Joint Fuel-Efficient Vehicle Platooning and Data Transmission Scheduling for MEC-Enabled Cooperative Vehicle-Infrastructure Systems

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***Abstract*—Platoon-based connected vehicles have recently received increasing attention from academia and industry since they are considered promising solutions to transform our mobility society into the next generation. Vehicular communication and platoon coordination are two aspects of enabling technologies for mobile edge computing (MEC)-enabled cooperative vehicle-infrastructure systems (CVIS), while few efforts have incorporated these two dimensions into a joint implementation framework. In this paper, we investigate the problem of joint car-following coordination and data transmission scheduling of vehicle platoons. We develop a two-tier hierarchical framework for vehicle platooning: a fuel-efficient mobility optimization layer for car-following coordination and a reliable vehicle-to-infrastructure (V2I) communication layer for data transmission scheduling. Specifically, we present a platoon-based fuel consumption minimization model and a car-following control protocol to derive fuel-efficient control inputs. We also propose a reliability-oriented and delay-constrained data transmission scheduling model that is driven by upper-layer car-following coordination. We derived a closed-form expression for the reliability-optimal data transmission scheduling solution, which incorporates platoon mobility, channel characteristics, and application requirements. With simulations, we show that our joint method improves fuel efficiency and communication reliability for platooning vehicles. In particular, the proposed method reduces the platoon's fuel consumption per time slot by 16.4%, meanwhile making the communication reliability 1.31 times higher than other traditional methods.**

***Index Terms*—Connected vehicles, vehicle platooning, fuel efficiency, communication reliability.**

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I. Introduction

PLATOON-based connected vehicles, known as autonomous vehicle platooning, are promising for the next generation of Cooperative Vehicle-Infrastructure Systems (CVIS) [1], [2]. A vehicle platooning system aims to operate a group of connected vehicles in a closely-spaced platoon such that they can reduce aerodynamic drag and improve the usage of road infrastructure. In this way, vehicle platooning can potentially boost road traffic efficiency and safety, thus attracting considerable attention in recent years [3]–[6]. From a control perspective, a fundamental issue of vehicle platooning is to guarantee motion safety, smoothness, and stability, meanwhile reducing energy consumption as much as possible. Thus, increasing research efforts have been made on fuel-efficient control of vehicle platoons. Different motion planning and control solutions have been developed in the context of control theory [7]–[10]. On the other side, the automation and connectivity of vehicle platoons heavily rely on vehicular communication and networking. In particular, current and envisioned intelligent vehicles are equipped with various sensors, such as motion sensors, high-resolution cameras, lidar, and onboard radar. They can generate hundreds of megabytes and terabytes of onboard data. Besides, the connectivity of vehicles promotes the integration of many mobile Internet applications and services with the vehicular system, such as software upgrading over-the-air (OTA), gaming, multimedia streaming, and other infotainment services. These onboard applications and services pose new challenges to vehicular communication, storage, and computing. Hence, tackling such explosively growing data and applications on the wheels becomes an important issue.

With the thriving of mobile edge computing (MEC) technologies, connected vehicles are provided the opportunity to access rich computing and storage resources in much closer proximity [11]–[13]. That is, vehicles can offload computation-intensive tasks and process their data-massive applications by leveraging the computing resource deployed nearer the vehicular user edge (such as cloudlet servers distributed along the roadside) rather than by a remote cloud center. At this point, the MEC paradigm, enabling connected vehicles to spin up nearby computing and storage resources on demand, offers significant benefits, including low-latency cloud services and backhaul cost saving [14]. In the foreseeable future, leveraging MEC, vehicle platoons will be able to achieve real-time updates of end-to-end autonomous driving models between the vehicle and the cloud [15]–[17]. Nevertheless, the application of MEC to connected vehicles generally encounters some fundamental challenges arising from wireless access in vehicular environments (WAVE), such as high vehicle mobility, non-line-of-sight (NLoS) signal propagation, and so on. These factors can introduce significant latencies and reduce the reliability of data transmissions. Therefore, proper data transmission scheduling is crucial to mitigate the effects of signal degradation and ensure consistent service quality. One of the most challenging issues is guaranteeing the integrity of delay-constrained data transmissions over highly-dynamic and unreliable communication links. In general scenarios, fast-moving vehicles lead to probabilistic packet loss, data bit errors, and harsh wireless channels. A MEC server may fail in fully presenting a computing task or an application when it only receives fragments or partial data content. Therefore, MEC-enabled connected vehicles should be intelligent enough to adapt to high mobility, delay constraints, and transmission integrity requirements of onboard applications. It is worth noting that the primary focus of this study is the performance of vehicles' fuel consumption and V2I communication. Therefore, in our research, MEC is utilized as an enabling technology to achieve these objectives. We did not consider the computational energy consumption of MEC itself, nor did we address the aspect of vehicle platoons switching between different MECs as they move, as these topics are not within the scope of this study.

Moreover, different from vehicle-to-vehicle (V2V) communication, with which platooning vehicles exchange small-size data (e.g., beacon messages) in a broadcast manner, vehicle-to-infrastructure (V2I) communication is employed for transmitting large-scale data between vehicles and roadside infrastructure. In V2I communication, addressing the challenges of extra delays caused by unreliable data transmission is vital for maintaining the quality of data transmission. The potential of MEC deployed at the roadside infrastructure depends on V2I communication performance, which is inherently coupled with platoon mobility [18]. Namely, V2I communication can provide a vehicle platooning system edge computing power. From this, the platoon benefits from processing sophisticated control tasks and infotainment applications, thus being propelled into a software-upgradeable platform. The mobility pattern of platooning vehicles determines the time-varying characteristics of V2I communication links, which dramatically influences MEC-oriented computation offloading.

Even though there already exist a wide range of studies focusing on computation offloading and resource management solutions for Internet of Things (IoT) or vehicular communications such as [19]–[21], limited research efforts have been made on the joint design and optimization of mobility and data transmission scheduling for platoon-based connected vehicles. A large amount of literature has also been published regarding either robust vehicle platoon control in the presence of uncertainties or integration of inter-vehicle communication (e.g., V2V broadcast) protocol and platoon controller [22]–[24], while few works have incorporated fuel-efficient vehicle platoon control with reliability-oriented V2I communication to achieve a co-design paradigm. To realize MEC-enabled vehicle platooning systems, reliable data transmission scheduling over V2I communication links is critical. Ideally, the data transmission scheduling solution should be dynamically adaptive to the behavior of platooning vehicles and channel conditions. Vehicular data transmission scheduling must also satisfy upstream applications' integrity and delay constraints. In this regard, we focus on developing a joint design methodology that can coordinate the motion of platooning vehicles to reach a fuel-efficient state and simultaneously schedule the data transmissions of each platooning vehicle to guarantee communication reliability under integrity and delay constraints.

A. Literature Review

Predictable reliability of vehicular connectivity is the key to promoting the architecture transformation from single-vehicle-oriented control to network-level control with safety and efficiency. Thus, many recent studies focus on improving vehicular communication and networking. For example, [25] proposes a Cyber-Physical Scheduling (CPS) framework to guarantee the reliability of inter-vehicle communication. As a new application scenario in 5G, Ultra-Reliable and Low-Latency Communication (URLLC) promotes considerable research interest [26]. Different power control and resource allocation schemes have been proposed for the URLLC realization, such as [27]–[30]. [31] proposes a framework for co-designing prediction and communication, showing that the tradeoff between user-experienced delay and reliability can be enhanced significantly with predictive communication scheduling. [32] investigates the influence of V2I communication reliability on traffic control performance under signalized intersection scenarios. [33] proposes a resource allocation strategy for vehicular communication systems with low latency and high reliability. To enable more reliable data retrieval and lower communication latency, [34] proposes a Mobility Prediction Retrieval (MPR) protocol, which can efficiently retrieve the output of offloaded applications. Differently, some other researchers study the energy efficiency problem of mobile networks. In [35], the authors propose an optimal pricing scheme based on a gradient descent method to achieve energy-efficient MEC. In [36], the authors design an energy-saving collaborative computing algorithm based on Lyapunov optimization. Moreover, [37], [38] discuss V2V communication reliability and cloud computing under mobile scenarios. However, the above works do not aim to co-design platoon-oriented control and communication.

In platooning scenarios, [39] proposes a connectivity-status-dependent feedback controller to solve the control problem of a leader-following (LF) vehicle platoon under different communication ranges. [40] shows how a distributed consensus-based longitudinal controller can simultaneously guarantee the stability and performance of a regime platoon. [41], [42] design resource allocation algorithms, and [43] presents a data-sharing strategy to improve the data transmission performance of vehicle platoons. [44] establishes a resource allocation scheme that can maximize the utility of vehicles surrounding a platoon using a contract-optimization approach.

For minimizing fuel consumption, [45] proposes a periodical switching control method. In [20], the authors propose a resource allocation strategy based on a service pricing strategy. [46] designs Radio Environment Maps (REMs) to support selecting a secondary spectrum channel for a vehicle platoon, which can guarantee communication reliability. Unlike the previous works, [47] presents novel platooning strategies, including front, middle, and tail merge operations, and analyzes the efficiency of these operations under different mobility scenarios. Although the above works achieve stability and efficiency in connected vehicle platooning, little attention has been paid to integrating data transmission mechanisms into a platoon coordination framework.

Many significant works aim to analyze the impact of the communication topology on vehicle platoon performance. For example, [48] develops a general framework based on graph theory to analyze the influence of undirected and directed communication topologies on platoon resilience under various cyber attacks. In [49], the authors propose a discrete hybrid stochastic control approach for vehicle platoons using non-ideal communication topologies. Besides, tremendous studies have also been achieved to develop novel robust platoon control solutions to guarantee the stability and robustness of vehicle platoons in the presence of various communication disturbances. Representative works in this direction include communication delay-aware min-max model predictive control (MPC) [50], switching topology-aware MPC [51], and joint sampled control regarding time-varying topology and channel fading [52]. In [53], the authors consider random switching topologies and design a stochastic stable platoon controller based on H_∞ robust control theory. In [54], the authors propose a distributed adaptive consensus control approach to deal with heterogeneous time-varying communication delays and switching topologies of vehicle platoons. In [55], the authors combine linear matrix inequality (LMI) transformation and eigenvalue decomposition to design a robust platoon controller under uncertain topologies. In our previous works [23], [24], we have exploited robust counterpart optimization, super-twisting sliding-mode controller, and observer techniques to achieve robust vehicle platooning in the presence of uncertain disturbances that result from both the control system and the communication network. Advanced robust platoon control designs to tackle communication factors (e.g., stochastic packet loss, limited transmission distance, and time-varying delays) can also be found in many other high-quality papers like [56], [57]. The above literature shows that great research efforts have been made on robust control designs for vehicle platoons regarding various communication impacts. Many advanced schemes have been proposed from the perspective of different robust control methodologies. Even though they consider the impact of time-varying network topologies and other communication factors (e.g., delay and packet loss), the resulting control designs do not incorporate the requirement of an upper-layer application, i.e., guaranteeing the integrity of data to be offloaded over stochastic and fading channels. Furthermore, most works mentioned above take time-varying communication topologies as exogenous disturbances on their vehicle platooning systems. However, they have yet to characterize vehicular communication reliability that relies on time-varying channel factors at the physical layer, vehicle mobility, and application constraints.

On the other side, the co-design of communication and control for connected and autonomous vehicles (CAVs) has received increasing attention. As shown in [22], a consensus control algorithm is successfully integrated with a vehicular data dissemination protocol using adaptive candidate selection mechanisms to achieve reliable vehicle platooning. In [58], the authors propose a relay selection-based channel allocation scheme for LTE-vehicle-to-vehicle (LTE-V2V) communications and incorporate the communication design into a distributed MPC control framework, guaranteeing the string stability in vehicle platooning and the reliable information dissemination within the platoon. In [59], the authors consider integrating a channel allocation scheme into a predecessor leader following-based platoon control strategy to minimize tracking errors. A similar radio resource allocation approach is also integrated into an MPC framework to control the spacing of a vehicle platoon [60]. Dynamic event-triggered scheduling mechanisms have also been developed for vehicle platooning, in which bandwidth and vehicles' motion states are jointly considered [61], [62]. In [63], the authors propose an integrated external positivity design for a cooperative adaptive cruise control (CACC) system. This design can guarantees graceful degradation in terms of collision avoidance and disturbance rejection when vehicles switch between adaptive cruise control (ACC) and CACC due to communication quality issues. In [64], the authors characterize wireless network reliability with the end-to-end delay of vehicle platoons and then optimize the control parameters of a CACC system based on the optimal velocity model. Their essential goal is to improve the reliability of the platoon-oriented wireless network. In [65], the authors aim to guarantee vehicle-to-infrastructure (V2I) quality-of-service (QoS) requirements. They develop a reinforcement learning-based approach to jointly control transmission power, beamforming, and vehicle spacing for platoon-based vehicular cyber-physical systems. Different from the above works on the co-design of radio resource allocation and platoon control, some other researchers are dedicated to selecting a proper communication topology to guarantee the controller performance of vehicle platoons [66]. It is witnessed from the above studies that a number of radio resource-aware or topology-aware platoon control approaches can successfully realize reliable and resource-efficient vehicle platooning. Their communication and control co-designs consider physical-layer communication factors in different control frameworks, e.g., MPC and consensus control frameworks. Nevertheless, the above co-designs do not aim to address the co-design problem of fuel-efficient platoon control and integrity-guaranteed data transmission scheduling. In particular, the proposed communication strategies in the above works either aim to allocate radio resources (e.g., transmit power, beamforming and channels) [58]–[60], [65], reduce data transmission packets in harsh fading channels [61], [62], [64], or adapt the communication topology by dynamic relay selection [22], [66]. But they have not incorporated the transmission demand of the upper-layer application into their communication and control co-design solutions. In general, an upper-layer application of a CAV in a MEC-assisted scenario requires its data bits to be fully offloaded to an edge node by a limited deadline in order to perform remote processing at the edge node. The integrity of computation offloading should be met, while it is unexplored how to characterize the reliability of communication links from a probabilistic perspective in the current literature, i.e., the possibility that vehicular communication links can successfully transmit the application data with a certain delay constraint (i.e., within a given deadline). We differentiate our work from those mentioned above by explicitly taking into account the transmission integrity required by the vehicular computation offloading application and addressing the challenge arising from joint fuel-efficient platoon coordination and reliability-aware data transmission scheduling under stochastic and fading channels and transmission integrity constraints.

Additionally, many researchers devote themselves to reducing the fuel consumption of platooning vehicles. For example, [67] develops models capturing the impact of inter-vehicle distance in a homogeneous vehicle platoon on the drag coefficient and proposes a fuel-saving platoon control approach. [68] presents a fuel-aware routing framework for autonomous vehicles, including multiple optimization objectives such as fuel consumption, trip delay, and refueling cost. [69] proposes a reinforcement learning approach to enhance the road traffic safety and fuel economy of autonomous vehicles with the assistance of V2I communication. Different fuel-efficient speed planning and control protocols have been proposed for heavy-duty truck platoons [9], [10]. However, developing a joint implementation framework that enables the adaptive response of vehicular data transmissions to fuel-efficient platoon control remains an open and challenging issue.

B. Motivation and Contribution

With V2I communication, platooning vehicles can be tightly integrated with MEC to process diverse computing tasks and upstream applications with large-scale data. The recent literature either focuses on various control-centric solutions to coordinate the platooning vehicles or targets at communication protocol designs from the perspective of transmission power optimization and network resource allocation. Nevertheless, it still needs to explore how reliable V2I communication of a vehicle platoon can be improved by jointly taking into account platoon coordination and data transmission scheduling, as this issue is critical for the practical realization of CVIS.

In this paper, we would like to fill the aforementioned gap and incorporate the perspectives of vehicle platooning and data transmission scheduling. We develop a joint platoon coordination and data transmission scheduling framework. Specifically, we theoretically characterize the V2I communication reliability of a vehicle platoon regarding vehicle mobility, channel characteristics, application integrity and delay requirements. The main contributions of our work include:

i) We propose a two-tier hierarchical framework for MEC-enabled vehicle platoons, including a fuel-efficient optimization layer for platoon coordination and a reliable V2I communication layer for data transmission scheduling. Notably, the data transmission scheduling of the platoon depends not only on channel conditions and application requirements but also on the temporal-spatial trajectory of the platoon.

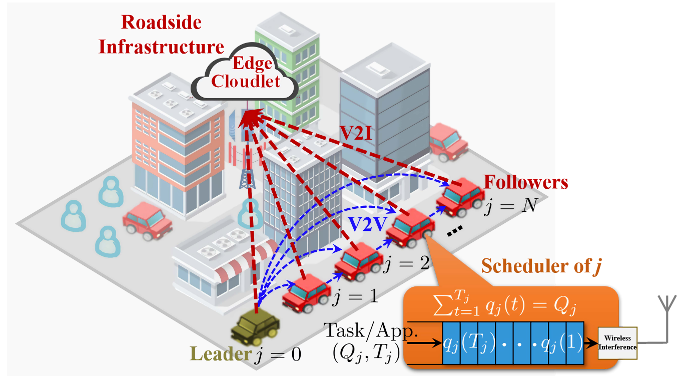

Fig. 1. A typical MEC-enabled vehicle platooning system with the cooperation of a resource-rich infrastructure and a platoon of moving vehicles.

ii) We propose a fuel-efficient optimization model and present a car-following control protocol considering the well-known leader-predecessor-follower information flow topology. The control protocol is incorporated into the fuel-efficient optimization model to realize car-following coordination between successive vehicles. It guarantees both stability and fuel efficiency of vehicle platooning.

iii) We theoretically characterize the V2I communication reliability of the platoon from a probabilistic perspective regarding vehicle mobility, stochastic channel characteristics, and integrity and delay constraints on data transmissions. We propose a reliability optimization model and derive a closed-form expression for the reliability-optimal scheduling solution. Our solution enables vehicular data transmissions to adapt to the coordinated mobility of the platoon.

The motivation and novelty of our work are further discussed in Appendix A in the online supplementary material due to the space limitation. The rest of this paper is organized as follows. Section II presents platoon coordination and V2I communication models. Section III proposes a two-tier optimization framework for joint platoon coordination and reliable vehicular communication. In Section IV, a closed-form solution for mobility-driven data transmission scheduling is derived. Section V provides simulation results to validate the proposed framework and method. Finally, Section VI concludes this study and remarks on our future work.

II. System Model

As shown in Fig. 1, we consider a platoon-based CVIS with MEC capacity, where a group of connected vehicles is moving as a closely-spaced platoon, and roadside infrastructure is an edge-computing provider. The platooning vehicles can exchange control information via V2V communication while offloading data-massive tasks or applications to the edge for processing via V2I communication. We remark that there already exist many optimization schemes and broadcast protocols focusing on V2V communication and that the size of inter-vehicle exchanged messages is usually much smaller than the data load over V2I communication links in reality. Hence, this paper mainly focuses on optimizing V2I communication reliability under the data-massive transmission integrity and delay constraints. In the V2I communication-based MEC paradigm, the data transmitted from platooning vehicles to the roadside infrastructure can be the input of sensor data-driven application programs. The roadside infrastructure equipped with MEC is essential in processing large-size sensor data and creating models and strategies fed back to the platooning vehicles to enhance their comfort and safety.

We denote the set of platooning vehicles by $\mathcal{N} = \{0, 1, \ldots, N\}$, where the leader is indexed by 0 and the other following vehicles are indexed from 1 to N. The operation of the system is considered to be slotted into a series of discrete time intervals, each with a constant duration of $\Delta\tau$ seconds. To enable mathematically-tractable analysis, we exploit a canonical model with two key parameters that characterize the transmission delay constraint and the data load of an up-stream application or a computing task to be offloaded from a vehicle $j \in \mathcal{N}$ to the roadside infrastructure [70], [71]:

i) The maximum number of time slots for data transmissions, T_j. That is, the application or task data of j must be successfully transmitted to the edge by the required deadline $T_j\Delta\tau$, i.e., within the given T_j time slots. $T_j\Delta\tau$ is indeed referred to as the allowed delay limit.

ii) The total data load of j, Q_j. Vehicle j expects to fully transmit the Q_j-bit data to the edge, such that the computing edge can intactly reconstruct the vehicular application or task.

The essential goal of reliable data transmission scheduling over a V2I communication link is to determine a proper number of data bits to be served in each time slot t, $q_j(t) \in \mathbb{R}_{\geq 0}$, such that the probability that the overall data bits Q_j are successfully transmitted by the delay limit $T_j\Delta\tau$ is maximized. Let $\boldsymbol{q}_j = [q_j(1), q_j(2), \ldots, q_j(T_j)]^{\mathrm{T}} \in \mathbb{R}^{T_j \times 1}$ denote a scheduling solution for vehicle j. According to the transmission integrity and delay requirements above, we have the following feasible set for j's data transmission scheduling

$$\mathcal{Q}_j = \left\{ \boldsymbol{q}_j \in \mathbb{R}^{T_j \times 1} : \sum_{t=1}^{T_j} q_j(t) = Q_j, \forall q_j(t) \geq 0 \right\}. \quad (1)$$

A. Platoon Mobility Formulation

In vehicle platooning control and connected vehicle communication, the most commonly used dynamics models are the double integrator model and the engine/powertrain dynamics model. The discrete-time double integrator model is widely employed for designing high-level controllers for vehicle platoons [6], [52], [53], [55], [56], [58], [72], [73]. While the engine/powertrain dynamics, capturing lower-layer effects like torque dynamics, actuator and communication delays, and inertia effects, are explored in other works [53], [55], [56], [74]. By comparing the advantages of the two modeling approaches and considering the primary focus of this paper, we chose the double integrator model to build the vehicle dynamics model. Given the small time slot duration $\Delta\tau$, each vehicle's kinematics can be approximated as constant within a time interval. Thus, we adopt the discrete-time double integrator model, which state-space form is as follows

$$\boldsymbol{x}_j(t+1) = \boldsymbol{A}\boldsymbol{x}_j(t) + \boldsymbol{B}a_j(t),\ j \in \mathcal{N}, \quad (2)$$

where $\boldsymbol{x}_j(t) \in \mathbb{R}^{2\times 1}$ is a kinematic state of vehicle j at t, and $\boldsymbol{A} \in \mathbb{R}^{2\times 2}$ and $\boldsymbol{B} \in \mathbb{R}^{2\times 1}$ are the coefficient matrices of state $\boldsymbol{x}_j(t)$ and control input $a_j(t)$, respectively. These mathematical terms are defined as follows

$$\boldsymbol{x}_j(t) = \begin{bmatrix} s_j(t) \\ v_j(t) \end{bmatrix},\ \boldsymbol{A} = \begin{bmatrix} 1 & \Delta\tau \\ 0 & 1 \end{bmatrix},\ \boldsymbol{B} = \begin{bmatrix} 0.5\,(\Delta\tau)^2 \\ \Delta\tau \end{bmatrix}. \quad (3)$$

where $s_j(t)$, $v_j(t)$, and $a_j(t)$ are the longitudinal position, velocity, and acceleration of vehicle j at time t, respectively. In (2), the acceleration, $a_j(t)$, is a key design parameter that is generally considered as the control input of vehicle j to coordinate the individual motion behavior. Besides, in reality, the kinematic parameters of vehicles should be physically bounded. We denote the bounds on $v_j(t)$ and $a_j(t)$ as $\mathcal{V} = [v_{\min}, v_{\max}]$ and $\mathcal{A} = [a_{\min}, a_{\max}]$, where $v_{\min}$ and $v_{\max}$ are the minimal and maximal allowed velocities, and $a_{\min}$ and $a_{\max}$ are the minimal and maximal allowed accelerations. We have $v_j(t) \in \mathcal{V}$ and $a_j(t) \in \mathcal{A}$ for all j and t.

