Transportation Research Part C 93 (2018) 335–350

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

An eco-driving system for electric vehicles with signal control under V2X environment

Ming Li[a], Xinkai Wu[a,b,*], Xiaozheng He[c], Guizhen Yu[a,b], Yunpeng Wang[a,b]

[a] School of Transportation Science and Engineering, Beihang University, Beijing 100191, China
[b] Beijing Advanced Innovation Center for Big Data and Brain Computing, Beihang University, Beijing 100191, China
[c] Department of Civil and Environmental Engineering, Rensselaer Polytechnic Institute, 110 8th St., Troy, NY 12180, United States

ARTICLE INFO

Keywords:
Electric vehicle
Signal control
Connected vehicles
Eco-driving system
Bi-objective

ABSTRACT

The benefit of eco-driving of electric vehicles (EVs) has been studied with the promising connected vehicle (i.e. V2X) technology in recent years. Whereas, it is still in doubt that how traffic signal control affects EV energy consumption. Therefore, it is necessary to explore the interactions between the traffic signal control and EV energy consumption. This research aims at studying the energy efficiency and traffic mobility of the EV system under V2X environment. An optimization model is proposed to meet both operation and energy efficiency for an EV transportation system with both connected EVs (CEVs) and non-CEVs. For CEVs, a stage-wise approximation model is implemented to provide an optimal speed control strategy. Non-CEVs obey a car-following rule suggested by the well-known Intelligent Driver Model (IDM) to achieve eco-driving. The eco-driving EV system is then integrated with signal control and a bi-objective and multi-stage optimization problem is formulated. For such a large-scale problem, a hybrid intelligent algorithm merging genetic algorithm (GA) and particle swarm optimization (PSO) is implemented. At last, a validation case is performed on an arterial with four intersections with different traffic demands. Results show that cycle-based signal control could improve both traffic mobility and energy saving of the EV system with eco-driving compared to a fixed signal timing plan. The total consumed energy decreases as the CEV penetration rate augments in general.

1. Introduction

The use of electric vehicles (EVs) has been viewed as an efficient way to reduce carbon emissions and oil dependence (e.g. Coria et al., 2015; Tanaka, 2009; Wu et al., 2015a). Due to these benefits, governments have allocated considerable subsidy and have taken a number of legislative and regulatory steps to promote EV deployment and adoption. With this momentum, it is very likely to see that in the near future EVs replace gas engine vehicles, particularly in densely populated urban areas with systemic air quality problems. However, we still need to ask ourselves these two questions: with more advanced technologies applied to transportation system, what further benefits can we get out of EVs beside low emission? How to improve efficiency, in both operation and energy consumption, for EV transportation system?

The connected vehicle technology, which enables real-time vehicle-to-vehicle (i.e. V2V) and vehicle-to-infrastructure (i.e. V2I) communications, is viewed as a promising tool to enhance traffic safety and efficiency (e.g. Malakorn and Park, 2010; Talebpour and Mahmassani, 2016; Guler et al., 2014; Jia and Ngoduy, 2016; Feng et al., 2015; Li and Ban, 2017). Its integration with local traffic control could initiate eco-driving, which is expected to significantly improve both operational and fuel efficiency (e.g. Xu et al., 2017;

* Corresponding author at: School of Transportation Science and Engineering, Beihang University, Beijing 100191, China.
E-mail address: xinkaiwu@buaa.edu.cn (X. Wu).

https://doi.org/10.1016/j.trc.2018.06.002
Received 12 October 2017; Received in revised form 4 June 2018; Accepted 5 June 2018

Zhao et al., 2016; Jung et al., 2016). Previous researches have verified that eco-driving can minimize fuel consumption (e.g., He et al., 2015; Wan et al., 2016; Hu et al., 2016, 2017; Zhou et al., 2017, Ma et al., 2017; Alsabaan et al., 2013). As for EVs, recent researches also show that it would make further contribution to energy (i.e., electricity) saving (e.g., Wu et al., 2015b).

Although the integration of eco-driving and signal control makes great contribution to saving energy, travel delay and energy consumption might not simultaneously converge to their optimal ranges. From the system perspective, the eco-driving model proposed in the previous section could save significant energy consumption, but with sacrifice in total travel delay, if the signal timing plan is kept unchanged (e.g. Wan et al., 2016; Islam and Hajbabaie, 2017). To account for the delay due to eco-driving, an intuitive idea is to introduce an additional objective to maximize system travel time saving by adjusting signal timings. For example, a bi-level optimization model has been proposed to discuss interactions between travel delay and fuel consumption of an isolated intersection (Jung et al., 2016). In addition, with advances in autonomous driving technology, the combinations of connected autonomous vehicles trajectories control and signal optimization are also carried out, e.g., Li et al. (2014), Feng et al. (2018) and Yu et al. (2018). However, the potential benefit of cooperation between signals at neighborhood intersections on energy consumption and traffic mobility has not been widely studied.

