Formation Eco-Driving for Heterogeneous Electric Vehicles

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***Abstract*—¡¡¡¡¡¡¡ HEAD Multiple-vehicle formation driving, which accelerates and cruises with the same acceleration and velocity, efficiently enhances transportation throughput. This paper introduces a *formation eco-driving* for battery electric vehicles (BEV or all-electric vehicles powered solely by the battery.) We derive the least-energy cruising speed of the BEVs in the same formation taking into account accurate electric powertrain models and vehicle dynamics. We assume V2V (vehicle to vehicle) communications that allows sharing of the vehicle power models in the same formation. We calculate the most efficient allowable speed for each BEV in the formation. To address the problem more practically, we assume the formation is not necessarily maintained as long as each BEV does not interfere other vehicles in the formation. We present accurate polynomial form of BEV power models that considers characteristics of electric powertrain as well as the optimization framework. Our experimental results show 12.81% total energy saving of the whole formation of BEVs compared with the baseline. ======= Multiple-vehicle formation driving, which accelerates and cruises the vehicles with the same acceleration and speed, gains a higher transportation throughput. This paper introduces a *formation eco-driving* for battery electric vehicles (BEV or all-electric vehicles powered solely by the battery.) We first calculate the least-energy cruising speed for each BEV in the same formation and derive the most energy-efficient formation speed. We assume V2V (vehicle to vehicle) communications that allows sharing the vehicle power models among the BEVs in the same formation. We address the formation eco-driving with a perspective of low-power embedded systems design in this paper.**

We formulate the formation eco-driving focusing more on energy efficiency such that the formation is not strictly necessarily maintained as long as each BEV does not interfere other vehicles in the formation, which is more realistic. We present accurate polynomial form of BEV power models that considers characteristics of electric powertrain as well as the optimization framework. Our experimental results show 12.81% total energy saving of the whole formation of BEVs compared with the baseline. ¿¿¿¿¿¿¿ aef80780927bb9e753f2403165abc6c1105ab082

***Index Terms*—Battery Electric vehicles, heterogeneous driving, formation eco-driving**

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIP) (No.2015R1A2A1A09005694.)

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I. INTRODUCTION

It is well known that eco-driving gains a significant fuel efficiency without upgrading the vehicles. Eco-driving methods have been widely mentioned for internal combustion engine vehicles, but such methods can hardly be used for battery electric vehicles (BEVs) due to the fundamental discrepancies between the internal combustion engine powertrain and electric powertrain. Recent previous research on BEV-specific eco-driving begins to reflect electric powertrain characteristics [1], [2], [3]. However, such work focuses on single BEV even though some work is aware of the traffic condition [4], [5], [2]. Currently, up to one hundred electronic control units (ECUs) are used for autonomous vehicle driving such as adaptive cruise control (ACC). In addition, computing techniques for processing a large amount of data with limited resources are proposed for V2V (vehicle to vehicle) communication [6]. As a result, formation driving, which accelerate and cruise the vehicles in the same group, is real. Formation driving efficiently enhances the transportation throughput and can also gain fuel economy due to the reduced air dragging as a byproduct.

This paper introduces a *formation eco-driving of heterogeneous BEVs* on a single lane. The BEVs accelerate and cruise without disturbing other BEVs in the same formation calculating the most efficient acceleration, cruising speed and deceleration for the formation. Unlike the previous work, this paper primarily saves energy consumption of BEVs through the proposed formation eco-driving. We formulate the formation eco-driving problem more realistic such that the formation is not necessarily maintained as long as a BEV does not interfere the other BEVs. For example, the first BEV in the formation may be driven faster than the formation speed if the most-efficient speed for the first BEV is higher than the optimal formation speed.

II. ELECTRIC VEHICLE MATHEMATICAL POWER MODELS

A. Vehicle Power Consumption Model

A vehicle dynamics equation is commonly used vehicle power consumption model (1). There is an assumption that efficiency of the powertrain (electric motor and drivetrain) is 100%.

$$\begin{gathered} P_{trac} = F\frac{ds}{dt} = Fv = (F_R + F_G + F_I + F_A)v \\ F_R \propto C_{rr}W,\ F_G \propto W sin\theta,\ F_I \propto ma,\ \text{and}\ F_A \propto \frac{1}{2}\rho C_d A v^2 \\ P_{trac} \approx (\alpha + \beta sin\theta + \gamma a + \delta v^2)mv \end{gathered} \tag{1}$$

where F_R, F_G, F_I, F_A, and F_B denote the rolling resistance, gradient resistance, inertia resistance, aerodynamic resistance, and brake force provided by hydraulic brakes, respectively [7]. The coefficients α, β, γ, and δ correspond to the rolling resistance, gradient resistance, inertia resistance, and aerodynamic resistance, respectively. Adding a traction motor efficiency in (1) makes more realistic EV power consumption characteristics. η_{EV*} is determined by motor loss and drivetrain. We borrow an EV-specific power (P_{EV*}) modeling method considering the loss in EV drivetrain using a multivariable regression method from the measured power data and achieve a polynomial fitting [8].

$$P_{EV*} = \frac{P_{trac}}{\eta_{EV*}} \tag{2}$$

$$\eta_{EV*} = \frac{P_{trac}}{P_{trac} + C_0 + C_1 v + C_2 v^2 + C_3 T^2}$$

where C_0, C_1, C_2, and C_3 mean coefficients for constant loss, iron and friction losses, drivetrain loss, and copper loss, respectively. The power consumption model (2) is commonly used in various analytical EV power managements [3], [5]. EVs mostly use regenerative braking during deceleration, which converts kinetic energy to electric energy. The harvested energy from regenerative braking is closely related to the electromagnetic flux inside of the motor, and the flux is proportional to the motor RPM. The regenerative braking model of an EV is simplified as (3).

$$P_{regen} = \varepsilon T v + \zeta \tag{3}$$

where ε and ζ are regenerative braking coefficients.

B. Electric Vehicle Power Model Library

ADVISOR is a vehicle simulator that takes into account various factors of vehicles including engines, electric traction motors, types of drivetrains, shape of chassis, etc. [9]. However, it is not practical to use ADVISOR for estimation of power consumption of multiple vehicles at the same time and exploration of design space due to the significant time overhead. So, instead of using ADVISOR for the speed optimization, we use ADVISOR for the model coefficient extraction. In other words, we use the same form of polynomial as (2) but derive the coefficients by running ADVISOR. We implement several types of BEV power model based on the vehicle specifications and reports for the driving performance and range at various constant road slopes [10], [11], [12], [13], [14]. Table I summarizes the model coefficients of (2) and (3) of each BEV.

III. Formation Eco-Driving

A. Motivational Example

We first demonstrate how the cruising speed, acceleration and deceleration affect BEV energy consumption. We perform a design space exploration (DSE) for all feasible BEV speeds and the acceleration pairs. The results of DSE on an BEV sedan (Model S) and bus (K9) are shown in Fig. 1. We obtain the minimum-energy speed and the initial and final acceleration for a given driving distance. The point at the minimum-energy consumption per distance (Wh/km) represents the least-energy-constant-speed driving. The energy consumption by the cruising speed and acceleration pairs also completely changes by the BEV type. Each BEV type has different curb weight, motor specification, body shape, and tire, which affect energy consumption by acceleration and cruising speed, and, therefore, each BEV type has different least-energy-constant-speed driving.