To ensure smooth motion and stability, each following vehicle $j \in \mathcal{N}/\{0\}$ should adaptively respond to its preceding vehicle $j-1 \in \mathcal{N}$. In this regard, the control input of vehicle j becomes a function of the kinematic parameters of its preceding vehicle. Thus, we propose a car-following control protocol for each j based on linear state feedback. Recently, the Constant Time Headway (CTH) policy is widely adopted in the vehicle platooning literature [22], [54], [56], [57], [61], [64]. The form of CTH can be expressed as $d_{j,j-1}(t) = \tau v_j(t) + l_{j-1}$, where τ denotes the desired time headway of the platooning vehicles and l_{j-1} is the desired constant inter-vehicle distance between vehicles j and $j-1$ that is independent of the vehicle velocity. Inspired by the relationship between vehicle accidents and speed differentials [75], we exploit a variant of the CTH policy to design the control protocol. To be specific, let $d_{j,j-1}(t) = \tau(v_j(t) - v_{j-1}(t)) + l_{j-1}$ be the desired inter-vehicle distance between vehicles j and $j-1$ at t for $j \in \mathcal{N} \setminus \{0\}$. Based on the aforementioned information, we propose a leader-predecessor-follower (LPF) control protocol, incorporating a variant of the CTH policy

$$a_j(t) = -\boldsymbol{\beta}_j^{\mathrm{T}}\left(\boldsymbol{x}_j(t) - \boldsymbol{x}_{j-1}(t)\right) - \boldsymbol{\beta}_j^{\mathrm{T}}\left(\boldsymbol{x}_j(t) - \boldsymbol{x}_0(t)\right) - \lambda_j, \quad (4)$$

where $\boldsymbol{\beta}_j = [\alpha_{1,j}, \alpha_{1,j}\tau + \alpha_{2,j}]^{\mathrm{T}}$ for $j \in \mathcal{N} \setminus \{0\}$, $\lambda_j = \alpha_{1,j}\left(l_{j-1} + \sum_{i=1}^{j} l_{i-1}\right)$ for $j \in \mathcal{N} \setminus \{0\}$, $\alpha_{1,j}$ and $\alpha_{2,j}$ are tunable parameters according to the car following behavior in the platoon. As seen in (4), each vehicle (except the platoon leader) generates its control input using state feedback from the preceding vehicle and the leader. By combining (4) and (2), we establish a car-following-based platoon control system, where each vehicle's kinematics depend on its predecessor and the leader's behavior. Thus, the overall platoon mobility hinges on the leader's control input. Due to the LPF information topology, each following vehicle detects the inter-vehicle distance and velocity relative to its predecessor via onboard sensors (e.g., radar) and receives position and velocity information from the leader via vehicular communications.

According to [6], the control gains $\alpha_{1,j}$ and $\alpha_{2,j}$ in (4), for $j \in \mathcal{N}\backslash\{0\}$, should be positive to ensure the stability of the platoon system. This stability means all vehicles reach consensus on the desired inter-vehicle spacing and velocity. Additionally, string stability is crucial to prevent disturbances in position or velocity from amplifying downstream. Various studies have examined theoretical criteria for string stability from frequency-domain and time-domain perspectives [22], [51], [56], [57], [64]. According to the $\mathcal{L}2$ string stability definition in [76], the control gains $\alpha 1, j$ and $\alpha_{2,j}$ in the LPF protocol with the CTH policy (4) can be chosen to satisfy the following condition to ensure string stability

$$\sup_{\Delta d_{\text{er},j-1}(t)\neq 0} \frac{\|\Delta d_{\text{er},j}(t)\|_{\mathcal{L}_2}}{\|\Delta d_{\text{er},j-1}(t)\|_{\mathcal{L}_2}} \leq 1,\ \forall t, \tag{5}$$

where $\Delta d_{\text{er},j}(t)$ is defined as the discrete-time spacing error between vehicles j and $j-1$ at time t, i.e., $\Delta d_{\text{er},j}(t) = s_{j-1}(t) - s_j(t) - l_{\text{veh},j-1} - d_{j,j-1}(t)$ for $j \in \mathcal{N}\backslash\{0\}$. Here, $l_{\text{veh},j-1}$ denotes the body length of vehicle $j-1$. The $\mathcal{L}_2$-norm of the spacing error $\Delta d_{\text{er},j-1}(t)$ is given as $\|\Delta d_{\text{er},j}(t)\|_{\mathcal{L}_2} = \left(\sum_{t=1}^{T_j} |\Delta d_{\text{er},j}(t)|^2\right)^{\frac{1}{2}}$ for $j \in \mathcal{N}\backslash\{0\}$. Let $Z\{\cdot\}$ denote the Z-transformation operator and $\Delta d_{\text{er},j}(z) = Z\left\{\Delta d_{\text{er},j}(t)\right\}$ for all j where z is the Z-transformation variable. Accordingly, we denote the transfer function between two spacing errors $\Delta d_{\text{er},j}(z)$ and $\Delta d_{\text{er},j-1}(z)$ by $\Gamma_j(z)$. Due to the linearity of the mobility model (2) and the control protocol (4), we have $\Delta d_{\text{er},j}(z) = \Gamma_j(z)\Delta d_{\text{er},j-1}(z)$ for $j \in \mathcal{N}\backslash\{0\}$. According to [77], [78], the $\mathcal{H}_\infty$-norm of the transfer function can be derived from (5) as follows

$$\|\Gamma_j(z)\|_{\mathcal{H}_\infty} = \sup_{\Delta d_{\text{er},j-1}(z)\neq 0} \frac{\|\Gamma_j(z)\Delta d_{\text{er},j-1}(z)\|_{\mathcal{L}_2}}{\|\Delta d_{\text{er},j-1}(z)\|_{\mathcal{L}_2}} \leq 1, \tag{6}$$

for $j \in \mathcal{N}\backslash\{0\}$. (6) provides the sufficient condition to guarantee the $\mathcal{L}_2$ string stability. In practice, the transfer function $\Gamma_j(z)$ for all j can be constructed by using the system identification technique based on measured data (i.e., frequency-domain data) or the theoretical approximation. As shown in [77], [78], $\left\|\Gamma_j(e^{i\omega})\right\|_{\mathcal{H}_\infty}$ provides a tight upper bound of the $\mathcal{L}_2$-norm in (5) for $j \in \mathcal{N}\backslash\{0\}$. Thus, we can configure the gain parameters of the car-following control protocol offline to guarantee $\left\|\Gamma_j(e^{i\omega})\right\|_{\mathcal{H}_\infty} \leq 1$ for any angular frequency $\omega \in [-\pi, \pi]$ where i denotes the unit imaginary number. Once the gain parameters are configured, they can be applied to compute the string stability-guaranteed control actions online by the platooning vehicles.[1]

[1]From the optimal control perspective, the control gains can also be treated as a kind of decision variable and then integrated into the optimization procedure. However, the gain-integrated optimization will increase the model complexity and may make computing control signals intractable since the constraints on the $\mathcal{L}_2$ string stability and the transfer function involving the control gains should be addressed at the same time. The optimal design of the control gains is really out of the scope of our current work, which is left as our future work. Besides, a more comprehensive survey of analysis methodologies for platoon string stability can be found in [76].

B. Vehicle Fuel Consumption Formulation

By forming a platoon, vehicles can travel with a smaller space headway, thus reducing aerodynamic drag over the front surface of each follower. Regarding the fuel efficiency of platooning vehicles, we adopt a velocity-dependent function to approximate the fuel consumption of vehicle j as in [79]

$$F_j(t) = \beta_{j3}v_j^2(t) + \beta_{j2}v_j(t) + \beta_{j1} + \frac{\beta_{j0}}{v_j(t)},\ j \in \mathcal{N}, \tag{7}$$

where $\beta_{j3}, \beta_{j2}, \beta_{j1}, \beta_{j0}$ are vehicle-specific parameters. To be specific, $\beta_{j3}v_j^2(t)$ is the fuel consumption associated with air resistance, $\beta_{j2}v_j(t)$ captures the engine-related fuel consumption, β_{j1} provides the fuel consumption due to acceleration, upgrade and friction, and $\frac{\beta_{j0}}{v_j(t)}$ describes fuel consumption for accessory purpose such as air conditioning. According to [79], the fuel consumption model (7) is sufficiently reasonable to fit power-based and regression-based statistical models like comprehensive modal emission model [80], MOVES [81], and VT-Micro model [82]. Therefore, it is employed here for the fuel-efficient optimization of the vehicle platoon.

While vehicles can improve driving range through braking energy recovery, our study does not account for this, as we primary focus on fuel consumption in internal combustion engine vehicles. The second reason is that it is common in fuel consumption studies not to emphasize braking energy recovery [83]–[85]. Additionally, we do not consider the aerodynamic effects on the leading vehicle caused by following vehicles in a platoon, as research shows this only significantly impacts fuel consumption when the vehicles are very close [86].

C. V2I Communication Model

The distance between the vehicle and the communication infrastructure is an important factor in the V2I communication model. This means that the quality of V2I communication is inherently coupled with the mobility of the vehicle platoon. To establish the distance model between the vehicle and the roadside infrastructure, we use the longitudinal position commonly employed in vehicle platooning studies (e.g., [63], [76]) to represent the longitudinal positions of the entities in our research scenario. We denote the longitudinal positions of the roadside infrastructure and vehicle j by s_I and $s_j(t)$, respectively. Meanwhile, we define the vertical relative distance from the infrastructure to the road centerline by ΔL. The time-varying distance between each vehicle j and the infrastructure, determined by the temporal-spatial trajectory of the vehicle, can be formulated as

$$L_j(t) = \sqrt{(s_\text{I} - s_j(t))^2 + (\Delta L)^2},\ j \in \mathcal{N}. \tag{8}$$

where $L_j(t)$ denotes the Euclidean distance between the vehicle j and the infrastructure at time slot t.

To model the V2I communication capacity, we consider the Single-Carrier Frequency Division Multiplexing Access (SC-FDMA) protocol for vehicular channel access according to the standard specification for Long Term Evolution-based Vehicle-to-Everything (LTE-V2X) networks and let $\theta_j(t)$ denote the amount of data bits that can be transmitted by vehicle j in time slot t, $j \in \mathcal{N}$. In general, $\theta_j(t)$ depends on the bandwidth allocated to the platooning vehicles, their transmission power, and the quality of the time-varying communication channel. Furthermore, we refer to Shannon's channel capacity formula to calculate $\theta_j(t)$ as follows

$$\theta_j(t) = \frac{B}{M+N+1} \log_2\left(1 + \omega_j g^2(L_j(t))\right), \tag{9}$$

where B is the available bandwidth, and M is the number of other accessing users (excluding $N+1$ platooning vehicles) contending the same channel simultaneously. $\omega_j = \frac{P_T}{N_0}$ represents the normalized power of vehicle j, where P_T is the transmission power and N_0 is the average noise power. $g(L_j(t))$ denotes the distance-dependent channel gain, which is inherently coupled with the vehicle mobility.[2]

