Research Article

Integrated-Hybrid Framework for Connected and Autonomous Vehicles Microscopic Traffic Flow Modelling

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In this study, a novel traffic flow modeling framework is proposed considering the impact of driving system and vehicle mechanical behavior as two different units on the traffic flow. To precisely model the behavior of Connected and Autonomous (CA) vehicles, three submodels are proposed as a novel microscopic traffic flow framework, named Integrated-Hybrid (IH) model. Focusing on the realization of the car following behavior of CA vehicles, the driving system (vehicle control system) and the vehicle mechanical system are modeled separately and linked by throttle and brake actuators model. The IH model constitutes the key part of the Full Velocity Difference (FVD) model considering the mechanical capability of vehicles and dynamic collision avoidance strategies to ensure the safety of following distance between two consecutive vehicles. Linear stability conditions are derived for each model and developing methodology for each submodel is discussed. Our simulations revealed that the IH model successfully generates velocity and acceleration profiles during car following maneuvers and throttle angle/brake information in connected vehicles environment can effectively improve traffic flow stability. The vehicles’ departure and arrival process while passing through a signal-lane with a traffic light considering the anticipation driving behavior and throttle angle/brake information of direct leading vehicle was explored. Our numerical results demonstrated that the IH model can capture the velocity fluctuations, delay times, and kinematic waves efficiently in traffic flow.

1. Introduction

Autonomous and Connected Vehicles (CAVs) have attracted increasing attention due to unique features of intelligent driving and Vehicle-to-Everything (V2X) communication technologies in the process of improving the safety, convenience, and efficiency of drivers [1–9]. During the last few years, CAV technologies have been accompanied by tremendous investments poured into startups from both public and private sectors to bring the idea of the CAVs to fruition [10]. Despite tremendous investments in CAVs technologies and numerous studies performed in this field [2, 11–29], the information associated with the behavior of autonomous vehicle prototypes that are recently on the market or under improvement is mainly unavailable. Therefore, researchers are still considering the features of the human-driving vehicle to model the behavior of CAVs at microscopic level. To fill this gap, a comprehensive modelling framework needs to be provided from a microscopic aspect view to be appropriate for the phase transition of CA vehicles utilizing the same road network as human-driving vehicles. Up to now, an enormous number of classical traffic models for human driving vehicles have been proposed through two categories (i.e., microscopic and macroscopic)
to explore empirical traffic phenomena in different levels of details required for network analysis. In particular, the Lighthill–Whitham–Richards (LWR) model [30, 31] and related continuum macroscopic traffic flow models [32–38]), as well as car following models [39–43], were firstly introduced by Pipes [44] in microscopic traffic flow model. Among all presented classical models, some car-following models such as desired measure, safety distance, and optimal velocity models have been modified and developed to describe traffic flow for CA vehicles. These models, their modified version, advantages, and limitations are summarized in Table 1. Helly [50] proposed the first desired measure model by assuming that each driver reaches the desired velocity and headway. To study the AVs behavior in traffic flow, Kern [52] proposed Three-Traffic-Phase ACC (TPACC) model based on the well-known assumption of Helly’s model in the framework of the three-phase traffic theory. The TPACC model was applied to simulate the features of CAVs in mixed traffic flow to capture the nucleation nature of real traffic breakdown [51, 53, 54]. The nucleation nature of real traffic breakdown is a random perturbation with a larger amplitude than critical one that does not decay through time and leads to traffic breakdown [53]. In the TPACC model, vehicles can reduce the possibility of traffic breakdown at the bottleneck in the mixed traffic flow involving human driving vehicles and CAVs compared to that CAVs modeled by the classical approaches [54]. Treiber et al. [47] proposed one of the most favored desired measures models for human driving traffic flow called Intelligent Driver Model (IDM) by considering both desired velocity and desired headway. Li et al. [45] used the IDM model to simulate car following behavior of CAVs, while Schakel et al. [46] exerted a minimization over the interaction and free-flow terms based on Helly’s model to propose a modified version of the IDM model for exploring CAVs traffic flow stability. The fundamental equilibrium diagram of the modified version of the IDM model [46] varies from a smooth topped-off shape to a triangular shape due to the separation of free-flow and interaction terms. Milanés and Shladover [65] implemented an adapted version of the IDM model on five vehicles to evaluate its response in real traffic conditions. They reported that the adopted IDM model caused a smooth car-following behavior, but with the prolonged response and significant clearance headway variations. Therefore, the IDM model was not successful to capture the main characteristics of CAVs. Collision avoidance models were firstly proposed by Kometani and Sasaki [55] using the assumption that the following vehicle attempts to keep sufficient distance from the leading vehicle instead of considering the velocity of leading vehicle. Safety distance models were reported to be too conservative compared to other types of car-following models because keeping an unnecessary large headway distance between two consecutive vehicles leads to capacity reduction of road networks, mainly at high velocities [56, 57]. To avoid unnecessary large headway between two consecutive vehicles while considering unpredictable behavior of leading vehicles, and to maintain an optimal balance among safe and efficient driving, Li et al. [45] introduced a collision avoidance headway. The numerical simulation results revealed that the proposed collision avoidance headway avoided unnecessary large headway between two consecutive vehicles and provided a good balance between safe driving behavior and efficient driving behavior for CAVs. The safety distance models have been criticized for concentrating only on the minimum requested car-following headway for modeling CAVs’ driving behavior.