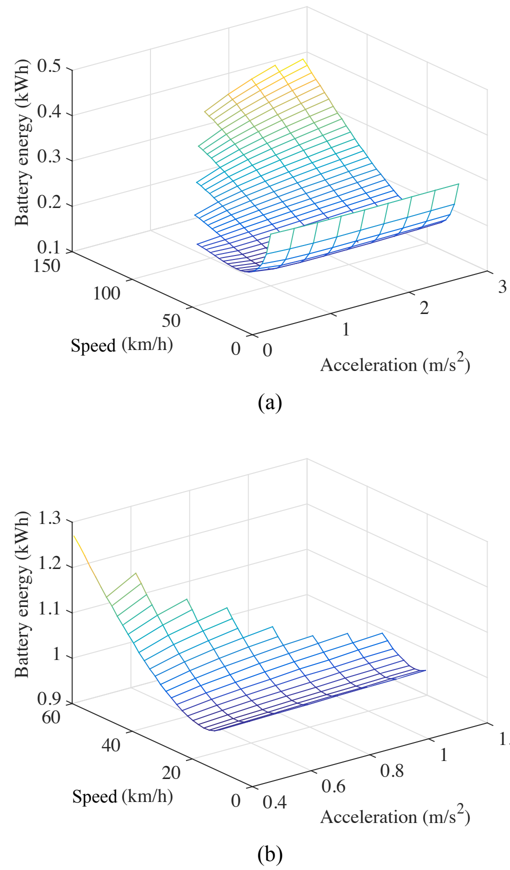

Fig. 1. Design space exploration of (a) Tesla Model S and (b) BYD K9.

Fig. 2. An example of a formation driving of heterogeneous BEVs on a single lane.

B. Problem formulation

A set of formation BEVs on the same lane. N BEVs, and a BEV EV_i has a power models defined by (1), (2), (3), and related coefficients in Table I. No interference is assumed for the formation, i.e., no other vehicles, no pedestrians, etc., nearby the formation. The formation driving consists of three stages: a constant acceleration, a constant-speed cruising and a constant deceleration. A segment of the formation driving is between two traffic signals, between two stop signs, and

TABLE I
POWER MODEL COEFFICIENTS OF BEVS.

BEV	α	β	γ	δ	C_0	C_1	C_2	C_3	ε	ζ
Chevrolet Bolt	0.06	9.5549	1.0013	0.00012352	1000	10.588	8.11	0.00031678	0.6633	5813.6
Tesla Model S 85	0.098	9.8794	0.9911	0.00016564	2300	11.927	4.4359	0.00032082	0.7642	2832.9
Tesla Roadster	0.0735	8.723	0.8461	0.000065721	2000	15.743	11.221	0.0033	0.7464	2857.1
Spark EV	0.098	10.7077	1.0567	0.00025082	700	24	8	0.00075648	0.6671	2412.9
BYD K9	0.098	9.8946	1.2324	0.00044	1000	492.56	90	0.000018696	0.4095	2178.5

TABLE II
LIST OF BEVS AND THEIR VEHICLE TYPE.

Index	Vehicle	Type	Index	Vehicle	Type
1	Bolt	hatchback	4	K9	bus
2	Spark	hatchback	5	Roadster	convertible
3	Model S	sedan			

so forth. Use of a V2V communication, BEVs in the same formation can share their vehicle information, i.e., power model coefficients. Each BEV weight is defined by the curb weight and the payload: passengers and cargos. The curb weight is known a priori, and the payload is measured by the sensor.

We define the baseline as follows:

1) Independent eco driving: each BEV has its own minimum-energy acceleration, cruising speed and deceleration. It is permitted to pass a preceding vehicle. This is possible when each BEV occupies its own lane.
2) Following the preceding vehicle: each BEV has its own minimum-energy acceleration, cruising speed and deceleration guideline. However, the acceleration or cruising speed of the following BEV is bounded by those of the preceding BEV.

The formation eco-driving problem can be rewritten such that for a given set of formation with the BEV models and lineup order, we minimize the total formation driving energy consumption. The problem formulation accommodates a more realistic situation. The formation acceleration, cruising speed and deceleration are regarded as a reference. Each BEV may not follow the formation driving reference as long as it does not interfere other BEV formation driving. For example, the first BEV may be driven faster than the formation cruising speed as long as it exhibits a smaller energy consumption.

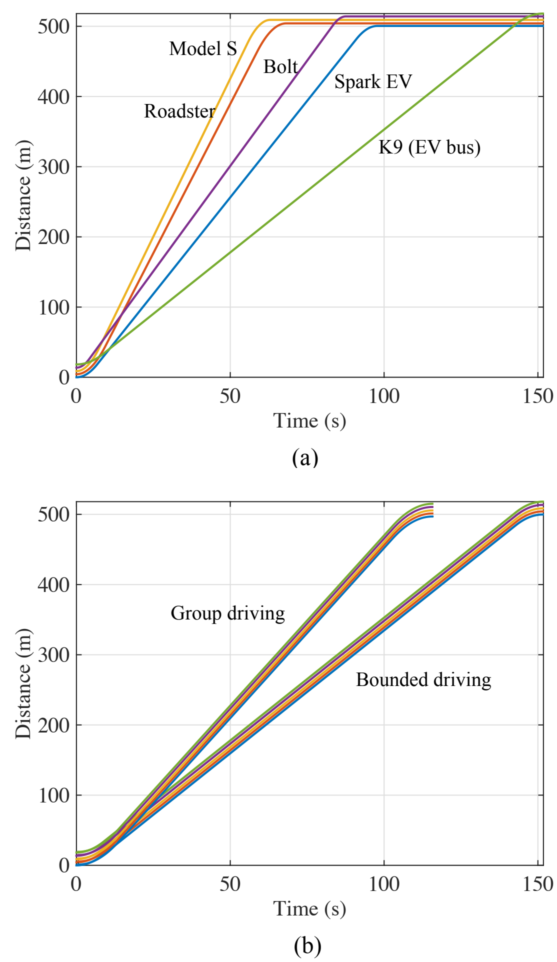

Fig. 3. Heterogeneous BEV driving by (a) passing a preceding vehicle is permitted, and (b) passing is not permitted.

IV. EXPERIMENTAL RESULTS

A. Comparison by Vehicle Types

We assume an example driving of five BEVs in Table II. A formation is Chevrolet Spark (tail) – Tesla Roadster – Tesla Model S – Chevrolet Bolt – Kia K9 (head.) The driving segement distance of this example is 500 m, and each BEV has its own minimum-energy acceleration and cruising speed. Fig. 3(a) shows the ideal driving of the five BEVs over time if it is permitted to pass a preceding vehicle. Each BEV arrives at the endpoint in different time because they drive with different acceleration and cruising speed. K9 starts at the forefront on the starting point. But, this BEV arrives at the endpoint the latest because the minimum-energy cruising speed of K9 is the slowest among all BEVs. Fig. 3(b) shows the drivings of the five BEVs if it is not permitted to pass a preceding vehicle.

In the case of conventional bounded driving, the acceleration and cruising speed are bounded to those of the preceding vehicle. Therefore, acceleration and cruising speed of all BEVs are bounded to those of K9 in this example. Total energy consumption of the five BEVs is as 109.7% of the energy consumption of the ideal driving. On the other hands, if they drive with the proposed driving guideline mentioned in Section III-B, it consume only 104.0% of energy consumption of the ideal driving. This means that increasing the acceleration and cruising speed of the bus is more efficient for all BEVs in the given formation.

TABLE III
LIST OF HETEROGENEOUS DRIVING FORMATIONS.

No.	EV formation from last to lead
1	3 2 3 5 3 5 1 5 3 4
2	3 2 3 5 3 5 3 4 5 1
3	3 5 3 4 5 3 5 3 2 1
4	4 3 2 3 5 3 5 1 5 3

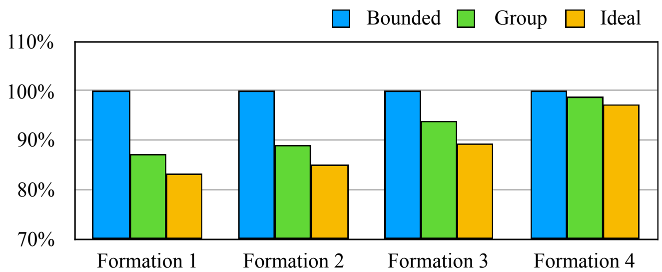

Fig. 4. Heterogeneous driving results by BEV formations.

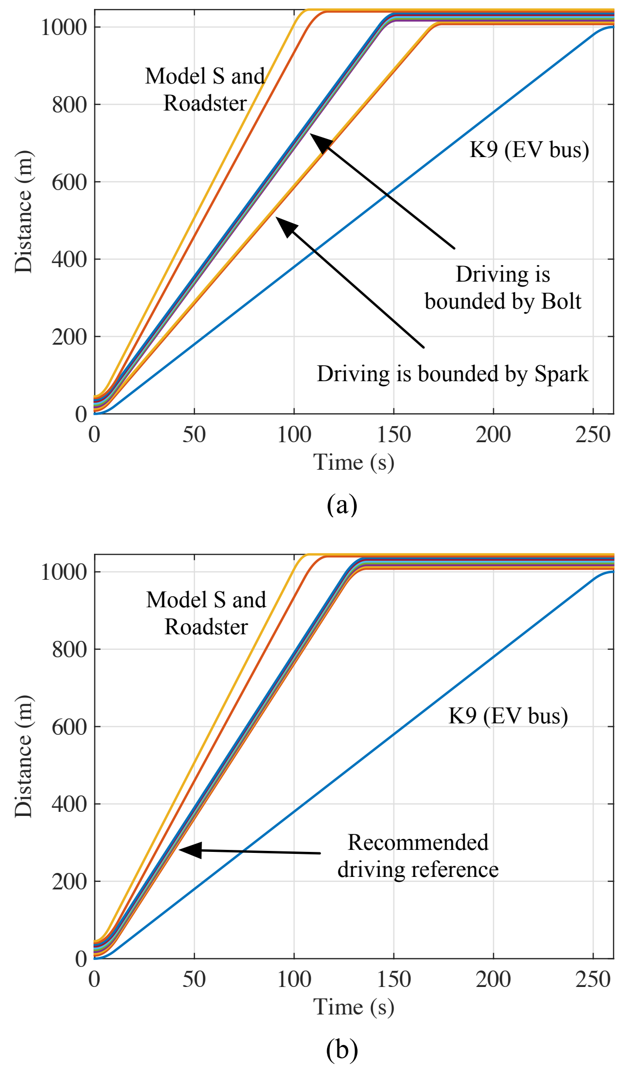

Fig. 5. Heterogeneous BEV driving result of (a) bounded driving and (b) proposed driving in case of formation 4.

B. Driving Case Study

We assume a case study of heterogeneous BEV driving with 10 BEVs. Table III shows the formations of 10 BEVs. Fig. 4 shows the comparisons of the energy consumption of 10 BEVs for the driving. Blue bars indicate the energy consumption by the bounded driving, in which the vehicle driving is bounded by the preceding vehicle. Blue bars show 100% energy consumption in this figure. Green bars indicate the energy consumption by the proposed group driving method, and orange bars indicate ideal driving, which is possible to pass a preceding BEV. The energy gain by the proposed group driving compared with the bounded driving is from 1.41% to 12.81%.

In case of formation 1, the bus is lead, and it is very common when group driving is limited by a bus ahead. In this formation, drivings of all BEVs are bounded to the least-energy-constant-speed driving of the bus. The gain by the proposed group driving is 12.81% compared with the bounded driving. In case of formation 4, the least-energy-constant-speeds of two leading BEVs (hatchback and convertible) are faster than a recommended reference, and that of the last BEV (bus) is slower than the reference. Therefore, these three BEVs drive their own optimal, and only seven BEVs follow the reference as shown in Fig. 5.

V. CONCLUSIONS

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