Energy-Efficient Adaptive Cruise Control for Electric Connected and Autonomous Vehicles

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Abstract—This paper presented an energy-efficient adaptive cruise control, called Energy-Efficient Electric Driving Model (E³DM), for electric, connected, and autonomous vehicles (e-CAVs) in a mixed traffic stream. E³DM is able to maintain high energy efficiency of regenerative braking by adjusting the spacing between the leading and the following vehicles. Moreover, a power-based energy consumption model is proposed to estimate the on-road energy consumption for battery electric vehicles, considering the impact of ambient temperature on auxiliary load. Using the proposed energy consumption model, the impact of E³DM on vehicle energy consumption is investigated. In particular, single-lane vehicle dynamics in a traffic stream with a mixed of e-CAVs and human-driven vehicles are simulated. The result shows that E³DM outperforms existing adaptive cruise control (i.e. Nissan-ACC) and cooperative adaptive cruise control (i.e. Enhanced-IDM and Van Arem Model) strategies in terms of energy consumption. Moreover, higher market penetration of e-CAVs may not result in better energy efficiency of the entire fleet. The reason is that more e-CAVs in the traffic stream results in faster string stabilization which decreases the regenerative energy. Considering mix traffic streams with battery electric (BEVs) and internal-combustion engine (ICEVs) vehicles, the energy consumption of entire fleet reduces when the market penetration of BEV (contains both e-CAV and human-driven BEV) increases. A higher ratio of e-CAV to human-driven BEV results in higher energy efficiency.

Index Terms— Electric connected and autonomous vehicle (e-CAV); Energy-efficient adaptive cruise control; Energy consumption model.

I. INTRODUCTION

Battery electric vehicle (BEV) technology is considered as a solution to reduce oil dependence and vehicle emissions because of its high energy efficiency and zero tailpipe emissions [1], [2]. To further improve the driving efficiency and extend the vehicle range, an energy-efficient management strategy is desired [3]. Previous studies have shown that driver behavior could affect the fuel economy of conventional gasoline vehicles by 10~40% [4]–[6]. Recent development in advance driving assistant systems, such as adaptive cruise control (ACC), presents opportunities to improve energy efficiency through automated vehicle operations.

The impacts of ACC-equipped vehicles on traffic flow, fuel consumption and emission have been widely investigated.

According to the studies conducted by Davis [7], Jiang et al. [8], and Yuan et al. [9], ACC-equipped vehicles is able to enhance the free flow stability and suppress wide moving jams. Kesting et al. [10] reported that traffic congestion was completely eliminated when the share of ACC-equipped vehicle reaches 25%. Mersky and Samaras pointed out that, depending on the control strategies, ACC-equipped vehicles may experience fuel economy gains by up to 10% or losses by up to 3% [11]. Using simulations and experiments, Ioannou and Stefanovic found that the smooth response of ACC-equipped vehicle decreased the emissions in presence of disturbances due to high-acceleration maneuvers, lane cut-ins, and lane exiting [12].

To improve fuel efficiency and decrease emissions, a typical method is to optimize the vehicle speed profile with smoother deceleration and acceleration rates [13]–[16]. Based on optimal control, Park et al. [17] and Ahn et al. [18] developed eco-ACC systems and demonstrated their potential in improving fuel efficiency. Vajedi and Azad proposed an eco-ACC for Toyota Prius Plug-in Hybrid to reduce the total energy cost [19]. Considering ACC-equipped vehicles in a mixed traffic environment, Wang et al. proposed model predictive controlbased control strategies to reduce platoon-level emissions [20]. The simulation results showed that a 20% share of ACCequipped vehicles could reduce emissions of the platoon by 18~27%. Moreover, Li et al. studied the performance of a fueloptimized ACC strategy, called Pulse-and-Glide, on traffic smoothness and fuel economy in a mixed traffic flow and found that the Pulse-and-Glide strategy can significantly improve the fuel economy of individual vehicles [21].

A few ACC models have been proposed for electric vehicles [13], [22]- [23]. For regenerative braking control, Huang et al. [22] proposed a nonlinear model predictive controller that is capable of restoring more regenerative braking energy than a conventional controller. Based on forward terrain profile preview information, Chen et al. [24], [25] introduced an energy-efficient driving control strategy that can optimally distribute the torque between the front and rear motors to save driving energy. Recently, Akhegaonkar et al. [26] proposed a longitudinal controller to minimize energy consumption and maximize energy regeneration. Moreover, Schwickart et al. [3] designed an ACC system based on model predictive control method with quadratic cost function, linear prediction model, and linear constraints. Considering terrain characteristics and

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preceding vehicle information, Zhang et al. [23] developed an energy management strategy for battery electric vehicles equipped with in-wheel motors. The simulation results showed that using the preceding vehicle movement information results in additional energy savings.

To assess energy efficiency of electric vehicles in a mixed traffic stream appropriate energy consumption models are needed. Using the controller area network (CAN) bus and Global Positioning System (GPS)-tracked trajectory data several BEV energy consumption models have been proposed in the literature. Yao et al. used instantaneous speeds and accelerations as predictors to estimate BEV energy consumption rate [27]. In their subsequent work, battery state of charge (SOC) was also taken into account as the energy consumption rate was found to be negatively correlated with SOC [28]. Liu et al. studied the effects of road gradients on electricity consumption and found that the consumption increases almost linearly with the absolute gradient increases [29]. Wang et al. studied the impact of ambient temperature on BEV energy usage and used a third-order polynomial regression model to describe the relationship between energy efficiency and temperature [30]. Another commonly used predictor in energy consumption models is vehicle specific power (VSP) that can be gauged by vehicle speed and acceleration. For example, Alves et al. and Yao et al. developed hybrid regression models to estimate BEV energy consumption based on different levels of VSP [27], [31]. One important feature of BEVs is regenerative braking-when the vehicle decelerates the electric motor converts kinetic energy to electricity that can be stored in batteries. Researchers have not reached consensus on the energy efficiency of regenerative braking as it is a very complex process. Fiori et al. modeled regenerative energy as a function of deceleration levels in their BEV energy consumption model [32], while Yang et al. [33] and Genikomsakis and Mitrentsis [34] assumed that regenerative braking efficiency is linearly related to vehicle speed.

In summary, most of existing ecological and energy-efficient ACC strategies are formulated as optimization problems, using either global optimization models or local optimization models such as particle swarm optimization and model predictive control. The major drawbacks of optimization-based approaches are the complicity and computational intensity. Rule-based control strategies, on the other hand, have monopolized the production vehicle market because of its low computational demand, natural adaptability to onlineapplications, and reliability [35]. Moreover, the existing control strategies for BEVs focused on optimizing the speed profile of individual vehicles. In this study, a rule-based energy-efficient ACC system is proposed, considering electric, connected, and autonomous vehicles (e-CAV) in a mixed traffic stream with human-driven vehicles. The proposed ACC system is evaluated using the energy consumption model that is developed and calibrated based on the CAN bus data collected from a BEV.

The rest of the paper is organized as follows. Section II presents related work, including car following models for autonomous and human-driven vehicles and BEV energy consumption models. Section III presents the proposed rulebased energy-efficient ACC model and the BEV energy consumption model. Stability analysis is presented in Section IV. Section V evaluates the energy efficiency of proposed ACC model by simulating single-lane vehicle dynamics in a traffic stream with different percentages of e-CAVs. The conclusion is presented in Section VI.

II. RELATED WORK

A. Human Driver Car-Following Model

In the past decades, a number of car-following models have been introduced to simulate human driver behavior [36]-[37]. In particular, based on Gipps model [38], Treiber et al. proposed a human driver model named Intelligent Driver Model (IDM) [39]. Since IDM provides greater realism than most of the deterministic acceleration modeling frameworks [40], it is widely applied to investigate the impact of autonomous vehicles on traffic flow stability, fuel consumption, and emissions in traffic streams with mixed autonomous and human-driven vehicles [20], [21], [40]. Accordingly, IDM is used in this paper to simulate the human-driven vehicles. The IDM is formulated as follows:

$$a_{IDM}^{n} = a_{max} \left[1 - \left(\frac{\mathbf{v}_{\mathbf{n}}}{\mathbf{v}_{0}}\right)^{\delta} - \left(\frac{s^{*}}{\Delta x}\right)^{2} \right]$$
(1)
$$s^{*} = s_{0} + \mathbf{v}_{\mathbf{n}}T + \frac{\mathbf{v}_{\mathbf{n}}(\mathbf{v}_{n} - \mathbf{v}_{n-1})}{2}$$
(2)

$$s^{*} = s_{0} + v_{n}T + \frac{v_{n}(v_{n} - v_{n-1})}{2\sqrt{a_{max}b}}$$
(2)

where a_{IDM}^n is the acceleration of the following vehicle (m/s²); δ is the acceleration exponent; s_0 is the standstill distance between stopped vehicles (m); a_{max} is the maximum acceleration (m/s²); Δx is the spacing between the leading and the following vehicle (m); T is the desired time headway (s); v_0 is the maximum speed (m/s); v_n is the speed of the following vehicle (m/s); v_{n-1} is the speed of the leading vehicle (m/s); s^* is the desired spacing (m); and b is the desired deceleration (m/s²).

B. Adaptive Cruise Control and Cooperative Adaptive Cruise Control

In recent years, car-following models have evolved to describe the behavior of vehicles with advanced cruise controls, which take advantage of the sensing and communication technologies. Several rule-based ACC methods have been proposed in the literature (e.g. [7], [41]). As an extension of ACC, several Cooperative ACC (CACC) strategies have been proposed (e.g. [41]–[45]). In particular, the cruise controls proposed by Kesting et al. [45], Shladover et al. [41], and Van Arem et al. [46] are used to compare with the proposed Energy-Efficient Electric Driving Model (E³DM).

Kesting et al. [45] proposed an CACC based on IDM, called Enhanced-IDM, which inherited the parameters proposed by Treiber et al. [39]. The acceleration according to constantacceleration heuristic (CAH) is computed as follows:

$$a_{CAH}^{n} = \begin{cases} \frac{v_{n}^{2}\tilde{a}_{l}}{v_{n-1}^{2}-2\Delta x\tilde{a}_{l}} & \text{if } v_{n}(v_{n}-v_{n-1}) \leq -2\Delta x\tilde{a}_{l} \\ \tilde{a}_{l} - \frac{(v_{n}-v_{n-1})^{2}\Theta(v_{n}-v_{n-1})}{2\Delta x} & \text{otherwise} \end{cases}$$
(3)

where, a_{CAH}^n is the constant-acceleration heuristic acceleration of the following vehicle (m/s²); Θ is the Heaviside step function; a_{n-1} is the acceleration of the leading vehicle; and \tilde{a}_l is the effective acceleration used to avoid artefacts that may be caused by leading vehicles with higher acceleration capabilities, $\tilde{a}_l = \min(a_{n-1}, a_{max})$.

The Enhanced-IDM is formulated as follows:

$$a_{\text{Enhanced}-\text{IDM}}^{n} = \begin{cases} a_{IDM}^{n} & a_{IDM}^{n} \ge a_{CAH}^{n} \\ (1-c)a_{IDM}^{n} + c\left[a_{CAH}^{n} + btanh\left(\frac{a_{IDM}^{n} - a_{CAH}^{n}}{b}\right)\right] \text{ otherwise} \end{cases}$$

$$(4)$$

where, $a_{\text{Enhanced-IDM}}^n$ is the acceleration of the following vehicle equipped with Enhanced-IDM (m/s²); and *c* is the coolness factor.

A rule-based ACC, which is proprietary to Nissan and was described by Shladover et al. [41], is called Nissan-ACC. The simplified representations of the Nissan Model contains speed control and spacing control. In the speed control, the control law is:

$$v_e = v_n - v_0 \tag{5}$$

$$a_{sc} = bound(-0.4 \times v_e, a_{max}, b_{max}) \tag{6}$$

$$a_{Nissan-ACC}^{n} = a_{sc} \tag{7}$$

where $a_{Nissan-ACC}^{n}$ is the acceleration of the following vehicle equipped with Nissan-ACC (m/s²); b_{max} is the maximum deceleration (m/s²); a_{sc} is the acceleration by speed control (m/s²); and v_e is the speed error (m/s).

The function bound () is defined as bound $(x, x_{ub}, x_{lb}) = max(min(x, x_{ub}), x_{lb})$, where ub is the upper bound and lb is the lower bound. This function restricts the acceleration within the range between the maximum acceleration and deceleration.

In the spacing control, the speed control law also applies. In addition, in order to maintain a constant time headway between vehicles, the spacing control law requires:

$$s^* = T \times v_n \tag{8}$$

$$s_e = \Delta x - s^* \tag{9}$$

$$a_{Nissan-ACC}^{n} = bound(\dot{s} + 0.25 \times s_e, a_{sc}, b_{max}) \quad (10)$$

where \dot{s} is the acceleration adjustment parameter (m/s²).

When $v_{n-1} = 0$, $v_n = 0$ and $s_e = s_0$, $a_{Nissan_ACC}^n$ should equal to 0. Since the desired speed and maximum acceleration are larger than 0, we have:

$$a_{sc} = bound(0.4 \times v_0, a_{max}, b_{max}) > 0$$
 (11)

Since $a_{Nissan_ACC}^n = 0$ and $a_{sc} > 0$, $\dot{s} + 0.25 \times s_0$ should equal to 0. Therefore, the acceleration adjustment parameter (\dot{s}) can be derived as follows:

$$\dot{s} = -0.25 \times s_0 \tag{12}$$

As a result, the spacing control law is modified as follows:

$$s^* = T \times v_n + s_0 \tag{13}$$

$$s_e = \Delta x - s^* \tag{14}$$

$$a_{Nissan-ACC}^{n} = bound(0.25 \times s_e, a_{sc}, b_{max}) \quad (15)$$

The acceleration of the Van Arem model equipped e-CAVs at every decision point is calculated as:

$$a_{\text{Van Arem model}}^{n} = \min(a_d, k(v_0 - v_n))$$
(16)

$$a_{d} = \kappa_{a} a_{n-1} + \kappa_{v} (v_{n-1} - v_{n}) + \kappa_{d} (\Delta x - s^{*}) \quad (1/)$$

$$s^* = max\left(Tv_n, s_0, \frac{v_n}{2}\left(\frac{1}{d_p} - \frac{1}{d}\right)\right) \tag{18}$$

where, k_a , k_v , and k_d are constants; d_p and d are the deceleration capabilities of the leading and following vehicles, which are equal to b_{max} in this study; and k is the constant-speed error factor. Based on the recommendations of Van Arem et al. [46], k = 1, $k_a = 1$, $k_v = 0.58$, and $k_d = 0.1$.

In this paper, Enhanced-IDM, Nissan-ACC, and Van Arem model are applied to simulate the CAVs. The performance of these three models are compared with the proposed energyefficient ACC model in Section III.A.

C. BEV Energy Consumption Model

This section introduces two BEV energy consumption models that are representative of mainstream methods of estimating energy consumption and can be easily calibrated using the vehicle CAN bus data.

First, Yao's BEV energy consumption model is a multivariate regression model consisting of linear, quadratic, and cubic combinations of speed and acceleration [27]. The model was developed based on chassis dynamometer experiment data. The model parameters are calibrated for different vehicle modes— acceleration, deceleration, cruising and idling. Yao's model is described as follows:

$$ECR = \begin{cases} \sum_{i=0}^{3} \sum_{j=0}^{3} (\omega_{i,j} \times v^{i} \times a^{j}) & a > 0\\ \sum_{i=0}^{3} \sum_{j=0}^{3} (\beta_{i,j} \times v^{i} \times a^{j}) & a < 0\\ \sum_{i=0}^{3} (\theta_{i} \times v^{i}) & a = 0, v \neq 0\\ \hline ecr & a = 0, v = 0 \end{cases}$$
(19)

where *ECR* is the energy consumption rate (W); v is the instantaneous speed (m/s); a is the instantaneous acceleration (m/s²); $\omega_{i,j}$, $\beta_{i,j}$, θ_i are the coefficients; and \overline{ecr} is the average energy consumption (W) in idling mode.

Second, Yang et al. proposed a BEV energy consumption model, considering vehicle specific power and auxiliary load, as well as the energy efficiency of regenerative braking [33]. When instantaneous acceleration $a \ge 0$, the energy consumption rate is calculated as:

$$ECR = \frac{m}{\eta_{te}\eta_e} VSP + P_{accessory} , \ a \ge 0$$
(20)

where *m* is the vehicle mass (kg); η_{te} is the BEV's transmission efficiency; η_e is the driving efficiency of the battery; *VSP* is the vehicle specific power (W/kg); and *Paccessory* is the electricity consumed by accessories (W).

When vehicle decelerates, a portion of kinetic energy is recovered and restored in batteries due to the regenerative braking feature of motors. The regenerative braking factor k in Eq. 18 indicates the percentage of braking energy that can be recovered, which changes with speed. Note that, in practice kis influenced by many factors, such as speed, deceleration, and braking force. In Yang et al. model, k is defined as a function of speed, as in Eq. 22.:

$$ECR = km\eta_{te}\eta_m VSP + P_{accessory} \quad a < 0 \tag{21}$$

$$k = \begin{cases} 0.5 \times \frac{1}{5}, \ \nu < 5\\ 0.5 + 0.3 \times \frac{\nu - 5}{20}, \ \nu \ge 5 \end{cases}$$
(22)

where η_m is the motor efficiency.

III. METHODOLOGY

Existing energy-efficient BEV cruise control strategies are optimization-based and do not consider mixed traffic consisting of autonomous and human-driven vehicles. In this paper, a rulebased ACC, named Energy-Efficient Electric Driving Model (E³DM) is proposed for BEVs in mixed traffic stream. A singlelane car-following scenario is considered to derive the properties of the proposed ACC and conduct stability analysis. Such scenario can be used to implement the concept of dedicated lanes, where one or more lanes are designated for autonomous vehicles to attain greater throughput gains in mixed traffic situations [47]. In addition, the following assumptions are made regarding e-CAVs:

- 1. Only e-CAVs are capable of communicating with other e-CAVs through vehicle-to-vehicle communication.
- 2. On-board sensors measure vehicle speed, gap (relative distance), and relative speed with respect to the preceding vehicle.

A. Energy-efficient Electric Driving Model

Electric connected and autonomous vehicle technologies are likely to be gradually implemented over time. Thus, e-CAVs and human-driven vehicles are likely to share the roads in the near future. An example of a platoon containing e-CAVs and human-driven vehicles is shown in Fig. 1. The human-driven vehicles and e-CAVs are represented by green vehicles and yellow vehicles, respectively. According to the aforementioned assumptions, information can be shared among e-CAVs, and an e-CAV can only measure the gap and speed of the humandriven vehicle immediately preceding it. Therefore, the number of human-driven vehicles between e-CAVs is unknown. As a result, human-driven vehicles separate the platoon into several vehicle sets. Human-driven vehicle is always the first vehicle in a vehicle set. That is, the location (N) of a human-driven vehicle is assigned as 1. The locations of e-CAVs in the vehicle sets are labeled from 2 to M. Note that the vehicle set definition is used to determine the location of e-CAV and design the E³DM strategy. A human-driven vehicle can still follow an e-CAV in the platoon, according to the proper car-following rules.



Fig. 1. A platoon with e-CAVs (yellow) and human-driven vehicles (green)

In the context of conventional gasoline vehicles, the environmental benefit has shown to vary with the position and penetration of CAVs in the string of mixed traffic [12]. Thus, it is necessary to consider the location of e-CAV when designing the adaptive cruise controller. Moreover, Fiori et al. [32] showed that marginal increment of energy regeneration 4

efficiency decreases exponentially with the increase of deceleration. To achieve high energy efficiency of regenerative braking, the ACC of e-CAVs should maintain a small deceleration for a long duration instead of applying a large deceleration for a short duration. Consequently, the acceleration of a following vehicle equipped with E³DM is determined by the following equation:

$$a_{E^{3}DM}^{n} = a_{max} \times \left[1 - \left(\frac{v_{n}}{v_{0}}\right)^{4}\right] - \frac{a_{max} \times \left[1 - \left(\frac{v_{n}}{v_{0}}\right)^{4}\right] + \frac{v_{n}^{2} - v_{n-1}^{2}}{2\Delta x}}{e^{\frac{\Delta x}{s_{0} + v_{n} \times T + \frac{v_{n}(v_{n} - v_{n-1})}{2\beta\sqrt{a_{max}b}} - 1 - \beta^{2} \times \frac{v_{n}}{v_{0}} \times \left[\frac{(v_{0} - v_{n})}{v_{0}}\right]^{Y}}}$$
(23)

where $a_{E^3DM}^n$ is the acceleration of the following vehicle that is equipped with E³DM (m/s²); γ is a parameter indicating the preceding vehicle type; and β is a parameter related to the position of e-CAV in the vehicle set.

In order to stabilize the string of vehicle in a mixed traffic stream quickly, the e-CAVs located closer to the human-driven vehicles have to react more dramatically to attenuate the disturbance from human-driven vehicles in front of them. Therefore, the parameter (β) of E³DM is determined as follows:

$$\beta = \frac{1}{\ln(N)} + 1 \tag{24}$$

where *N* is the location of an e-CAV in a vehicle set, $N \ge 2$. The parameter (γ) of E³DM is determined as follows:

$$\gamma = \begin{cases} 1, & \text{if follows an e-CAV} \\ 0.5, & else \end{cases}$$
(25)

According to Eq.23 to Eq.25, e-CAVs with E³DM accelerate with $a_{max} \left[1 - \left(\frac{v_n}{v_0}\right)^4 \right]$ when Δx is large, which is the same as IDM [39]. An e-CAV will brake while the speed of the e-CAV is greater than the leading vehicle speed and Δx is less than the desired spacing. When there is no speed difference between the leading and following vehicle, an e-CAV's acceleration increases with the ratio of Δx to the desired spacing. According to the characteristics of exponential function, the jerk of e-CAV, which represents the changing rate of e-CAV's acceleration, decreases with the ratio of Δx to the desired spacing. Moreover, an e-CAV adjusts its speed-dependent spacing based on the location of the e-CAV in a vehicle set and type of leading vehicle. Consequently, the e-CAVs equipped with E³DM can achieve smooth acceleration and efficient regenerative braking.

Several properties of E³DM are discussed as follows, considering special cases:

First, when an e-CAV is cruising (i.e. $a_{E^3DM}^n = 0, v_n - v_{n-1} = 0$), the speed-dependent spacing Δx between the preceding and the following vehicle is given by:

$$\Delta x = \left(1 + \beta^2 \times \frac{\nu_n}{\nu_0} \times \left[\frac{(\nu_0 - \nu_n)}{\nu_0}\right]^{\gamma}\right) (s_0 + \nu_n \times T)$$
(26)

In particular, when the vehicle is stopped or reached the maximum speed (i.e. $v_n = 0$ or $v_n = v_0$), speed-dependent spacing Δx equals to the desired spacing, that is, $\Delta x = s_0 + v_n \times T$. The desired spacing is composed of a standstill distance

 (s_0) and an additional speed-dependent term, $v_n T$. When an e-CAV follows other e-CAVs, β decreases with the location (N) and the speed-dependent spacing Δx of the e-CAV is closer to the desired spacing. Note that in equilibrium traffic of arbitrary density, the speed-dependent spacing Δx of both Enhanced-IDM and Nissan-ACC models are the desired spacing; while the speed-dependent spacing Δx of E³DM would only equal to the desired spacing when v_n is equal to 0 or the maximum speed.

Second, when the traffic density is low (i.e. Δx is large), e-CAVs will accelerate to the maximum speed. When $\Delta x \rightarrow \infty$, $\frac{v_n^2 - v_{n-1}^2}{2\Delta w}$ is close to 0 and:

$$e^{\left(\frac{\Delta x}{s_0+v_n\times T+\frac{v_n(v_n-v_{n-1})}{2\beta\sqrt{ab}}-1-\beta^2\times\frac{v_n}{v_0}\times\left[\frac{(v_0-v_n)}{v_0}\right]^{\gamma}\right)}$$
 is

As a result, the acceleration of E^3DM is approximately equal to the maximum acceleration, $a_{E^3DM}^n \approx a_{max}$. After the speed reaches the maximum speed, acceleration of E^3DM is 0.

Third, when e-CAV is following a slower vehicle or approaching a stopped vehicle (i.e. $v_n - v_{n-1} > 0$) with a limited spacing ($\Delta x \rightarrow s_0 + v_0 \times T$), the acceleration equation is given by:

$$a_{E^{3}DM}^{n} \rightarrow a_{max} \times \left[1 - \left(\frac{v_{n}}{v_{0}}\right)^{4}\right] - \frac{a_{max} \times \left[1 - \left(\frac{v_{n}}{v_{0}}\right) + \frac{v_{n-1}}{2(s_{0}+v_{n}\times T)} \right]}{exp\left(-\beta^{2} \times \frac{v_{n}}{v_{0}} \times \left[\frac{(v_{0}-v_{n})}{v_{0}}\right]^{Y}\right)}$$
(27)

Specially, when an e-CAV with the maximum speed approaches a stopped vehicle (i.e. $v_n = v_0, v_{n-1} = 0$), the maximum kinematic deceleration is applied to avoid a collision, as follows:

$$a_{E^{3}DM}^{n} = -\frac{v_{0}^{2}}{2(s_{0}+v_{0}\times T)}$$
(28)

close to infinity.

Fourth, when the spacing is much smaller than the desired spacing $(\Delta x \ll s_0 + v_0 \times T)$ and there is no significant speed differences $(v_n - v_{n-1} \approx 0)$, the acceleration is determined as follows:

$$a_{E^{3}DM}^{n} \approx a_{max} \times \left[1 - \left(\frac{v_{n}}{v_{0}}\right)^{4}\right] - \frac{a_{max} \times \left[1 - \left(\frac{v_{n}}{v_{0}}\right)^{*}\right]}{e^{\frac{\Delta x}{s_{0} + v_{n} \times T + \frac{v_{n}(v_{n} - v_{n-1})}{2\beta\sqrt{ab}} - 1 - \beta^{2} \times \frac{v_{n}}{v_{0}} \times \left[\frac{(v_{0} - v_{n})}{v_{0}}\right]^{Y}}}$$
(29)

Specially, when $\Delta x \rightarrow 0$, Eq. 29 reduces to

$$a_{E^{3}DM}^{n} \approx a_{max} \times \left[1 - \left(\frac{v_{n}}{v_{0}}\right)^{4}\right] \times \left(1 - \frac{1}{e^{-1 - \beta^{2} \times \frac{v_{n}}{v_{0}} \times \left[\frac{(v_{0} - v_{n})}{v_{0}}\right]^{Y}}}\right) (30)$$

Since $\beta^2 \times \frac{v_n}{v_0} \times \left[\frac{(v_0 - v_n)}{v_0}\right]^{\gamma}$ is always greater than 0, $e^{-1 - \beta^2 \times \frac{v_n}{v_0} \times \left[\frac{(v_0 - v_n)}{v_0}\right]^{\gamma}}$ is always less than 1. The following vehicle will adjust its deceleration according to its speed.

In the numerical experiment presented in Section IV, a traffic stream containing both e-CAVs and human-driven vehicles is simulated. IDM is used to describe the driver behavior of the human-driven vehicles. The e-CAVs are simulated by using, Enhanced-IDM, Nissan-ACC, Van Arem model, and E³DM. The acceleration model parameters of the human-driven

TABLE I							
PARAMETERS OF THE ACCELERATION MODELS							
Parameters	IDM	Enhanced- IDM	Nissan- ACC	Van Arem	E ³ DM		
Maximum speed v ₀ (m/s)	33.3	33.3	33.3	33.3	33.3		
Free acceleration exponent δ	4	4		—	—		
Desired time headway T (s)	1.5	1.5	1.5	1.5	1.5		
Standstill distance $s_0(m)$	2	2	2	2	2		
Maximum acceleration a_{max} (m/s ²)	1.4	1.4	1.4	1.4	1.4		
Desired deceleration b (m/s ²)	2	2	_		2		
Maximum deceleration b _{max} (m/s ²)	6	6	6	6	6		
Coolness factor c	_	0.99	_		—		

vehicles and e-CAVs are based on the parameters of IDM proposed by Kesting et al. [45], as listed in TABLE I.

B. Proposed Energy Consumption Model

Most of the existing energy consumption models were developed based on the data collected in heterogeneous driving conditions. For example, Yao et al. and Fiori et al. used data collected from chassis dynamometer experiments [27], [32], Zhang and Yao collected data in low-speed urban traffic conditions [28]. Alves et al. collected data under constant ambient temperature [31]. By using real-world driving data collected on urban roads and highways over an extended time period, an energy consumption model that considers vehicle specific power, regenerative braking, auxiliary load, and ambient temperature is proposed to estimate BEV on-road energy consumption.

VSP provides an estimate of the battery output power per mass unit for getting over the resistance encountered by a BEV [31], [48]. It is calculated using vehicle dynamics in Eq. 31. Energy consumption is heterogeneous at different VSP levels [31]. Negative values of VSP indicate that due to regenerative braking some electricity is converted from kinetic energy and restored in the batteries. Therefore, the proposed energy consumption model is calibrated based on VSP levels (>0, =0, or <0) to account for regenerative braking.

$$VSP = v(1.1a + C_{rr}) + C_{aero}v^3$$
 (31)

where C_{rr} is the rolling resistance coefficient (N/kg); and C_{aero} is the aerodynamics drag coefficient (N s²/m² kg).

Auxiliary systems, especially heating and air conditioning systems, consume considerable electricity [32], [49]. The relationship between average auxiliary load and ambient temperature for each trip is illustrated in Fig. 2. The data were collected using an on-board diagnostics (OBD-II) logger and a GPS device installed on a passenger BEV (2013 Nissan Leaf) for 6 months in real-world driving conditions. Since the data were collected from November 2016 to April 2017 in Iowa, USA, the ambient temperature range only covers -17 °C to 23 °C. Thus, part of the curve (i.e. ambient temperature from -17 °C to 23 °C) is calibrated using the data. The R-squared is 0.46. c_0 and c_1 are 6.71 and -0.0894, respectively. Yuksel and Michalek [50], Wang et al. [30], and Liu et al. [50] explored the U-shaped relationship between BEV energy consumption and ambient temperature, where the energy consumption is lowest at 20 °C ~ 25 °C and increases as the temperature becomes colder or hotter, with similar trends. In this study, a symmetric equation is assumed to estimate the auxiliary load from 23 °C to 40 °C, as shown in Eq. 32:

$$\ln P_{aux} = \begin{cases} c_0 + c_1 t, & if - 17 \le t \le 23\\ c_0 + c_1(46 - t), & if 23 < t \le 40 \end{cases}$$
(32)

where t is ambient temperature (°C); c_0 , and c_1 are coefficients.



Fig. 2. Relationship between auxiliary load and ambient temperatures

Considering the VSP and auxiliary load, a hybrid linear regression model is proposed to estimate BEV energy consumption:

$$ECR = h_0 + h_1 VSP + h_2 P_{aux} \tag{33}$$

where h_0 , h_1 , h_2 are the parameters.

The model parameters are calibrated at different VSP levels to consider regenerative braking. Moreover, unlike internal combustion engine vehicles that are more fuel efficient on highways, BEVs driving at high speeds consume more electricity per distance unit than at low speeds [31], [32], [51], [52]. Therefore, the model parameters are also calibrated at different instantaneous speed levels. The threshold of 12.5 m/s (or 45 km/h) is used to separate high speed driving from low speed driving.

Note that the impact of road gradient on energy consumption is not considered. The data service provider, FleetCarma, did not provide road gradient information. Also, Iowa is located in the Interior Plains of central North America, where gradient has relatively weaker impacts on energy consumption.

IV. STABILITY ANALYSIS

The linear stability method is widely applied to analyze the stabilization performance of car-following models [53]–[59]. In this section, we applied the linear stability method to study the

stability of the E³DM model. The general form of timecontinuous car-following models is

$$\ddot{x}_n(t+\tau) = f(v_n(t), s_n(t), \Delta v_n(t))$$
(34)

where τ is the total time delay caused by vehicle-to-vehicle (V2V) communication, sensor, and vehicle actuator.

The stability condition is calculated as [60]

Stability
$$=\frac{1}{2}f_{v}^{2} - f_{s} + f_{v}f_{\Delta v} + \frac{\tau}{2}f_{v}f_{s} > 0$$
 (35)

where
$$f_v = \frac{\partial f}{\partial v_n}\Big|_{(v_e, s_e, 0)} \le 0$$
, $f_{\Delta v} = \frac{\partial f}{\partial \Delta v_n}\Big|_{(v_e, s_e, 0)} \le 0$, and $f_s = \frac{\partial f}{\partial s_n}\Big|_{(v_e, s_e, 0)} \ge 0$.

Based on Eq.23, the partial derivatives of E^3DM at equilibrium can be calculated as follows:

$$f_{s} = \frac{a_{max} \left[1 - \left(\frac{v_{e}}{v_{0}}\right)^{4}\right]}{exp \left(-\beta^{2} \frac{v_{e}}{v_{0}} \left[\frac{(v_{0} - v_{e})}{v_{0}}\right]^{Y}\right)} \left(1 + \frac{a_{max} \left[1 - \left(\frac{v_{e}}{v_{0}}\right)^{4}\right]}{2\beta \sqrt{a_{max}b}}\right) (37)$$

$$f_{v} = -\frac{a_{max} \left[1 - \left(\frac{v_{e}}{v_{0}}\right)^{4}\right] \left(\frac{(s_{0} + v_{e}T)T}{\left(\beta^{2} \frac{v_{e}}{v_{0}} \left[\frac{(v_{0} - v_{e})}{v_{0}}\right]^{Y}\right)^{2}} - \frac{\beta^{2} \gamma v_{e} \left[\frac{(v_{0} - v_{e})}{v_{0}}\right]^{Y}}{v_{0} (v_{0} - v_{e})} + \frac{\beta^{2} \left[\frac{(v_{0} - v_{e})}{v_{0}}\right]^{Y}}{v_{0}}\right)}{exp \left(-\beta^{2} \frac{v_{e}}{v_{0}} \left[\frac{(v_{0} - v_{e})}{v_{0}}\right]^{Y}\right)}{\left(1 + \frac{1}{exp \left(-\beta^{2} \frac{v_{e}}{v_{0}} \left[\frac{(v_{0} - v_{e})}{v_{0}}\right]^{Y}\right)}\right)} (38)$$

The sensor delay is between 0.1 and 0.3 seconds, the actuator lag is in the order of 0.1-0.2 seconds [61]–[63], and the communication delay is between 0.1 and 0.4 seconds [64]. Therefore, the range of the total time delay is 0.3-0.9 seconds. The stability of a platoon of E³DM-equipped vehicles can be evaluated based on Eq. 35 by varying the time delay between 0 and 1.5 s. Fig.3 presents the stability of E³DM-equipped vehicle considering different time delays. The parameters, shown in TABLE I, are used to plot the stability against equilibrium speeds. Fig.3 shows that using the parameters listed in TABLE



Fig. 3. Stability of E^3DM -equipped vehicle with different time delays (τ)

V. RESULTS

A. Performance of the BEV Energy Consumption Models

The parameters of the proposed BEV energy consumption model are calibrated using the vehicle data collected from a 2013 Nissan Leaf. C_{rr} equals 0.0981 N/kg and C_{aero} equals 0.0002 N s²/m² kg for the 2013 Nissan Leaf [32], [52], [65]. This vehicle was primarily used on urban roads and major highways. The data fields include timestamp, GPS location, TABLE II

PARAMETERS OF THE ELECTRICITY CONSUMPTION MODEL FOR THE 2013 NISSAN LEAF BEV

VSP	v	h_0	h_1	<i>h</i> ₂	C ₀	c_1
. 0	<12.5	3.22E+03	1.16E+03	2.15E+00		
>0	≥12.5	8.43E+03	7.57E+02	2.60E+00		
0	<12.5	6.10E+02	_	1.19E+00	6.715.00	0.045.03
=0	≥12.5	_	_	_	6.71E+00 -8.94E-0	
<0	<12.5	7.20E+02	5.58E+02	2.10E+00		
	≥12.5	8.12E+03	5.94E+02	2.57E+00		

vehicle speed, ambient temperature, battery current and voltage, and battery SOC. Energy consumption is the product of battery voltage and current. Acceleration is the derivative of vehicle speeds. During the 6-month data collection period, 512 valid trips were recorded. The calibrated model parameters are listed in TABLE II.

Moreover, Yao's model and Yang et al.'s model described in Section II.C are calibrated and validated using the same data. The trip level energy consumptions estimated by the proposed model, Yao's model and Yang et al.'s model are compared with the actual energy consumption for the same trip. As shown in Fig. 4, the proposed model can estimate trip level energy consumptions fairly close to the actual values and outperforms Yao's and Yang et al.'s models.

The Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are calculated and compared for these three models, as listed in TABLE III.

$$MAPE = \frac{1}{p} \sum_{i=1}^{p} \left| \frac{EC_{a,i} - EC_{e,i}}{EC_{a,i}} \right| \times 100\%$$
(39)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (EC_{a,i} - EC_{e,i})^2}{p}}$$
(40)

where,

 $EC_{e,i}$ is the estimated energy consumption of trip *i* (kWh); $EC_{a,i}$ is the actual energy consumption of trip *i* (kWh); and *p* is the total number of trips in the dataset (i.e. 512).

TABLE III					
VALIDATION METRICS FOR BEV ENERGY CONSUMPTION MODELS					
Energy Consumption Models	MAPE	RMSE			
Proposed model	13.3%	0.296 kWh			
Yao's model	19.5%	0.495 kWh			
Yang et al.'s model	16.7%	0.511 kWh			

Among these models, the proposed model has the lowest MAPE and RMSE. Consequently, the proposed model is used to estimate energy consumption of BEVs.



Fig. 4. Validation of the electricity consumption models for the 2013 Nissan Leaf BEV.

The numerical experiments are performed by simulating a traffic stream with 1000 vehicles on a 7.45-mile long single lane road. As the platoon size on urban arterials usually ranges from 14 to 81 vehicles [66], [67], when the number of lane is less than 4, the traffic stream is divided into several platoons with sizes ranging from 14 to 81 vehicles. The lead vehicle of each platoon is assumed to follow the Urban Dynamometer Driving Schedule (UDDS), as shown in Fig. 5. In each platoon, the initial spacing and time headway are the desired spacing and desired time headway, respectively. Various scenarios are simulated, considering traffic streams with all e-CAVs, all human driven vehicles, or a mixed of the two. In the case of a mixed traffic stream, different market penetrations of e-CAVs are simulated. The car following behavior of human driven vehicles is assumed to follow IDM. For e-CAVs, different adaptive cruise control strategies are tested, including Enhanced-IDM, Nissan-ACC, Van Arem model, and E³DM.



Fig. 5. Urban Dynamometer Driving Schedule (UDDS) [68]

C. Homogenous Traffic Stream

To demonstrate the impact of e-CAVs on individual vehicle and platoon-level energy consumption, one platoon consisting of 16 BEVs is examined. Fig. 6 compares the energy consumption of each following vehicle in the traffic streams with all human driven vehicles (i.e. Manual) or all CAVs (i.e. Enhanced-IDM, Nissan-ACC, Van Arem model and E³DM). In the homogeneous traffic stream, the e-CAVs equipped with E³DM and Nissan-ACC, consume less energy than the human driven vehicles. Enhanced-IDM equipped e-CAVs, however, consume more energy than the human driven vehicles. The reason is that Enhanced-IDM provides smoother deceleration which may reduce the regenerative energy of BEVs. E³DM outperforms Enhanced-IDM, Van Arem model, and Nissan-ACC in terms of energy consumption. E³DM reduces energy consumption of the entire platoon by approximately 5.2%, compared to the all-manual case. Moreover, the average travel times of IDM, Enhanced-IDM, Nissan-ACC, Van Arem model,



and E^3DM are 22.7, 22.6, 22.7, 22.5, and 22.8 minutes, respectively. E^3DM slightly increases travel time compared to the human-driven fleet. However, the increase in travel time is not significant.

The reason for the better performance of E³DM is to apply small decelerations for long durations instead of large decelerations for short durations, as shown in Fig. 7. Thus, E³DM is able to keep high regenerative braking efficiency for longer duration compared to Nissan-ACC, Van Arem model and Enhanced-IDM. In addition, E³DM also provides smoother deceleration and acceleration compared to Nissan-ACC, Van Arem model and Enhanced-IDM. As shown in Fig. 7, with ACC and CACC, e-CAVs towards the end of the platoon tend to reach smooth deceleration and acceleration. E³DM stabilizes the string much faster than Nissan-ACC, Van Arem model and Enhanced-IDM.

D. Mixed Traffic Stream

To examine the impact of e-CAV location on the total energy consumption a platoon with one e-CAV and 15 human driven BEVs is selected. The location of the e-CAV varies from immediately following the lead vehicle (i.e. a human driven vehicle that follows the UDDS drive cycle) to the end of the platoon. As shown in Fig. 8, Nissan-ACC and E³DM strategies reduce fleet-level energy consumption with only one equipped vehicle. For E³DM, an e- CAV towards the front of the platoon has larger impacts on the fleet-level energy efficiency, compared to the case when the e-CAV is towards the end of the platoon. One E³DM-equipped e-CAV may result in up to 2.4% reduction in total energy consumption if placed at the front of the platoon. However, with Nissan-ACC and Enhanced-IDM, there is no obvious relationship between the location of e-CAV and total energy consumption.

Furthermore, the impact of different market penetration of e-CAVs on energy consumption is examined by simulating traffic



streams with mixed e-CAVs and human-driven vehicles. Two

scenarios are considered.



Fig. 8. Impact of E-CAV Location on Total Energy Consumption

First, to examine the impact of e-CAV market penetration on the total energy consumption, 500 simulations are generated for each ACC strategy and each market penetration rate, by randomly assigning e-CAV locations in the platoon. The mean energy consumption reduction of the entire fleet, compared to the all human driven BEVs scenario, is shown in Fig. 9. The higher market penetration of e-CAVs may not result in better energy efficiency of the entire fleet. With E³DM, the highest fleet-level energy efficiency is achieved when the market penetration of e-CAVs is 20%. The major reason is that a higher percentage of e-CAVs in the traffic stream results in faster string stabilization, which decreases the regenerative energy.



Fig. 9. Impact of e-CAV Market Penetration on Total Energy Consumption

Second, to examine the synergistic effect of CAV and BEV technologies, mixed traffic streams with e-CAV, human-driven BEV (m-BEV) and human-driven internal-combustion engine vehicle (m-ICEV) are simulated. The fuel consumption of m-ICEV is computed by applying the VT-Micro model calibrated by Lu et al. [69] and then converted to electricty [70]. The impact of different market shares of e-CAV, m-BEV and m-ICEV on energy consumption reduction of entire fleet is investigated, as shown in Fig.10. The marginal improvement in energy efficiency decreases when the market penetration of BEV, including e-CAVs and m-BEVs, exceed 20%. Moreover, the larger the market penetration ratio of e-CAV to m-BEV is, the faster the marginal improvement in energy efficiency reaches the turn point.



Fig. 10. Impact of Different Market Penetration of e-CAV, Human-driven BEV and Human-driven ICEV on Total Energy Consumption

VI. CONCLUSIONS

This paper proposed an Energy-Efficient Electric Driving Model, namely E^3DM , for adaptive cruise control of e-CAVs in traffic streams mixed with human driven vehicles. Considering the location of an e-CAV relative to other e-CAVs and human driven vehicles, E^3DM is able to maintain high efficiency of regenerative braking and provide smooth deceleration and acceleration by adjusting the spacing between the leading and the following vehicles. Moreover, a power-based energy consumption model is proposed to estimate the on-road energy consumption for battery electric vehicles. Using the proposed BEV energy consumption model, the impact of E^3DM on energy consumption of individual vehicles and the entire fleet is investigated.

By simulating single-lane vehicle dynamics in mixed traffic stream with different market penetration rates of e-CAVs, the result shows that e-CAVs equipped with E³DM and Nissan-ACC consume less energy than the human driven vehicles. E³DM outperforms Enhanced-IDM, Van Arem model, and Nissan-ACC in terms of energy efficiency. In addition, higher market penetration of e-CAVs may not result in better energy efficiency of the entire fleet. With E³DM, the highest energy efficiency is achieved when the market penetration of e-CAVs is 20%. This is because that more e-CAVs in the traffic stream results in faster string stabilization and decreases the regenerative energy. Considering mixed traffic streams with BEVs (e-CAVs and m-BEVs) and ICEVs (m-ICEV), the marginal improvement in energy efficiency decreases when the market penetration of BEV, including e-CAVs and m-BEVs, exceed 20%. Moreover, the larger the market penetration ratio of e-CAV to m-BEV is, the faster the marginal improvement in energy efficiency reaches the turn point.

The present paper has the following limitations. First, the lane-changing behavior is ignored. An energy-efficient lane-changing strategy should be designed for e-CAVs and implemented in tandem with E³DM to simulate real world driving behavior. Second, since the lead vehicle in each platoon is assumed to follow UDDS, the simulation is not able to represent different traffic congestion levels. In the future,

different traffic states should be simulated to investigate the impact of E³DM under different congestion levels.

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