Zhao et al. [41] constructed a two-dimensional vehicular movement model based on optimal control to study driving behavior (i.e., turning the steering wheel and pushing the brake or throttle pedals) of HD vehicles at intersections. The results provided a new insight into the future implementation of signal control strategies.

By hypothesizing the fact that each vehicle possesses an optimal (safe) velocity that depends on the distance from the leading vehicle, Bando et al. [58] represented the first optimal velocity (OV) model to overcome high acceleration and unrealistic declaration observed in previous classical models and revealed the relation between individual human driving behavior at microscopic level and the aggregate traffic flow at macroscopic level. Several researchers [59, 60, 66–68] developed the OV model to depict CAVs’ driving behavior based on the headway and velocity information of downstream vehicle with the aid of V2X communication in order to enhance local stability of traffic flow and reduce shock waves. However, unrealistic decelerations and high accelerations still occurred in traffic flow during the simulation, similar to the classical OV model. To overcome unrealistic decelerations and high accelerations of the OV model, both negative and positive velocity differences between two consecutive vehicles have been considered in the full velocity difference (FVD) model proposed by Jiang et al. [61]. Numerical simulations indicated that the FVD model had better agreement with the field data than the OV model, and unrealistic decelerations and high accelerations did not occur in traffic flow. Sun et al. [33] developed a classical FVD model for CAVs by incorporating the driving memory (feedback) effect. The numerical simulations have been conducted in different traffic scenarios (three regular scenarios of stop-and-go, approaching, and circular road) to explore model performance [69]. Results showed that the developed model performed better at intelligent driving modelling for CAVs than OV, FVD models in terms of good vehicle dynamics and string stability. Saifuzzaman and Zheng [62] compiled a list of human driving characteristics incorporated into classical microscopic models. Some of them (e.g., context sensitivity, desired velocity, desired space headway, and desired time headway, anticipation) are applicable for microscopic traffic flow modelling of CAVs. It is clear that the efficiency of CAVs is different based on the type of vehicles, and each commuter sets their personalized trade-offs when commuting with AVs [70]. Such differences lead to various intelligent driving systems requiring their associated car-following models for AV-incorporated traffic.

To the best knowledge of the authors, however, kinematics-based car-following models made substantial contributions to traffic flow modelling, but there are still some contradictions and conceptual weaknesses in their capability
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of describing the car following behavior in traffic flow. Besides, the aforementioned models are not developed based on kinematic theories for active particles, while vehicles are active particles whose mechanical properties play an essential role in traffic flow behavior [70–72]. In addition, driving behavior was only considered in these models to provide fast and efficient simulation, and models did not effectively consider Daganzo’s remark [73]. However, considering the mechanical capability of a vehicle in traffic flow modelling makes the model complex in terms of mathematical representation and development, but it cannot be neglected due to its significant impact on traffic flow behavior.

Accordingly, performing an appropriate link between the driving unit and vehicle unit models is the key point in proposing a driving-vehicle system model. An intelligent driving control system controls the velocity of vehicle to an optimal (desired) value utilizing the throttle/brake input. The longitudinal control system architecture for CAVs is designed with upper- and lower-level controllers. The upper-level controller (driving unit) generates CAV’s optimal acceleration/deceleration based on the predetermined driving strategy (e.g., car-following model) by using real-time traffic information (e.g., downstream vehicles’ velocity and space headway, the maximum velocity of the current road, etc.) through sensors (e.g., Lidar, Radar)/V2V communication, and provides required inputs to the lower-level controller (vehicle unit). The lower-level controller (vehicle unit) determines the throttle actuator angle or brake pressure line to operate the following vehicle to meet optimal acceleration/deceleration.

This paper aims to provide a novel framework in the area of CAVs traffic flow modelling by establishing a new microscopic model, named Integrated-Hybrid (IH) model, based on the longitudinal control system architecture of AC vehicles that considers the optimal velocity and collision-free requirements, and mechanical capability of vehicles. The first step consists of proposing the Integrated-Hybrid (IH) microscopic model for replicating vehicles’ individual behavior during car-following mode. To achieve that, vehicles’ driving behavior and mechanical capability are modeled using two separated units which are linked by the throttle/brake actuator control model.

The main contribution and key improvement of the IH model over other microscopic models are as follows: (1) the optimal velocity of the following vehicle is based on minimum collision avoidance distance that dynamically can be updated according to current traffic information and anticipation of space headway; (2) it models driving behavior and vehicle behavior individually; (3) it models the throttle and brake actuators; (4) it has the capability of adopting different car-following strategies; (5) when the velocity of the following vehicle is higher than a leading vehicle, a shorter space headway than steady state is allowed; (6) it characterizes the acceleration/deceleration of AC vehicle based on the power output from the vehicle’s engine and power losses resulting from external resistance forces; and (7) variable velocity limits in an inactive V2I communication are considered in this model. The remaining parts of this paper are organized as follows. First, three submodels are proposed considering driving behavior and vehicles’ mechanical capability to establish the IH model. Next, linear stability analysis of the IH model is carried out. Then, numerical simulations are conducted during starting and braking process to compare IH model with FVD model at signalized intersections. Finally, the conclusion of the paper is drawn, and future work is discussed.

### 2. Model Formulation

Three submodels are proposed to establish a novel microscopic traffic flow model, named Integrated-Hybrid (IH)
model, in which the driving system (vehicle control system) and the vehicle are two separate units that linked by throttle and brake actuators. This model tends to depict the car-following behavior of AC vehicles more realistically by considering driving system, the mechanical capability of vehicles, resistant forces, and downstream traffic situation (Figure 1).

2.1. Anticipative Collision Avoidance Driving Model. In the car-following mode of human driving vehicles, drivers control the throttle and brake actuators to adjust their vehicle based on their anticipation of downstream traffic information (i.e., whether leading vehicle accelerates, decelerates, or maintains constant velocity) considering unpredictable variations of leading vehicle. In the case that the intelligent driving system controls the autonomous vehicle’s throttle and brake actuators, the driving system needs to constantly receive data (i.e., velocity, headway) from the leading vehicle through wireless safety unit and from its Controller Area Network (CAN) using on-board sensors (i.e., cameras, radars, and lidars) and then updates its optimal velocity based on its anticipation of downstream traffic information, while considering unpredictable variations of the leading vehicle.

Considering vehicle car-following behavior, our new microscopic model uses the linear functional form proposed by Zheng et al. [74] based on dynamic anticipation information as determined in (1) to anticipate the space headway between following and leading vehicle considering velocity differences according to real field driving behavior.

\[ S_n^{AN}(t) = S_n(t) + T\Delta v_n(t), \]  

(1)

where anticipation time \( T \) denotes the dependence of anticipation space headway on the relative velocity \( \Delta v_n(t) \). The term \( T\Delta v_n(t) \) is the anticipation of space headway at the next moment. \( S_n(t) \) is the anticipation current space headway between two successive vehicles.

The collision avoidance component of the modified optimal velocity under an active V2I communication is presented by (2), in which \( S_j \) is an additional space headway for improved safety margins in standstill condition, the term \( (v_j^2(t)/2a_{\max,\text{decc}} - v_{n+1}^2(t)/2a_{\max,\text{decc}}) \) is the space headway that the CA vehicle needs to maintain from the leading vehicle to avoid collision under some extreme stop situations, \( a_{\max,\text{decc}} \) represents maximum admissible deceleration for an efficient breaking to ensure that the autonomous vehicle mitigates its current velocity to reach leading vehicle’s velocity, and \( v_n\tau \) is following distance based on the reaction time. The third term of (2) computes a comfortable braking distance at which the brake actuator of the Autonomous Vehicle operates with maximum comfortable deceleration level \( (a_{\max,\text{decc}}) \) until reaching the leading vehicle’s velocity; \( S_n^{CA} \) is the minimum collision avoidance headway.

\[ S_n^{CA}(t) = S_j + v_n\tau + \left( \frac{v_j^2(t)}{2a_{\max,\text{decc}}} - \frac{v_{n+1}^2(t)}{2a_{\max,\text{decc}}} \right). \]  

(2)

To ensure that the AC vehicles make the given promises to commuters such as safety, comfort, high efficiency, optimized fuel consumption, low emission rate, and high road capacity, the CA vehicle needs to adjust its reaction according to the impending variation of downstream traffic.

In order to prevent frequent deceleration and acceleration, or extreme deceleration when leading vehicle breaks suddenly, the deviation of anticipation space headway from minimum collision avoidance headway proposed in (3) can be the basis of longitudinal velocity control of CA vehicle during car following mode in the present model.

\[ H_n(t) = (S_n(t) + T\Delta v_n) - \left( S_j + v_n\tau + \left( \frac{v_j^2(t)}{2a_{\max,\text{decc}}} - \frac{v_{n+1}^2(t)}{2a_{\max,\text{decc}}} \right) \right). \]  

(3)

Equation (3) allows the following vehicle to move with space headway smaller than safe space headway when the leading vehicle velocity is higher than the following vehicle velocity.

Substituting (2) and (3) with \( S_n(t) \) and \( h_n \) in optimal velocity function (4) proposed by Bando et al. [58], respectively, the anticipative collision avoidance optimal velocity is developed in (5) to generate the optimal velocity for longitudinal motion of the following CA vehicle utilizing known space headway and velocity.

\[ V_n(S_n(t)) = \frac{v_{\max}}{2}\left[ \tanh(S_n(t) - h_n) + \tanh(h_n) \right], \]  

(4)

\[ V(S_n(t) + T\Delta v_n) = \frac{v_{\max}}{2}\left[ \tanh(S_n(t) + T\Delta v_n) - S_n^{CA}(t) \right] + \tanh(S_n^{CA}(t)). \]  

(5)

The Autonomous Vehicle can receive \( v_{\max} \) (i.e., variable velocity limit) from the traffic management center (TMC) by using the capability of vehicle-to-infrastructure (V2I) communication. When an Autonomous Vehicle loses its V2V communication, then there is no communication to receive maximum safe velocity from TMC, and the information needed for safe and efficient driving will be collected only by on-board sensors (i.e., cameras, radars, and lidars). In this case, the Autonomous Vehicle is not able to observe the vehicles located outside of its sensors’ detection range. This is equivalent to assuming a stopped vehicle right outside the sensors’ detection range, which the sensors cannot detect at the time of decision [75]. Furthermore, in the case that leading vehicle is in the detection range of the CAV’s
sensors, it is reasonable to assume that the velocity of the AC vehicle needs to be low enough to allow the leading vehicle to stop or decrease its velocity if it decides to decelerate with its maximum deceleration rate. Considering the above information, Talebpour and Mahmassani [76] proposed the TMC decision about variable velocity limits in an inactive V2V communication. After redefining the optimal velocity function in both active and inactive V2V communication phase, the effect of anticipation and collision avoidance space headway is incorporated in the expression of the AAFVD model proposed by Jafaripournimchahi et al. [69]:

\[
\frac{dv_n}{dt}_{\text{driving}} = a[V(S_n(t) + T\Delta v_n) - v_n(t)] + \lambda \exp(-\mu\Delta v_n(t)) \Delta v_n(t),
\]

where \(a\) denotes the sensitivity coefficient of longitudinal motion controller to the difference between the optimal velocity and the current velocity, \(\lambda\) is the sensitivity coefficient of longitudinal motion controller to the velocity difference between two successive vehicles, \(\mu\) denotes an asymmetric constant, and \(\exp(-\mu\Delta v_n(t))\) is the asymmetrical term presented considering the technical limitation of vehicle’s engine during acceleration process when the relative velocity between leading and following vehicle is too big (\(\Delta v_n \rightarrow \infty\)). The driving model and mechanical model of CA vehicles are two separated units in our paper to ensure that the impact of CA vehicle’s driving system is considered on traffic flow during the simulation as well as the impact of the CA vehicle’s mechanical characteristics.

The driving model process during the simulation is as follows:

**Figure 1:** System architecture of IH model.
(1) Equation (5) generates the optimal velocity of the driving model according to downstream traffic information (i.e., velocity, headway) and ensures that the optimal velocity is a safe velocity.

(2) The AAFVFD model equation (6) computes the required acceleration/deceleration for an optimal and safe velocity in order to transmit to the throttle/brake actuator controller.

In order to respond quickly to unpredictable events, the driving model needs to monitor the downstream traffic and updates its interpretation of the current situation. The model repeats the entire process of evaluation, selecting an action every millisecond (msec). Since the situation can be updated, the model does not need a memory parameter to remember any detailed information from the last moment to the following input.

2.2. Throttle/Brake Actuator Control Model. The throttle/brake actuator control model is the second component of the Integrated-Hybrid (IH) model to link the driving model with the vehicle mechanical model. To achieve comfortable and safe driving, the output of throttle opening angle or the brake line pressure to the vehicle mechanical model can be proposed as follows [77]:

\[ \theta_n(t) = \theta_o + \frac{1}{b_1} \left( \frac{dv_n(t)}{dt} \right)_{\text{Driving}} + a(v_n(t) - v_o) - d, \]

for throttle, where \( \theta_n \) and \( P_{nBr} \) are the throttle pedal angle and brake line pressure, respectively, \( R_n \) is the sum of residence forces, \( \theta_o \) represents steady-state opening angle for corresponding steady state velocity \( v_o \), \( b_1 \) and \( a \) are parameters that changing with \( v_o \) and need to be computed in advance at each type of engine operating point \((\theta_o, v_o)\) and sorted in the look-up table for \((\theta_o, v_o)\), and \( d \) is unmodeled disturbances. \( f_0 \) denotes the static friction force; \( c_2 v_n(t) \) and \( c_3 (v_n(t))^2 \) represent the rolling friction and air resistant forces, respectively. \( c_1 \) is the effective gear ratio of engine to the wheels; \( b_2, c_2, c_3 \) are constants obtained from experiments [14]. In Integrated-Hybrid (IH) model, the throttle and brake actuators are not allowed to be active simultaneously. The lower-limit throttle angle is essential to avoid a strong nonlinearity that appears when the throttle angle reaches zero; thus, \( \theta_{\text{min}} \) is defined as the minimum throttle angle for Idle velocity. To minimize the energy consumption, the brake actuator needs to be switched on (equation (8)) only if the required throttle angle is smaller than the minimum throttle angle \((\theta_{\text{min}})\). Otherwise, the throttle actuator alone is capable of handling optimal driving. When the brake actuator is switched on, the throttle angle remains at the minimum throttle angle \((\theta_{\text{min}})\).

2.3. Vehicle Mechanical Model. The third component of the Integrated-Hybrid (IH) model is the vehicle mechanical model confirming that the mechanical capability of vehicles is considered in the IH model, and the system can depict realistic behavior of the AC vehicle during acceleration or deceleration processes. The longitudinal mechanical model of a vehicle can be written based on Newton’s second law according to equation (8), in which \( F_n \) represents driving force or brake force, and the sum of residence forces is shown by \( R_n \):

\[ \frac{dv_n(t)}{dt} = \frac{F_n - R_n}{M}, \]

\[ F_n = \frac{3600 \alpha P}{v_n}, \]

where \( P \) and \( \alpha \) represent maximum engine power and power transmission ratio (gear ratio), respectively, which can be obtained from the vehicle specifications [78]. \( P \) is a constant power that a vehicle engine can produce for reaching the maximum acceleration. It is clear that in real-world driving, drivers control the engine power transmission (engine load) using the throttle actuator to control the vehicle’s acceleration according to downstream traffic condition.

To ensure that the vehicle mechanical model captures the impact of throttle angle variation, which is linked to the driving system on the engine power transmission (engine load) during the driving process, the throttle angle sensitivity parameter \( \eta \) is defined as presented in (9), in which \( \theta_{\text{max}} \) is the maximum throttle opening angle of a vehicle. \( \eta \) varies from zero to one, when the throttle plate angular position varies from zero (completely closed) to maximum (completely opened), respectively. When the driving model requests the maximum value of throttle angle \((\theta_{\text{max}})\), then \( \eta = 1 \).

\[ \eta = \frac{\theta_n(t)}{\theta_{\text{max}}}. \]

Equation (8) is modified considering throttle angle sensitivity parameter \( \eta \) as follows:

\[ \frac{dv_n(t)}{dt} = \frac{F_n - R_n + d}{M}, \]

\[ F_n = \frac{3600 \alpha \eta P}{v_n}, \]

\[ F_n = \frac{3600 \alpha (\theta_{\text{max}}/\theta_{\text{max}}) P}{v_n} - c_1 P_{nBr}(t), \]

for brake. (13)

The vehicle mechanical model presented in (10) shows vehicle acceleration/deceleration after receiving the driving unit commands. In other words, including throttle angle sensitivity parameter \( \eta \) in driving force during acceleration process certifies that the driving characteristic and downstream traffic dynamic are captured in mechanical model to yield more realistic acceleration behavior.

In most cases, the CA vehicle can accomplish car following task by applying only throttle actuator using (11) in

\[ \frac{dv_n(t)}{dt} = \frac{F_n - R_n + d}{M}, \]
an attempt to generate requested acceleration or deceleration from driving unit, except in sudden deceleration of leading vehicle or during downhill vehicle following situations that requires activating the brake actuator (12) to achieve vehicle following.

In the current model, three switching logic conditions for throttle and brake are defined as follows.

**Condition 1.** \(S_{AN} < S_{CA}^n\) and \(v_n > v_n + 1\).

This condition occurs when the following vehicle is at high velocity (i.e., \(v_n > v_n + 1\)), and the anticipation of space headway \(S_{AN}^n\) between two successive vehicles is less than the collision avoidance headway \(S_{CA}^n\).

When this condition occurs, the throttle actuator is switched on, and the driving unit requests bigger deceleration pressure differences between following and leading vehicles can provide; thus, brake actuator needs to be switched on (11) and maintains switched on until the following vehicle's anticipation of space headway at next moment reaches the safe space headway; then, throttle angle takes charge of controlling longitudinal movement.

**Condition 2.** \(S_{AN} \gg S_{CA}^n\) and \(v_n < v_n + 1\).

In this condition, the anticipation distance is large, and the brake system is not essential to be switched on.

**Condition 3.** \(S_{AN} = S_{CA}^n\) and \(v_n < v_n + 1\).

In this condition, the throttle actuator is switched off and lets the vehicle decelerate; if the driving unit requests a bigger deceleration than what minimum throttle angle \(\theta_{\min}\) and the sum of residence forces \(R_n\) can provide, then the brake actuator of the following vehicle needs to be switched on.

\[
\frac{\theta_{n+1}(t) - \theta_n(t)}{b_1} = \frac{1}{b_1} \left[ \left( \frac{dv_{n+1}(t)}{dt} \right)_{\text{Driving}} - \left( \frac{dv_n(t)}{dt} \right)_{\text{Driving}} + \alpha \Delta v_n(t) \right],
\]

\[
\frac{P_{n+1}^{br}(t) - P_n^{br}(t)}{c_1} = \frac{1}{c_1} \left[ M \left( \frac{dv_{n+1}(t)}{dt} \right)_{\text{Driving}} - \left( \frac{dv_n(t)}{dt} \right)_{\text{Driving}} + c_2 \Delta v_n(t) \right],
\]

where \(\alpha\) and \(c_2\) are the feedback gain of the leading vehicle and change between 0 and 1 [77].

It is notable that the air-resistant force is neglected during braking activation because of moving in a platoon. The linear stability of car-following model was firstly conducted on GHR model [79] by Chow [80]. Wilson and Ward [81] studied the details of the linear stability criterion of several car-following models proposing a general framework.

This section presents an analytical study of linear stability of CA vehicles platoon. Considering the fact that driving behavior is locally stable in real traffic flow the linear stability is necessary for any microscopic model. According to real traffic data, Wilson and Ward [81] found that there was an equilibrium relationship between velocity and space headway so that \(f(S, V(S)) = 0\), where \(S\) and \(V(S)\) denote steady-state space headway and optimal velocity in uniform flow, respectively.

In the current study, it is assumed that \(N\) vehicles move uniformly with same space headway \(b\) and same optimal velocity \(V(b)\). All vehicles follow the leading vehicle of the platoon based on car-following model presented in (6).

The steady state position of \(n\) th vehicle in platoon of vehicles can be written as

\[
x_n^0(t) = bn + V(b)t, \quad n = 1, 2, \ldots N,
\]

where \(b\) represents steady-state space headway defined as \(b = D/N\), \(N\) is the total number of vehicles in a platoon, \(D\) is the length of platoon, and \(V(b)\) is the steady-state velocity.

### 3. Linear Local Stability Analysis

The local stability analysis needs to be performed on the driving model as upper controller of CA vehicles to assess whether the proposed model is locally stable or unstable in traffic flow. To consider the effects of throttle and brake variation on local stability, the throttle angle and brake line pressure differences between following and leading vehicles are added into (6) separately as proposed in (13) and (14) to analyze the local stability of driving model when applying throttle or brake actuators in car-following mode.

\[
\left( \frac{dv_n(t)}{dt} \right)_{\text{Driving}} = a[V(S_n(t) + T \Delta v_n) - v_n(t)] + \lambda \Delta v_n(t) + \beta(\theta_{n+1}(t) - \theta_n(t)),
\]

\[
\left( \frac{dv_n(t)}{dt} \right)_{\text{Driving}} = a[V(S_n(t) + T \Delta v_n) - v_n(t)] + \lambda \Delta v_n(t) + \gamma(P_{n+1}^{br}(t) - P_n^{br}(t)).
\]

For the sake of simplicity, we assume \(\beta = b_1\), \(\gamma = c_1\), expand the variables \(V(S_n(t) + T \Delta v_n)\) to the second order by using the Taylor series expansion, and neglect the higher order terms; then, we have

\[
V(S_n(t) + T \Delta v_n) = V(S_n(t)) + TV'(S_n(t)) \Delta v_n.
\]

The dynamic equation of throttle angle and brake line pressure differences between following and leading vehicles can be written using (13) and (14) as follows:

\[
\left( \frac{dv_n(t)}{dt} \right)_{\text{Driving}} = a[V(S_n(t) + T \Delta v_n) - v_n(t)] + \lambda \Delta v_n(t) + \beta(\theta_{n+1}(t) - \theta_n(t)),
\]

\[
\left( \frac{dv_n(t)}{dt} \right)_{\text{Driving}} = a[V(S_n(t) + T \Delta v_n) - v_n(t)] + \lambda \Delta v_n(t) + \gamma(P_{n+1}^{br}(t) - P_n^{br}(t)).
\]
Zhang and Jarrett [82] noted that the following vehicles’ reactions to the leading vehicle changes were the basis of local stability definition. A slight deviation of the leading vehicle’s velocity or space headway from steady state (e.g., a small variation on steady-state space headway of leading vehicle or velocity of leading vehicle by applying throttle or brake actuators) will force the following vehicles to react to this deviation. Assuming that $y_n(t)$ stands for a slight deviation of the vehicle steady state position $x_n^0(t)$, when throttle actuator applies, we have

$$x_n(t) = x_n^0(t) + y_n(t). \tag{19}$$

And for brake actuator application,

$$x_n(t) = x_n^0(t) - y_n(t). \tag{20}$$

Substitute (19) and (20) into a linear form of (13) and (14), respectively.

After ignoring higher terms of $y_n(t)$, the linearized equations are obtained as follows.

For applying throttle,

$$y''_n(t) = a[V'(b)\Delta y_n(t) + TV'(b)\Delta y_n'(t) - y_n'(t)] + \frac{\beta}{b_1} (\Delta y''_n(t) + \alpha \Delta y_n'(t)). \tag{21}$$

For applying brake,

$$y''_n(t) = a[-V'(b)\Delta y_n(t) - TV'(b)\Delta y_n'(t) + y_n'(t)] + \frac{V}{c_1} [-M \Delta y''_n(t) + c_2 \Delta y_n'(t)], \tag{22}$$

where

$$V'(b) = \frac{dV(\Delta x_n)}{d\Delta x_n}_{\Delta x_n=0},$$

$$\Delta y_n(t) = \Delta x_n(t) - b,$$

$$y'_n(t) = x_n'(t) - V(b), y''_n(t) = x_n''(t), \Delta y_n'(t) = \Delta x_n'(t). \tag{23}$$

Expanding steady state deviation $y_n(t)$ into a Fourier series as an orthonormal set where $y_n(t) = e^{(i\omega x_n t)}$, (13) and (14) can be written as follows:

For applying throttle,

$$z^2 = a[V'(b)(\exp(i\omega k) - 1) + TV'(b)z(\exp(i\omega k) - 1) - z] + \lambda \omega (\exp(i\omega k) - 1) + az(\exp(i\omega k) - 1). \tag{24}$$

For applying brake,

$$z^2 = a[-V'(b)(\exp(i\omega k) - 1) - TV'(b)z(\exp(i\omega k) - 1) + z] + \lambda \omega (\exp(i\omega k) - 1) + Mz^2(\exp(i\omega k) - 1) + c_2 z(\exp(i\omega k) - 1). \tag{25}$$

Inserting the expansion of $z = z_1(ik) + z_2(ik)^2 + \cdots$ into the above equations yields the following.

For applying throttle,

$$z_1 = V'(b),$$

$$z_2 = - \frac{(V'(b))^2 - (aTV'(b) + \lambda + \alpha - 1/2a)V'(b)}{a}, \quad \text{for throttle},$$

$$z_2 = - \frac{(V'(b))^2 + (aTV'(b) + \lambda + c_2 - 1/2a)V'(b)}{a}, \quad \text{for brake}. \tag{28}$$

When the slight deviation of steady state imposed by applying throttle actuator of leading vehicle, the oscillation will shrink exponentially with time evaluation and vehicles will eventually return to steady state, if the derivative of steady-state velocity $V(b)$ at $b$ satisfies the below condition:

$$V'(b) < \left( aTV'(b) + \lambda + \alpha - \frac{1}{2}a \right). \tag{29}$$

When the slight deviation of steady state imposed by applying break actuator of leading vehicle, the oscillation will enhance through time and the state of traffic flow will become unstable.

If the condition expressed in (30) is not satisfied,

$$V'(b) > \left( -aTV'(b) + \lambda + c_2 - \frac{1}{2}a \right). \tag{30}$$

The stability state of traffic flow implementing IH model depends on the value of sensitivity constants of driving model, anticipation time, and derivative of optimal velocity $V(S_n(t))$ at steady-state space headway $b$ of steady-state.
traffic flow. In other words, our proposed model is locally stable under the above conditions.

Figure 2 depicts the critical stability curves of the IH model and the FVD model in the parameter space \((\Delta x, a_t)\) under various amounts of \(T\) and \(\beta\). In Figure 2, the solid red lines and the dashed blue lines represent the stability curves of IH model and the FVD models, respectively, and the apex of every curve defines the critical point \((h_c, a_c)\) for various amounts of \(T\) and \(\beta\), where \(h_c\) and \(a_c\) are the safety distance and the critical sensitivity, respectively. The region below the critical lines shows the unstable regions where density waves appear in traffic flow, and the region above the critical lines indicates the stable regions of traffic flow. Figure 2 depicts that by taking the throttle angle/brake pressure line information and anticipation driving behavior into account during car following maneuvers, the stable region gradually increases. From Figure 2, it is obvious that the stable region achieved from the IH model is bigger than those of the FVD model, and the critical points are significantly lower than the FVD model, which means with increasing the impact of the driving anticipation the critical vehicular gap \(h_c\) will be smaller than that in the FVD model and the capacity of the road in steady condition will increase effectively.

4. Numerical Simulations

In this section, the numerical simulations are conducted to provide a brief comparative analysis between the
performance of the IH model and the FVD model and allow the reader to visualize and evaluate the performance of the IH model under different traffic scenarios.

4.1. The Starting Process. Emulating the same scenario defined in research work by Jiang et al. [61], we compare the departure process of a platoon of AC vehicles simulated by IH model at a signalized intersection during the green period of a traffic signal with a platoon of vehicles simulated by FVD model.

We suppose eleven CA vehicles stop in a queue during the red period of a traffic signal with identical vehicular gaps of 7.4 m at time \( t < 0 \). At time \( t = 0 \), the traffic signal shifts from its red period to its green period and leader of the platoon instantly starts up, the other vehicles gradually move and follow their direct leading vehicle based on switching logic conditions defined in Section 3.2 in a connected system. The velocity of the platoon leader is defined by 

\[
v_{n+1} = v_{n+2} = v_0 (t)
\]

Figures 3(a)–3(c) and (d) show how the following vehicles of the platoon simulated by IH model duplicate fundamentally the velocity of leading vehicles with a delay time; that is, \( v_n = v_0 (t - \delta t) \), in which \( \delta t \) is the delay time of vehicle’s motion. From the delay time of vehicle’s motion, we can further predict the velocity of kinematic waves (i.e., disturbance propagation velocity) at traffic jam with density \( c_j \), which is defined by \( c_j = 7.4/\delta t \). Based on empirical observation, Bando et al. [83] found that the order of the time lag \( \delta t \) is 1 s; the range of the kinematic wave velocity was derived by Del Castillo and Benitez [84] to be between 17 and 23 km.

Comparing the velocity profiles depicted in Figures 3(a) and 3(b), we compare the performance of IH model with FVD model qualitatively and confirm that the variation of simulated velocity profiles resulting from IH model successfully generates velocity profiles over the time for the following vehicles at a signalized intersection during the green period of a traffic signal.

To study further the impact of anticipation and throttle angle information used in IH model on starting delay time, we depict Figure 3(c) under bigger amount of sensitivity parameter \( \beta \) for \( T = 0.1 \).

From Figures 3(b) and 3(c) and Table 2, it is obvious that the following vehicles quickly respond to the change of the leading vehicles by receiving the throttle angle information through V2V communication from their next nearest leading vehicle.

Comparing Figures 3(b) and 3(c), we can find that the following vehicles’ starting process is getting faster when the sensitivity on throttle angle information increases, the delay \( \delta t \) is getting shorter, and the velocity of kinematic wave \( c_j \) falls into the defined boundary of observed data (17 km/h and 23 km/h), which is critical for safety and operation.

4.2. Braking Process. In this section, the braking process of eleven vehicles is simulated numerically at a signalized intersection by using the IH model under the following initial conditions to examine the performance of IH model during braking process qualitatively. When \( t < 0 \), the traffic signal is green and eleven vehicles are moving forward with same velocity of 4.66 (m/s); all vehicles are distributed uniformly with the same space headway 7.4 m on the road. The distance between the platoon leading vehicle and the stop line is supposed to be 10 m.

The red light is assumed to be a virtual vehicle with the velocity of zero at the stop line. At time \( t = 0 \), the traffic signal changes to red phase and the first vehicle of the platoon immediately brakes, and the following vehicles copy the platoon leading vehicle’s behavior with a delay time and begin to slow down gradually and all vehicles eventually will reach the velocity of zero before reaching the crosswalk.

The numerical simulations revealed that the following vehicles copy the velocity of the leading vehicles with a delay time and eventually reach the velocity of zero in a queue before reaching the crosswalk. The delay time of vehicles’ motion simulated by the IH model and FVD model is 1.39 s and 1.43 s, respectively. It is clear that the IH model has a shorter delay time than FVD model.

To investigate the impact of anticipation and brake information on the following vehicles’ velocity during braking process more clearly, we choose the 6th vehicle (i.e., platoon leader) and 9th vehicle (i.e., vehicle) as target vehicles.

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### Table 2: Delay time \( \delta t \) (s) of vehicle motions in a signalized intersection and the velocity of kinematic wave \( (c_j) \) at traffic jam simulated by FVD and IH model.

<table>
<thead>
<tr>
<th>Model</th>
<th>( a ) (1/s)</th>
<th>( T ) (s)</th>
<th>( \beta )</th>
<th>( \delta t ) (s)</th>
<th>( c_j ) (km/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FVD</td>
<td>0.6</td>
<td>0</td>
<td>0</td>
<td>1.45</td>
<td>18.37</td>
</tr>
<tr>
<td>IH</td>
<td>0.6</td>
<td>0.1</td>
<td>0.1</td>
<td>1.39</td>
<td>19.16</td>
</tr>
<tr>
<td>IH</td>
<td>0.6</td>
<td>0.1</td>
<td>0.3</td>
<td>1.30</td>
<td>20.49</td>
</tr>
</tbody>
</table>

---
The velocity evolution of two vehicles during the arrival process when vehicles start applying the brake pedal \( t = 0 \) until that time both vehicles reach the velocity of zero in a queue before reaching the crosswalk is displayed in Figure 4 using the FVD model and IH model.

We can split the velocity of the 6th vehicle and 9th vehicle into two different phases in Figure 4. In the first phase, the following vehicles simulated by the IH model start releasing the throttle pedal earlier and applying the brake pedal faster than that one simulated by FVD model.

At the second phase, the following vehicles simulated by the IH model reach the required amount of deceleration faster than FVD model until the vehicles stops completely.

In accordance with above information, vehicles will be brought comfortably, gently, and safely to a standstill using the IH model.

Figures 5 depicts the simulation of acceleration’s evolution of eleven vehicles due to traffic signals using the FVD model and IH model, respectively. In this figure, the required level of deceleration in the IH model is lower than FVD model and is not beyond the limited range of empirical deceleration (−3, 4) \( \text{m/s}^2 \) [85] observed from real driving behaviors.

To study more how receiving braking information can affect each vehicle’s acceleration in a platoon of vehicles during arrival process, we select 6th vehicle and 9th vehicle to compare the IH model with the FVD model. Figure 6 depicts that the curve of the IH model is in front of FVD model and is lower.

Based on above analysis, we can draw the conclusion that taking brake information through V2V communication into account indeed has significant impacts on the evolution of each vehicle’s deceleration and enhances the capacity of signalized intersections.

5. Conclusion

This paper represents a novel framework of CAV traffic flow modelling. Methods and procedures leading to the development of a new microscopic model have been described.
The new IH model enhances the original FVD model and the vehicle mechanical model, keeps the key components of both models, and incorporates driving variability into the vehicle mechanical model. The driving and vehicle units are modeled separately and linked by the throttle/brake actuator control model. Flexibility of the IH model is proved due to having the ability to depict driving behavior and vehicle mechanical behavior individually or simultaneously based on users’ needs at microscopic level. As a distinctive feature, different driving strategies can be potentially embedded into the IH model. This model is modified based on the current state-of-the-art traffic flow modelling for CAVs. The driving unit of the IH model utilizes collision-avoidance strategies to ensure a safe following distance among vehicles. Mechanical features and longitudinal motion of AVCs in active V2V communication and inactive V2V communication have been considered. The acceleration framework has been developed by including anticipation driving behavior. Current study conducts linear stability analysis of the new model and finds the critical stability conditions in the face of small perturbations. We carried out numerical simulations to compare qualitatively the performance of the IH model with FVD model during starting and braking process. Our results revealed that high acceleration and deceleration will not appear, and considering the throttle angle/brake line pressure information and anticipation driving behavior for designing the control strategy of autonomous traffic systems can increase traffic metrics safety and efficiency. Considering the considering the throttle angle/brake line pressure information even in two different units increases the stability of traffic flow by eliminating unnecessary, dangerous interactions among vehicles, achieves a better traffic flow in terms of safety, and reaches a better condition for traffic flow to operate. The results illustrated that comparing with FVD model, the IH model can more successfully anticipate the two important traffic parameters: the delay time of vehicle motion and the kinematic wave speed at jam density. It means that efficiency and safety can be improved in signalized intersection by considering throttle angle/brake line pressure information and anticipation driving behavior. The IH model increases our capability to not only analyze a single leading vehicle, but also the entire ambient traffic conditions in the vicinity of the subject vehicle. This can be implemented accurately through V2V wireless communication. The results of this study provide a robust mathematical-physical tool to explore the impact of CAVs on transportation systems, propose a realistic traffic model at a different level of detail in the ITS environment to enrich the motion planning and decision-making of CAVs in terms of accurate traffic semantics, resemble real-world traffic at the street level, and help to improve autonomous vehicles design through dynamic traffic environment [11].

Data Availability
The data published in this paper can be available and accessible from the corresponding author upon written official request with a legitimate justification.

Conflicts of Interest
The authors declare that they have no conflicts of interest.

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