Eco-driving of an individual EV has been studied by many existing researches (e.g. Wu et al., 2015b). But when it is expanded to a whole EV traffic system, the way EV-to-EV interaction influences both energy and operational efficiency still remain unknown. All these lead to two challenging problems: (1) how EVs interact with each other and form an eco-driving EV system with optimal energy consumption; and (2) how local signal timing control integrates with eco-driving EV system to achieve not only energy efficiency, but also operational efficiency in a systematic manner.

This research aims to address the above challenges by developing an energy and efficiency optimal control system for EVs with urban traffic signal control. A V2X environment is assumed, but only a portion of EVs are equipped with connected vehicle (CV) technology. In this system, the connected EVs (CEVs) follow an eco-driving speed profile characterized by a multi-stage optimization model, in which, each segment between two neighborhood intersections is treated as one control stage. The complete energy-optimal speed profile is the summation of results from each control stage with the linkages of adjacent control stages defined as boundary conditions in the model. The proposed eco-driving EV system assumes that the dynamics of non-CEVs follow a car-following model, i.e., the Intelligent Driver Model (IDM; Treiber et al., 2000). Adopting the IDM not only helps explicitly define the interactions between EVs, but also facilitates non-CEVs to achieve eco-driving. More importantly, the eco-driving EV system factors both energy efficiency of EVs and traffic delay at the system level simultaneously, which leads to a multi-stage and bi-objective optimization model. When this model is applied to an urban network, it becomes even more complicated. Heuristic methods, such as genetic algorithm (GA) and particle swarm optimization (PSO), are preferred ways to solve such complicated problems. In this research, a hybrid algorithm uniting GA and PSO is adopted. This research is expected to provide valuable references for the future development of Cooperative Vehicle Infrastructure System (CVIS) and make contributions to establish intelligent traffic control.

This paper is organized as follows. Section 2 briefly overviews an energy consumption model adopted in this research for EV. Section 3 presents the concept of the eco-driving EV system with an energy-optimal signal control method and a heuristic algorithm collaborating GA and PSO for resolving the problem. Section 4 demonstrates the effectiveness of the proposed model by a validation example. In the end, Section 5 concludes this paper with some remarks for future work.

2. Background: an energy consumption model for electric vehicles

This study seeks to manage the energy consumption of EVs under signal control. In context of this purpose, an accurate energy consumption estimation method of EVs is critical. Here, we briefly present the adopted energy consumption model proposed by Wu et al. (2015a), which analytically describes the individual EV's instantaneous power as a function of velocity, acceleration, and roadway grade.

The adopted energy consumption method is based on vehicle dynamics. The formulation is simple and suitable for real-time applications. First, since EVs have little energy losses compared to internal combustion vehicles, the electrical power generated by an EV is assumed to be equal to the power required to produce tractive effort. Note that we ignore the energy used for climate control and vehicle accessories. The tractive effort can be described as:

$$F = ma + kv^2 + f_{rl}mg + mg\sin\theta \tag{1}$$

where F is tractive effort; m is vehicle mass; v is velocity; a is acceleration; $k = \frac{\rho}{2}C_D A_f$; ρ is air density; C_D is coefficient of drag; A_f is frontal area of the vehicle; f_{rl} is rolling resistance constant; g is gravity acceleration; and θ is the roadway grade.

Since the electrical losses are proportional to the square of current (I^2), the relationship between power (P) and tractive effort can be represented as:

$$P = I^2 r + Fv \tag{2}$$

where I is the current, and r is the resistance of the conductor in a motor. Therefore, essentially r is the resistance of motor.

In addition, the force, F, generated by the torque of the motor, can be simplified as a product of the armature constant, magnetic flux, and current, which can be formulated as:

$$F = \frac{K \cdot I}{R} \tag{3}$$

where $K = K_a \Phi_d$; K_a is the armature constant; Φ_d is the magnetic flux; I is the current; and R is the radius of the tire.

Combining (1)–(3), an EV's instantaneous power can be estimated by: