic predictions for the state of the road network. This further implies that the focus is on battery EVs used as passenger cars.

To exemplify the intended application, it is pertinent to note that the representation of a route plan in MOVESMART includes position and time of presence information in the form of a sequence of tuples, i.e. <latitude, longitude, time of presence>, as generated by the MOVESMART routing services, given the traffic predictions for the state of the road network provided by the MOVESMART traffic prediction mechanism (note: the integration of the routing services with the traffic prediction mechanism in MOVESMART is clearly out of the scope of the present paper). Then, for a given EV, the estimated energy consumption over a suggested route is calculated as the sum of the products $d_k EC_k$, where d_k (in m) denotes the length of route segment k and EC_k (in W h/m) denotes the EV energy consumption per unit of distance for route segment k that depends on the EV characteristics, road gradient and level of service (in route segment k). Taking into account the area type, road type and speed limit of the route segment k, the level of service is inferred from the average traversal speed (in m/s) in the corresponding route segment k, i.e. $V_{avg,k} = d_k / \Delta Time\_of\_presence$, where $\Delta Time\_of\_presence$ (in s) is the difference between the time of presence at the starting points of route segments k and $k+1$ of a route plan. In this framework, the developed energy consumption model is employed to create a database of EC_k factors for the possible combinations of: