Abstract—This study proposes a new car-following (CF) model incorporating the effects of lateral gap and roadside device communication to capture the characteristics of electric vehicle (EV) traffic stream in Transportation-Cyber-Physical-Systems (T-CPS). Stability of the proposed CF model is analyzed using the perturbation method. Furthermore, the energy consumption (EC) of EV traffic stream is investigated based on the drive cycles produced by the proposed model. Numerical experiments analyze three scenarios: start, stop, and evolution processes for the scenarios of no lateral gap, lateral gap, and lateral gap with roadside device, respectively. Results demonstrate that: (i) The non-lane-discipline-based model is more responsive than the lane-discipline-based model; (ii) The non-lane-discipline-based model for EV traffic stream consumes more energy in the acceleration phase and recuperates more energy in the deceleration phase compared with the lane-discipline-based model; (iii) The non-lane-discipline-based model with roadside device communication for EV traffic stream consumes more energy in the acceleration phase and recuperates more energy in the deceleration phase than the model without roadside devices.

Index Terms—Car-following Model, Electric Vehicle, Roadside Device, Non-lane Discipline

I. INTRODUCTION
A. Cyber-Physical-Systems: Context and Issues

CYBER-PHYSICAL-SYSTEMS (CPS) refers to a system of collaborating cyber elements controlling physical entities [1]. Transportation-Cyber-Physical-Systems (T-CPS) are envisioned to achieve full coordination of transportation systems via communication, interaction and adaption between the transportation cyber systems and transportation physical systems [2]. In this study, we consider the T-CPS involving vehicle-to-infrastructure (V2I)-based communications. In it, equipped vehicles are able to send information to or receive information from other equipped vehicles via communication through roadside devices [3-5]. A roadside device can be deployed permanently at a fixed location, or can be temporarily located in the vicinity of a traffic accident or roadway construction. It provides communication capabilities for passing vehicles. In T-CPS, a roadside unit can communicate with vehicles to exchange information, such as safety and traffic flow characteristics. Hence, a T-CPS can aid in avoiding traffic accidents and smoothening traffic flow. This study seeks to leverage roadside device-based communications under V2I to analyze its impact on traffic stability and energy consumption (EC) for an electric vehicle (EV) traffic stream, by proposing a new car-following (CF) model.

B. Traffic Flow Models

Traffic flow models aim to capture and replicate the characteristics of vehicle dynamics in traffic. They can be classified as microscopic, mesoscopic or macroscopic models [6-8]. Microscopic models use variables like velocity, position, and acceleration to capture local interactions between vehicles. They include car-following (CF) models or cellular automation (CA) models. CF models describe the interactions with preceding vehicles in the same lane based on the notion that a driver controls a vehicle in response to stimuli from the preceding vehicle. They include the Gazis-Herman-Rothery (GHR) model [9] and its variants [6-8], Gipps model [10], optimal velocity (OV) model [11] and its variants [12-20], intelligent driver model [21], fuzzy-logic model [22], as well as psycho-physical models [23]. CA models address traffic flow dynamics using a stochastic discrete approach, such as Rule 184 model [24], Bilham-Middleton-Levine model [25], as well as Nagel-Schreckenberg model [26] and its variants [7].

Macroscopic models use variables such as density, volume, and average speed to measure traffic flow properties. They can be further classified into kinematic, dynamical, anisotropic, and lattice hydrodynamic models. Kinematic models describe traffic flow as a continuum fluid flow. The Lighthill-Whitham-Richards (LWR) model [27, 28] relies on the assumption that the movement of vehicles satisfies the equilibrium speed-density relationship, which does not cover the characteristics of traffic flow under the non-equilibrium state [29]. It has led to the development of a few variants of the LWR model to address this issue. Dynamical models are represented by the
Payne-Whitham (PW) model [30, 31], which captures the stop-and-go wave in time and space. Later, several variants of the PW model were proposed, with an emphasis on the momentum equation [32, 33]. Anisotropic models focus on the anisotropic characteristics of traffic [34]. Lattice hydrodynamic models introduce the concept of a discrete lattice to derive the modified Korteweg de Vries (mKdV) equation to characterize the density wave profiles [35].

The aforementioned traffic flow models are lane-discipline-based models, where all vehicles follow the lane discipline, and move in the middle of the lane without lateral gaps [36]. However, in many countries, such as China and India, lanes may not be clearly demarcated on a road though multiple vehicles travel in parallel. Therefore, lane-discipline-based models cannot be readily applied to this scenario. This motivates the need to study the impact of lateral gaps on the behavior of the “following” vehicles. Unlike lane-discipline-based traffic flow models, a few non-lane-discipline-based microscopic traffic flow models have been proposed in recent years, with a focus on the lateral gap [37, 38]. However, these non-lane-discipline-based models have not been addressed under T-CPS. This motivates the study of the effects of V2I communications on traffic flow in a non-lane-discipline-based road system.

### C. Energy Consumption Model

Compared to internal combustion vehicles, EVs have better energy efficiency and no tailpipe emissions. This has led to increased EV utilization to enhance energy efficiency, promote environment sustainability and improve community livability, especially in countries with densely populated urban areas such as China and India [38, 39]. According to a recent study [40], the EV market share may be about 7% of the light-duty vehicles by 2020, due to improvements in EV technologies and the increasing public acceptance. This motivates the consideration of an EV traffic stream in this study, and an analysis of the associated EC. However, existing studies focus on the EC on a road with lane discipline [41]. When an EV travels on a road without lane discipline, its speed profile and acceleration/deceleration pattern would be affected by the lateral gaps with vehicles in its vicinity, resulting in a different EC pattern. Therefore, it is necessary to investigate the EC of EVs under the non-lane-discipline environment.

The primary study objective is to develop a new cooperative CF model to capture the characteristics of an EV traffic stream with roadside device communication on a non-lane-discipline-based road system. The study contributions are as follows. First, based on the definition of a parameter that characterizes the effect of lateral gap, a new cooperative CF model is proposed which incorporates the effects of lateral gap and the information of ambient vehicles dynamics through roadside device communication. Further, the stability of the proposed model is analyzed using the perturbation method to obtain the stability condition. Theoretical analyses show that the proposed model is more generalized than the FVD model [12] and the NLBCF model [37]. Second, an energy consumption model for EVs is presented by considering power loss and power recuperation. Third, the effects of lateral gap and roadside device communication on EV energy consumption are investigated by analyzing drive cycles produced by the proposed CF model. Results from numerical experiments suggest that the responsiveness and energy efficiency of the proposed CF model are better than those of the FVD and NLBCF models under identical conditions.

The remainder of the paper is organized as follows: Section II proposes a new CF model that considers the effects of lateral gap and roadside device communication, and performs the stability analysis. Section III presents an EC model that includes the power loss and power recuperation. Section IV discusses the numerical experiments and results. The final section provides some concluding comments.

### II. Derivation of CF Model

#### A. Lane-discipline-based CF model

Fig. 1 shows the scenario related to the lane-discipline-based CF model. In Fig. 1, vehicle $i$ follows vehicle $i+1$ in the same lane with space headway $\Delta x_i$ and velocity difference $\Delta v_i$, where $\Delta x_i = x_{i+1}(t) - x_i(t)$ and $\Delta v_i = v_{i+1}(t) - v_i(t)$. $x_i(t)$ and $v_i(t)$ represent position and velocity of vehicle $i$ at time $t$, respectively. To address this scenario, Jiang et al. [12] propose a FVD model, as follows:

$$ a_i(t) = k[V(\Delta x_i(t)) - v_i(t)] + \lambda \Delta v_i(t), $$

where $x_i(t)$, $v_i(t)$, and $a_i(t)$ represent position (in m), velocity (in m/s) and acceleration (in m/s²) of vehicle $i$ at time $t$, respectively. $\Delta x_i(t) \equiv x_{i+1}(t) - x_i(t)$ and $\Delta v_i(t) \equiv v_{i+1}(t) - v_i(t)$ are the space headway and velocity difference between the lead vehicle $i+1$ and the following vehicle $i$, respectively. $k > 0, k \in \mathbb{R}$ and $\lambda \geq 0, \lambda \in \mathbb{R}$ are the sensitivity coefficients.

$$ V(\Delta x_i(t)) \text{ is the optimal velocity function defined in [12]:} $$

$$ V(\Delta x_i(t)) = V_1 + V_2 \tanh[C_1(\Delta x_i - l_e) - C_2], $$

where $V_1, V_2, C_1, C_2$ are constant parameters, $l_e$ is vehicle length, and $\tanh(\cdot)$ is the hyperbolic tangent function.

#### B. Non-lane-discipline-based CF model

Fig. 2 shows the scenario related to the non-lane-discipline-based CF model. In Fig. 2, vehicle $i$ follows vehicle $i+1$ in the same lane with space headway $\Delta x_{i+1}$ and velocity difference $\Delta v_{i+1}$, where $\Delta x_{i+1} = x_{i+2}(t) - x_{i+1}(t)$ and $\Delta v_{i+1} = v_{i+2}(t) - v_{i+1}(t)$. $x_{i+1}(t)$ and $v_{i+1}(t)$ represent position and velocity of vehicle $i+1$ at time $t$, respectively. To address this scenario, Jiang et al. [12] propose a FVD model, as follows:

$$ a_i(t) = k[V(\Delta x_{i+1}(t)) - v_{i+1}(t)] + \lambda \Delta v_{i+1}(t), $$

where $x_{i+1}(t)$, $v_{i+1}(t)$, and $a_i(t)$ represent position (in m), velocity (in m/s) and acceleration (in m/s²) of vehicle $i$ at time $t$, respectively. $\Delta x_{i+1}(t) \equiv x_{i+2}(t) - x_{i+1}(t)$ and $\Delta v_{i+1}(t) \equiv v_{i+2}(t) - v_{i+1}(t)$ are the space headway and velocity difference between the lead vehicle $i+2$ and the following vehicle $i+1$, respectively.

$k > 0, k \in \mathbb{R}$ and $\lambda \geq 0, \lambda \in \mathbb{R}$ are the sensitivity coefficients. $V(\Delta x_{i+1}(t)) \text{ is the optimal velocity function defined in [12]:}$

$$ V(\Delta x_{i+1}(t)) = V_1 + V_2 \tanh[C_1(\Delta x_{i+1} - l_e) - C_2], $$

where $V_1, V_2, C_1, C_2$ are constant parameters, $l_e$ is vehicle length, and $\tanh(\cdot)$ is the hyperbolic tangent function.
By considering the effect of lateral gap on one side on the CF behavior, as shown in Fig. 2, Jin et al. [37] propose a NLBCF model, as follows:

\[ a_i(t) = k[V(\Delta x_{i,i+1}(t), \Delta x_{i,i+2}(t)) - v_i(t)] + \lambda G(\Delta v_{i,i+1}(t), \Delta v_{i,i+2}(t)), \] (3)

where \( \Delta x_{i,i+1} \equiv x_{i+1} - x_i \), and \( \Delta v_{i,i+1} \equiv v_{i+1} - v_i \) are the longitudinal space headway and the velocity difference between the lead vehicle \( i + 1 \) and the following vehicle \( i \) at time \( t \), respectively. \( \Delta x_{i,i+2} \equiv x_{i+2} - x_i \), and \( \Delta v_{i,i+2} \equiv v_{i+2} - v_i \) are the longitudinal space headway and the velocity difference between the lead vehicle \( i + 2 \) and the following vehicle \( i \) at time \( t \), respectively.

The functions \( V(\Delta x_{i,i+1}(t), \Delta x_{i,i+2}(t)) \) and \( G(\Delta v_{i,i+1}(t), \Delta v_{i,i+2}(t)) \) are defined as follows [37]:

\[ V(\Delta x_{i,i+1}(t), \Delta x_{i,i+2}(t)) = V((1 - q_i)\Delta x_{i,i+1}(t) + q_i \Delta x_{i,i+2}(t)), \] (4)

\[ G(\Delta v_{i,i+1}(t), \Delta v_{i,i+2}(t)) = (1 - q_i)\Delta v_{i,i+1}(t) + q_i \Delta v_{i,i+2}(t), \] (5)

where \( q_i \equiv L_{g_{i,i+1}}/L_{g_{\max}} \) is a parameter measuring the effect of lateral gap. \( L_{g_{i,i+1}} \) is the lateral gap between vehicle \( i + 1 \) and vehicle \( i \), and \( L_{g_{\max}} \) is the maximum lateral gap.

C. Non-lane-discipline-based CF model with roadside device

Roadside devices in a T-CPS can receive and store relevant traffic flow information, such as speed and position, from the equipped vehicles within communication range. Similarly, roadside devices can also provide information to equipped vehicles in their vicinity, as feedback to assist driving.

Fig. 3 shows a non-lane-discipline-based CF scenario with a roadside device. To formulate this scenario, we assume that the communication range of the roadside device is \( R \), and \( N \) vehicles travel on the road. If vehicle \( i \) is within the range of the roadside device, namely \( x_i < R \), we define the parameter \( p_i = 1 - \sqrt{\frac{\Delta x_i^2 + (L_{g_{\max}} - L_{g_{i,i+1}})^2}{\Delta x_i^2 + (L_{g_{\max}} - L_{g_{i,i+1}})^2}} \) to denote the intensity of the communication signal. The smaller the value of \( \Delta x_i^2 \), the closer is the vehicle to the roadside device, and the higher is its probability to receive information from the roadside device successfully. Also, we define the parameter \( q_i = \frac{L_{g_{i,i+1}}}{L_{g_{\max}}} \) to denote the effects of lateral gap. In addition, we define \( \mu_i = true \) to imply that communication has been established successfully between the roadside device and the vehicle \( i \), and \( \mu_i = false \) to indicate communication failure. In this study, \( \mu_i \) is determined as follows: Generate a random number using uniform distribution between 0 and 1, and compare it with \( p_i \); if the random number is no more than \( p_i \), then \( \mu_i = true \); otherwise \( \mu_i = false \). Hence, we obtain the following model:

\[ a_i(t) = k[V(\Delta x_{i,g}(t), \Delta x_{i,t}(t)) - v_i(t)] + \lambda G(\Delta v_{i,g}(t), \Delta v_{i,t}(t)). \] (6)

\[ V(\Delta x_{i,g}(t), \Delta x_{i,t}(t)) = V((1 - q_i)\sum_{j=1}^{m} \Delta x_{i,j} + q_i \sum_{\sigma=2}^{n} \Delta x_{i,\sigma}), \] (7)

\[ G(\Delta v_{i,g}(t), \Delta v_{i,t}(t)) = (1 - q_i)\sum_{j=1}^{m} \Delta v_{i,j} + q_i \sum_{\sigma=2}^{n} \Delta v_{i,\sigma}, \] (8)

\[ V(\Delta x) = V_1 + V_2 \tanh(C_1(\Delta x - \Delta_c) - C_2). \] (9)

Else

\[ a_i(t) = k[V(\Delta x_{i,g}(t), \Delta x_{i,t}(t)) - v_i(t)] + \lambda G(\Delta v_{i,g}(t), \Delta v_{i,t}(t)). \] (10)

\[ V(\Delta x_{i,g}(t), \Delta x_{i,t}(t)) = V((1 - q_i)\Delta x_{i+1} + q_i \Delta x_{i+2}), \] (11)

\[ G(\Delta v_{i,g}(t), \Delta v_{i,t}(t)) = (1 - q_i)\Delta v_{i+1} + q_i \Delta v_{i+2}. \] (12)

where \( m \) and \( n \) are the maximum vehicle ID with and without lateral gap within the range, respectively. We label this model as the non-lane-discipline-roadside-based (NLDR) CF model hereafter.

Remark 1: Eqs. (6)-(12) imply that: (i) If there is no lateral gap, namely \( q_i = 0 \), the proposed NLDR model is similar to the lane-discipline-based FVD model [12]; and (ii) If there is just one vehicle with lateral gap and one vehicle without lateral gap within the range of roadside communication, the NLDR model is reduced to the NLBCF model [37]. Hence, the lane-discipline-based FVD model and NLBCF model are special cases of the proposed NLDR model.

D. Stability Analysis

We use the perturbation method to perform the stability analysis of the proposed NLDR model starting with the following assumption.

Assumption I: The initial state of the traffic flow is a uniform equilibrium flow characterized by an identical equilibrium optimal velocity \( V(h, 2h) \).

Theorem I: The uniform traffic flow in Eq. (6) is unstable if:

\[ \tau > \frac{16[(1 - q_i)\sum_{j=1}^{m} j^2 + q_i \sum_{\sigma=2}^{n} \sigma^2]}{[(1 - q_i)(m + 1)^2 + q_i n(n + 2)]^2 V'[V'(h, 2h)]}, \] (13)

where \( V' = V'(h, 2h) = \frac{\partial V(\Delta x)}{\partial \Delta x} \mid \Delta x = (1 + q_i)h \).

Proof: We perform the linear stability analysis under the scenario of \( \mu_i = true \) as shown in Eq. (6). Using the asymmetric forward difference, we re-write Eq.(6) as follows:

\[ x_i(t + 2\tau) = x_i(t + \tau) + \tau V[(1 - q_i)\sum_{j=1}^{m} \Delta x_{i,j} + q_i \sum_{\sigma=2}^{n} \Delta x_{i,\sigma}] + \lambda \tau[(1 - q_i)\sum_{j=1}^{m} \Delta v_{i,j} + q_i \sum_{\sigma=2}^{n} \Delta v_{i,\sigma}], \] (14)
Following Assumption 1, the solution of the vehicles’ positions under steady flow is:

\[ x_i^0(t) = h_i + V(h, 2h)t \]  

(15)

where \( V(h, 2h) = V[(1 - q_i)h + q_i2h] \) is the optimal velocity under uniform traffic flow, \( h \) is the steady headway, and \( x_i^0(t) \) is the position of the \( i \)th vehicle at steady state.

Adding a small disturbance \( y_i(t) \) to the steady-state solution \( x_i^0(t) \), i.e.,

\[ y_i(t) = x_i(t) - x_i^0(t) \]  

(16)

Substituting Eq. (16) into Eq. (14) and linearizing the resulting equation using the Taylor expansion, it follows that:

\[ y_i(t + 2\tau) = y_i(t + \tau) + \tau V'[1(1 - q_i) \sum_{j=1,3, \ldots, m} \Delta y_{i+j} + q_i \sum_{\sigma=2,4, \ldots, n} \Delta x_{i+\sigma}(t + \tau) - \Delta x_{i+\sigma}(t)] + q_i \sum_{\sigma=2,4, \ldots, n} [\Delta x_{i+\sigma}(t + \tau) - \Delta x_{i+\sigma}(t)]] \]  

(17)

Set \( y_i(t) \) in the Fourier models, i.e., \( y_i(t) = A \exp(ik_i + zt) \), where \( k \) is the wave number \((0 \leq k \leq \pi)\), \( i \) is the vehicle number, \( z = \omega t \), and \( \omega \) is the wave angular frequency. Substituting it in Eq. (17), the resulting equation is:

\[ e^{2\tau z} = e^{\tau z} + \tau V'[1(1 - q_i) \sum_{j=1,3, \ldots, m} (e^{ik_j} - 1) + q_i \sum_{\sigma=2,4, \ldots, n} ((e^{ik_j} - 1)) + \tau V'[1(1 - q_i) \sum_{j=1,3, \ldots, m} [j(k_j) + \frac{q_j}{2}(ik_j)^2] + q_i \sum_{\sigma=2,4, \ldots, n} [\sigma(k_i) + \frac{q_i^2}{2}(ik_i)^2] + \tau V'[1(1 - q_i) \sum_{j=1,3, \ldots, m} j + q_i \sum_{\sigma=2,4, \ldots, n} \sigma] \]  

(18)

Let \( z = z_1(ik) + z_2(ik)^2 + \cdots \); substitute it into Eq. (18) and expand it to the second term of \((ik)\). We have:

\[ 1 + 2\tau z_1(ik) + (2\tau z_2 + 2\tau z_1^2)(ik)^2 = 1 + \tau z_1(ik) + \tau z_2 + \frac{1}{2} \tau^2 z_1^2 (ik)^2 + \tau V'[1(1 - q_i) \sum_{j=1,3, \ldots, m} j(k_j) + \frac{q_i}{2}(ik_j)^2] + q_i \sum_{\sigma=2,4, \ldots, n} [\sigma(k_i) + \frac{q_i^2}{2}(ik_i)^2] + \tau V'[1(1 - q_i) \sum_{j=1,3, \ldots, m} j + q_i \sum_{\sigma=2,4, \ldots, n} \sigma] \]  

(19)

It follows from Eq. (19) that:

\[ \left\{ \begin{aligned} z_1 &= \frac{V'}{4}[1(1 - q_i) \sum_{j=1,3, \ldots, m} j + q_i n(n + 2) + q_i n(n + 2) + 4] \sum_{\sigma=2,4, \ldots, n} \frac{(\lambda m + 1)^2}{4} (1 - q_i) + \frac{\lambda n(n + 2)}{4} \left( 3(1 - q_i) \frac{(m + 1)^2}{4} + q_i n(n + 2) + 4 \right)] \]  

(20)

Thus, the neutral stability condition is given by:

\[ \tau = \frac{16(1 - q_i) \sum_{j=1,3, \ldots, m} j + q_i n(n + 2)}{[(1 - q_i)(m + 1)^2 + q_i n(n + 2)]^2(3V^2 - 2\lambda)} \]  

(21)

Based on the method of small disturbance with long wavelengths, we can conclude that the uniform traffic flow in Eq. (6) is unstable if the condition in Eq. (13) holds.

Using a similar method, we can obtain the unstable condition for the scenario of \( \mu_i = \text{false} \) as shown in Eq. (10), in terms of Eq. (13) with \( m = 1, n = 2 \), as follows:

\[ \tau > \frac{1 + 3q_i}{(1 + q_i)^2(3V^2 - 2\lambda)} \]  

(22)

Remark 2: Based on Eqs. (13) and (22), we can verify the effectiveness of the stability analysis. Eq. (21) is the neutral stability condition of the FVD model in [12] with the condition \( m = 0, n = 2, q_i = 0 \); and Eq. (21) is the neutral stability condition of the NLBCF model in [37] with the condition \( m = 1, n = 2 \).

III. ENERGY CONSUMPTION MODEL

This section investigates the effects of roadside device communication and lateral gap on the EC of the EV traffic stream. The EC model considers both the power loss and power recuperation, as an EV can recuperate a part of the kinetic energy lost during the deceleration phase to recharge the battery. The power loss is the power consumed by the travel resistance, motor, and ancillaries. The power recuperation is the power re-charged by the regenerative braking system (RBS) during the braking phase.

A. Power Loss \( P_i \)

To formulate the EV power loss, the required tractive effort can be described as follows [42, 43]:

\[ F = Ma + \alpha v^2 + f_r Mg + \frac{bv}{R_t} \]  

(23)

where \( F \) is the tractive effort (in N); \( M \) is the vehicle mass (in kg); \( a \) is acceleration (in m/s\(^2\)); \( v \) is the vehicle velocity (in m/s); \( \alpha = 0.5 \rho C_D A_f \) is an aerodynamic resistance constant determined by air density \( \rho \) (in kg/m\(^3\)), frontal area of the vehicle \( A_f \) (in m\(^2\)) and coefficient of drag \( C_D \); \( f_r \) is rolling resistance constant and \( g \) is the gravity acceleration \((g = 9.81 m/s^2)\); \( b \) is the bearings’ damping coefficient and \( R_t \) is the effective EV tire radius.

On the other hand, the tractive effort \( F \) is generated by the torque of the motor, which is simplified as a product of armature constant \( (K_a) \), magnetic flux \( (\phi_d) \), and current \( (I) \):

\[ F = \frac{J}{R_t} = \frac{K_a \cdot \phi_d \cdot I}{R_t} \]  

(24)

where \( J \) (in Nm) is the torque; \( K_a \) is the armature constant; \( \phi_d \) (in weber) is the magnetic flux; and \( I \) (in A) is the current.

For simplicity, by defining \( K = K_a \cdot \phi_d \), we obtain:

\[ F = \frac{K \cdot I}{R_t} \]  

(25)

In addition, part of the electricity energy of EV may be consumed by some vehicle ancillaries. Thus, the ancillary power loss is given by:

\[ P_a = P_{ac} + P_{bm} + P_{el} + P_{au} \]  

(26)

where \( P_{ac}, P_{bm}, P_{el}, P_{au} \) are ECs of air-conditioner, battery management, external lights and audio, respectively. Note that all of the above ancillary ECs are independent of velocity.
The regenerative braking power is as follows [42, 43]:

\[ P_{r} = \eta \cdot Mav \]  

(28)

where \( \eta \) is the efficiency of the generator.

Based on the above discussion, an EV’s instantaneous power can be measured by:

\[ P = P_{1} + P_{r} \]  

(29)

IV. NUMERICAL EXPERIMENTS

The values of parameters used in the CF and EC models for the simulation-based analysis are summarized in Tables I and II [12, 37, 38, 42], respectively. To analyze the effect of the roadside device on the EC of EV traffic stream under the non-lane discipline, we compare three models, i.e., lane-discipline-based FVD model, non-lane-discipline-based NLBCF model, and NLDR model, under the start, stop and evolution processes, respectively. The initial condition is as follows. Eleven EVs are distributed in a road with an equal space headway of 7.4m. The 11th vehicle is the lead vehicle.

A. Start process

The start process is set up as follows. Initially, the traffic signal is red, and all EVs wait behind the signal with the uniform space headway. At time \( t = 0 \) s, the signal changes to green and the EVs start to move. The lead vehicle starts to accelerate until it reaches the optimal speed. Other vehicles follow the lead vehicle by accelerating. Eventually, all vehicles travel at the same optimal velocity. For comparison, the velocity, acceleration, and power consumption profiles of the FVD, NLBCF, and NLDR models are shown in Figs. 4, 5 and 6, respectively.

Fig. 4 demonstrates that the NLDR model is the most responsive one, followed by the non-lane-discipline-based NLBCF and lane-discipline-based FVD models. The responsiveness of the CF models is defined as the time taken by the velocity of a vehicle to increase from zero to the maximum optimal value or reduce from this optimal value to zero. It indicates that the roadside device can increase the responsiveness of velocity. Here, the responsiveness of the EV traffic stream implies that vehicles react by accelerating/decelerating quickly. Fig. 5 demonstrates that the magnitude of acceleration for FVD model is the largest, followed by NLBCF model, and then the NLDR model. Specifically, the acceleration in the NLDR model is no more than \( 3 \text{m/s}^2 \), which is less than those of the FVD and NLBCF models. It shows that roadside device communication helps to reduce the magnitude of acceleration. On the other hand, vehicles in the FVD and NLBCF models appear to accelerate one by one with some response time. Vehicles in the NLDR model accelerate with a much quicker response time.

Based on Eqs. (27) and (28), the power consumption is closely relevant to the velocity and acceleration profiles of EVs. Fig. 6 shows that there are three stages in the power consumption profile for all models. In the first stage, the power consumption increases sharply due to the increase of velocity and acceleration. In the second stage, the power consumption decreases because acceleration is reduced though the velocity keeps increasing. In the third stage, acceleration becomes zero, and the power consumption becomes stable mainly for the ancillary power usage. Table 2 illustrates that vehicles in the FVD model consume the least energy, and vehicles in the NLDR model consume the most energy. This is because vehicles in the NLDR model with roadside device accelerate earlier and thus travel longer distances, and therefore consume more energy than those in the FVD and NLBCF models. Hence, roadside device communication under non-lane discipline increases the EC in the start process. In addition, Fig. 6 shows that the power consumption starts from a non-zero value, which is due to the ancillary power loss being a constant value.
B. Stop process

The stop process is as follows. Initially, the traffic signal is green, and all EVs travel at the same constant velocity. At time $t = 0$, the signal changes to red and EVs begin to slow down. The lead vehicle begins to decelerate until it reaches a full stop. Other vehicles follow the lead vehicle in decelerating. Finally, all vehicles fully stop behind the signal. For comparison, the velocity, deceleration, and power consumption profiles of the FVD, NLBCF, and NLDR models are illustrated in Figs. 7, 8 and 9, respectively.

Fig. 7 shows that the NLDR model is the most responsive one, followed by the NLBCF model, and then the FVD model. This pattern is similar to the start process, which indicates that roadside device communication can increase the responsiveness of velocity. Fig. 8 shows that the magnitude of the deceleration for the NLDR model is the largest, followed by the NLBCF model, and then the FVD model. This pattern is opposite to that of the start process. Specifically, the maximum deceleration in the NLDR model exceeds $-4\text{m/s}^2$, which is more than that of the FVD and NLBCF models. It implies that roadside device communication increases the magnitude of deceleration. In Fig. 9, the value of power consumption is negative, which implies that the battery is re-charged through the RBS during the deceleration phase. Similar to the start process, there are three stages in the power consumption profile. In the first stage, the power recuperation increases sharply due to the decrease of velocity and deceleration. In the second stage, the magnitude of battery recuperation decreases, but still recharges the battery. In the third stage, the velocity and deceleration are zero, and the power consumption becomes stable only for the ancillary power usage. Table 2 indicates that vehicles in the NLDR model recuperate the most energy, and vehicles in the FVD model recuperate the least energy.

C. Evolution process

This section discusses the evolution process by combining the start and stop processes. The lead vehicle first starts to move from the zero velocity to free flow velocity, and then decelerates to a full stop. Other vehicles follow the lead vehicle according to the FVD, NLBCF, and NLDR models. For comparison, Figs. 10-12 show the velocity, acceleration, and power consumption profiles, respectively.

Fig. 10 demonstrates that the NLDR model is the most responsive one, followed by the NLBCF model, and then the FVD model, which is consistent with the observations in the start and stop processes. Fig. 11 demonstrates that the response time of the FVD model is the largest, and the response time of the NLDR model is the least. This implies that in the NLDR model, vehicles accelerate/decelerate more quickly, and this is the reason the proposed NLDR model takes the least time to complete the whole evolution process, followed by the NLBCF model, and then the FVD model. In Fig. 12, the EC can be divided into two parts: (i) power consumption during the acceleration phase, and (ii) power recuperation during the deceleration phase. Overall, vehicles in the FVD model consume the least energy in the first part, and recuperate the least energy in the second part. By contrast, vehicles in the proposed NLDR model consume the most energy in the first part, but also recuperate the most energy in the second part.

The power consumption profile of the FVD, NLBCF and NLDR models in the evolution process are shown in Fig. 13. Fig. 13 illustrates that the roadside device communication under non-lane discipline in a T-CPS environment consumes more energy. To verify this point, the values of total energy consumption of the three CF models are shown in Table III. Table 3 shows that the total energy consumption of the FVD, NLBCF, and NLDR models are $3.2031 \times 10^6$, $3.1612 \times 10^6$ and $3.1453 \times 10^6$, respectively. Note that we compare the total energy consumption of the nine following EVs in the traffic stream for comparison purpose, because the 10th and the 11th vehicles form the boundary in the NLDR model.

Based on Sections IV.A-IV.C discussed heretofore, the main findings can be summarized as follows. First, the non-lane-discipline-based model for EV traffic stream consumes more energy in the acceleration phase and recuperates more energy in the deceleration phase compared with the lane-discipline-based model. This is because vehicles under the non-lane discipline react more quickly than under the lane discipline. It can represent the scenario that drivers operate their vehicles more aggressively on a road without lane discipline. Second, the non-lane-discipline-based model with roadside device communication for EV traffic stream consumes more energy in the acceleration phase and recuperates more energy in the deceleration phase than the model without a roadside device. This is because vehicles in this scenario can receive information from the surrounding vehicles through the roadside device via V2I communications in advance, to aid driving. Consequently, a driver can react more quickly and is more prepared to accelerate/decelerate via V2I communications. Hence, the evolution process in the proposed NLDR model is the fastest, followed by the NLBCF model, and then the FVD model.

V. CONCLUSION

This study analyzes the EC of an EV traffic stream based on CF models with roadside device communication. To evaluate the effects of roadside device communication, three CF models, FVD model without lateral gap, NLBCF model with one-sided lateral gap, and the proposed NLDR model with
roadside device, are investigated. An EC model consisting of both power loss and power recuperation due to EV characteristics is used to analyze the energy consumption. Numerical experiments are performed to illustrate the effects of roadside device communication on the velocity, acceleration, and EC profiles in three different traffic flow scenarios.

Simulation results show that EV traffic stream consumes more energy during the start and stop processes under the non-lane-discipline-based road system although it can recuperate more energy back to the battery. This is because the EVs are more responsive, resulting in an earlier acceleration that enables them to recuperate more energy during the start and stop processes. During the evolution process, EVs with a capability for communication to the roadside device reduce EC due to increased energy recuperation. The study findings provide insights that it is beneficial to incorporate roadside device communication into a traffic flow model to reduce the EC, especially for EVs. In addition, the study findings motivate the analysis of the EC in mixed traffic situations.

REFERENCES


Fig. 4 Velocity profiles in start process: (a) FVD model; (b) NLBCF model; (c) NLDR model.

Fig. 5 Acceleration profiles in start process: (a) FVD model; (b) NLBCF model; (c) NLDR model.

Fig. 6 Power consumption profiles in start process: (a) FVD model; (b) NLBCF model; (c) NLDR model.

Fig. 7 Velocity profiles in stop process: (a) FVD model; (b) NLBCF model; (c) NLDR model.
Fig. 8 Deceleration profiles in stop process: (a) FVD model; (b) NLBCF model; (c) NLDR model.

Fig. 9 Power consumption profiles in stop process: (a) FVD model; (b) NLBCF model; (c) NLDR model.

Fig. 10 Velocity profiles in evolution process: (a) FVD model; (b) NLBCF model; (c) NLDR model.

Fig. 11 Acceleration profiles in evolution process: (a) FVD model; (b) NLBCF model; (c) NLDR model.
Fig. 12 Power consumption profiles in evolution process: (a) FVD model; (b) NLBCF model; (c) NLDR model.


Yongfu Li (M’16) received the Ph.D. degree in Control Theory and Control Engineering from Chongqing University, Chongqing, China, in 2012. From April 2014, he is working as a Postdoc Research Associate in NEXTRANS Center, Purdue University. He is currently an Associate Professor of Control Science and Engineering with Chongqing University of Posts and Telecommunications. His research interests include intelligent transportation systems, connected and autonomous vehicles, and control theory. Dr. Li was the recipients of both Outstanding Dissertation and Young Scientific and Technological Talent of Chongqing in 2014.

Li Zhang received his B.S. degree in Electrical Engineering and Automation from Chongqing University of Posts and Telecommunications, Chongqing, China, in 2014. He is currently working toward the M.S. degree in Control Science and Engineering with Chongqing University of Posts and Telecommunications, Chongqing, China. His research interests include intelligent transportation systems (ITS), traffic flow model and control theory. Mr. Zhang was the recipients of the National Scholarship in 2015 and the First Prize of Huawei Scholarship in 2016.

Hong Zheng received his Ph.D. degree in Civil Engineering from the University of Arizona, Arizona, U.S.A., in 2009. He is currently a Postdoc Research Associate in NEXTRANS Center, Purdue University. Before he joined NEXTRANS, he was a Research Assistant Professor in Department of Civil Engineering & Engineering Mechanics, University of Arizona. His research interests include electric vehicle, network design, and system optimization.

Xiaozheng(Sean) He received his Ph.D. degree in Civil Engineering from the University of Minnesota, Twin Cities, U.S.A., in 2010. He is currently an Assistant Professor in the Department of Civil and Environmental Engineering at Rensselaer Polytechnic Institute, Troy, NY, USA. His research interests include equilibration modeling, information network analysis, and infrastructure network reliability.

Srinivas Peeta received the Ph. D degree in Civil Engineering from University of Texas at Austin, U.S.A., in 1994. He is currently the Jack and Kay Hockema Professor at Purdue University and the Director of NEXTRANS Center. His research interests include intelligent transportation systems (ITS), operations research, and computational intelligence techniques. He serves on the Editorial Advisory Boards of the journals Transp. Res. Part B. He serves as area editor for NETS. He has previously served as Chair of the Transportation Network Modeling Committee of the Transportation Research Board of the National Academies. He is also a member of IFAC Technical Committee on Transportation Systems.

Taixiong Zheng received the Ph.D degree in Mechanical Engineering from Chongqing University, Chongqing, China, in 2003. He is currently a Professor of Control Science and Engineering with Chongqing University of Posts and Telecommunications, Chongqing, China. His research interests include engine control and vehicle active safe control.

Yinguo Li received the Ph. D degree in Mechanical Control from Chongqing University, Chongqing, China, in 1996. He is currently a Professor and the President with Chongqing University of Posts and Telecommunications, Chongqing, China. He is also the Director of the Center for Automotive Electronics and Embedded System Engineering. His research interests include automotive electronics, intelligent transportation systems (ITS), and engine control.