Consider that heavily built-up urban environments can significantly affect vehicular signal propagation along V2I links. There are many obstacles in such environments, such as high-rise buildings, trees, and heavy-duty trucks, that frequently scatter the radio signal between the platooning vehicles and the infrastructure, resulting in no-line-of-sight (NLoS) propagation. Thus, Rayleigh fading is viewed as a most reasonable model for NLoS signal propagation [87]. According to [11], [88], [89], we consider that cellular V2I channels follow the well-known Rayleigh fading, such that $g^2(L_j(t))$ follows an exponential distribution with the distance-dependent parameter $(L_j(t))^\gamma$ where γ is the path-loss exponent, i.e., $g^2(L_j(t)) \sim \exp\left((L_j(t))^\gamma\right)$. From the probabilistic perspective, vehicle j, $j \in \mathcal{N}$, is able to successfully offload the application data of $q_j(t)$ bits only when the channel capacity in time slot t should not be less than the required data load, i.e., $\theta_j(t)\Delta\tau \geq q_j(t)$. Therefore, we let the probability of successfully transmitting $q_j(t)$-bit data in time slot t be $p_j(q_j(t)) = \Pr\left\{\theta_j(t) \geq \frac{q_j(t)}{\Delta\tau}\right\}$, $j \in \mathcal{N}$. By substituting (9) into the definition and following the exponential distribution on $(L_j(t))^\gamma$, we can derive the success probability as follows[3]

$$\begin{aligned} p_j(q_j(t)) &= \Pr\left\{\theta_j(t) \geq \frac{q_j(t)}{\Delta\tau}\right\} \\ &= \exp\left(-\frac{2^{\frac{(M+N+1)q_j(t)}{B\Delta\tau}} - 1}{\omega_j} L_j^\gamma(t)\right) \\ &= \exp\left(\frac{L_j^\gamma(t)}{\omega_j} - \frac{L_j^\gamma(t) 2^{\frac{(M+N+1)q_j(t)}{B\Delta\tau}}}{\omega_j}\right), \ j \in \mathcal{N}. \end{aligned} \tag{10}$$

[2]The channel capacity formula (9) or its variant is widely adopted in the field of wireless communications, and networking [11]. Basically, it results from Shannon's information theory. It characterizes the physical-layer relationship between the available bandwidth, the channel access number, the transmission power, and the quality of the stochastically fading channel.

[3]The fading channel model captures physical-layer characteristics, which inherently determine upper-layer performance metrics like packet loss rate and delay. Studies like [90] show that a Rayleigh fading channel can be mapped to an ON-OFF channel to model Bernoulli packet loss distribution. When the channel capacity $\theta_j(t)\Delta\tau$ meets or exceeds the transmission load $q_j(t)$, the channel is ON, and packets are received successfully. Otherwise, the channel is OFF, leading to packet loss. Additionally, a Poisson distribution, statistically related to Bernoulli, describes the discrete probability of packet loss in the fading channel, thus enabling the fading channel model to underpin upper-layer packet loss analysis and derive packet-oriented performance metrics.

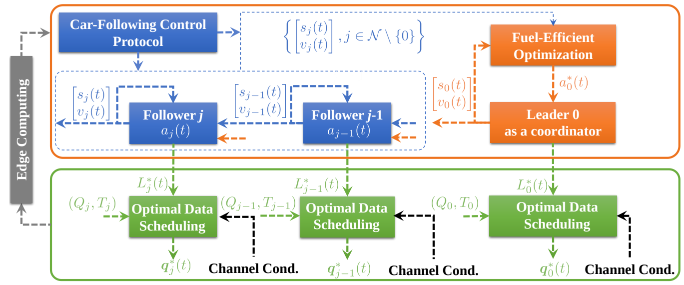

Fig. 2. The two-tier hierarchical framework for joint platoon coordination and data transmission scheduling. The platoon leader sends its real-time position and velocity to all the followers via V2V communications; meanwhile, the followers can share their real-time position and velocity with their leader. Besides, each follower detects the position and velocity of its predecessor by the onboard sensors. Due to the distributed nature of the car-following control protocol, the following vehicles can calculate their control actions locally using their sensing information in a distributed manner. The platooning vehicles also schedule their application data transmitted to the edge cloud using the closed-form scheduling solution based on their mobility information.

Based on (10), we further calculate the overall probability of success in transmitting all the scheduled data bits $\boldsymbol{q}_j = \mathrm{col}\{q_j(1), q_j(2), \ldots, q_j(T_j)\}$ for each vehicle j by the principle of probability multiplication as follows

$$\begin{aligned} \phi_j(\boldsymbol{q}_j) &= \prod_{t=1}^{T_j} p_j(q_j(t)) = \\ &\exp\left(\sum_{t=1}^{T_j}\left(\frac{L_j^\gamma(t)}{\omega_j} - \frac{L_j^\gamma(t) 2^{\frac{(M+N+1)q_j(t)}{B\Delta\tau}}}{\omega_j}\right)\right), \ j \in \mathcal{N}. \end{aligned} \tag{11}$$

In (11), $\phi_j(\boldsymbol{q}_j)$ is referred to as *the V2I communication reliability* of an individual vehicle. It characterizes the possibility from a probabilistic perspective that vehicle j is able to transmit all the Q_j-bit data to the roadside infrastructure by a required deadline $T_j\Delta\tau$ successfully.

Regarding all the platooning vehicles, the overall V2I communication reliability of the platoon is formulated as

$$\begin{aligned} \phi_{\text{platoon}}(\boldsymbol{q}) &= \prod_{j=0}^{N} \phi_j(\boldsymbol{q}_j) = \\ &\exp\left(\sum_{j=0}^{N}\sum_{t=1}^{T_j}\left(\frac{L_j^\gamma(t)}{\omega_j} - \frac{L_j^\gamma(t) 2^{\frac{(M+N+1)q_j(t)}{B\Delta\tau}}}{\omega_j}\right)\right), \end{aligned} \tag{12}$$

where $\boldsymbol{q} = \mathrm{col}\{\boldsymbol{q}_j, j \in \mathcal{N}\}$. When carefully looking into (12), it is seen that the platoon-oriented V2I communication reliability, $\phi_{\text{platoon}}(\boldsymbol{q})$, is inherently coupled with the temporal-spatial trajectories of the platooning vehicles via the time-varying distance measures $\{L_j(t), j \in \mathcal{N}\}$. Thus, a basic optimization problem is how to maximize the communication reliability meanwhile minimizing the resource consumption by jointly controlling platoon mobility and scheduling data transmissions. We address this issue in the following section.

III. Two-Tier Optimization Model

To enable the adaptive response of V2I communication to the platoon mobility, we propose a two-tier hierarchical framework for the co-design of fuel-efficient platoon coordination and data transmission scheduling as shown in Fig. 2. In the upper layer, a car-following mobility optimization is realized to obtain the fuel-efficient control inputs for each platooning vehicle. The platoon leader solves the fuel efficiency optimization model to get a fuel-efficient acceleration control to adjust its mobility; meanwhile, the other vehicles adapt their mobility by following their proceeder in a car-following manner. The upper layer can provide the temporal-spatial kinematic information to the lower layer. In the lower layer, a V2I communication reliability optimization is solved by each vehicle locally to obtain a data transmission scheduling solution. Each vehicle can schedule its computation data offloaded to the edge cloud using a closed-form scheduling solution based on coordinated platoon mobility. Computation offloading enabled by reliable data transmission scheduling can implicitly preserve local computing resources for vehicular task execution and thus benefit mobility optimization and platoon control in the upper layer. The models operated in these two layers are detailed in the following subsections.

A. Fuel-Efficient Car-Following Mobility Optimization

The following vehicles in the platoon use the control protocol (4) to coordinate their mobility in a car-following manner, in which the control input of each follower depends on the kinematics of its preceding vehicle and the leader. Hence, the overall platoon mobility is determined by the leader and we can optimize the platoon mobility by controlling the leader. Let T be $T=\max\{T_j, j\in\mathcal{N}\}$, i.e., the allowed maximum slot number among the platooning vehicles. The collection of the leader's control inputs over T time slots is defined by $\boldsymbol{a}_0=\mathrm{col}\{a_0(t), t=1,2,\ldots,T\}$. $s_j(0)$ and $v_j(0)$ are the given initial position and velocity for vehicle $j\in\mathcal{N}$, respectively. Combining (2), (4) and (7), we formulate a fuel-efficient optimization model as follows

$$\boldsymbol{a}_0^*\in\arg\min_{\boldsymbol{a}_0}:\sum_{j=0}^{N}\sum_{t=1}^{T}F_j(t)$$
$$\text{s.t.}\begin{cases}a_j(t)\in\mathcal{A},\forall j,t;\\ v_j(t)\in\mathcal{V},\forall j,t;\\ s_{j-1}(t)-s_j(t)\geq d_{j,j-1}(t),\forall j,t;\\ (2),\ (4).\end{cases}\tag{13}$$

In (13), the first two constraints bound the acceleration and velocity of the vehicles, respectively. The third constraint guarantees rear-end collision avoidance in the platoon. By solving (13), we can obtain the optimal control input of the leader in terms of the fuel efficiency of the whole platoon, $\boldsymbol{a}_0^*$. Using the car-following protocol (4), we can also obtain the optimal control inputs of all the following vehicles $j=1,2,\ldots,N$ during the individual time slots, $\boldsymbol{a}_j^*=\mathrm{col}\{a_j^*(t), t=1,2,\ldots,T_j\}$. The optimal velocity and trajectory of each vehicle $j\in\mathcal{N}$, $\boldsymbol{v}_j^*=\mathrm{col}\{v_j^*(t), t=1,2,\ldots,T_j\}$ and $\boldsymbol{s}_j^*=\mathrm{col}\{s_j^*(t), t=1,2,\ldots,T_j\}$, are determined by using the mobility model (2) as long as $\boldsymbol{a}_j^*$ is given. For notation simplicity, we denote the set of the optimal fuel-efficient trajectories of the platooning vehicles by $\boldsymbol{s}^*=\mathrm{col}\{\boldsymbol{s}_j^*, j\in\mathcal{N}\}$. It is recognized that (13) is a classical MPC problem with linear constraints. In general, this problem can be effectively solved by using the well-known numerical optimization method, the interior-point method, that is available in various high-performance large-scale optimization solvers like CPLEX, Gurobi, MOSEK, and IPOPT. The computational complexity in solving (13) with the interior-point method is polynomial-time, i.e., in the order of $\mathcal{O}\left(T^{3.5}\right)$, which relies on the number of decision variables, i.e., the size of the leader's control signal $\boldsymbol{a}_0$.

B. Data Transmission Scheduling Optimization

Let the conditional V2I communication reliability of the platoon depending on the optimal trajectories of the vehicles be $\phi_{\text{platoon}}(\boldsymbol{q};\boldsymbol{s}^*)$, i.e.,

$$\phi_{\text{platoon}}(\boldsymbol{q};\boldsymbol{s}^*)=\exp\left(\sum_{j=0}^{N}\sum_{t=1}^{T_j}\left(\frac{(L_j^*(t))^\gamma}{\omega_j}-\frac{(L_j^*(t))^\gamma 2^{\frac{(M+N+1)q_j(t)}{B\Delta\tau}}}{\omega_j}\right)\right),\tag{14}$$

where $L_j^*(t)=\sqrt{(s_{\mathrm{I}}-s_j^*(t))^2+(\Delta L)^2}$, and $s_j^*(t)$ for $t=1,2,\ldots,T_j$ and $j\in\mathcal{N}$ is obtained from (13).

Now, based on (14), we propose a V2I communication reliability optimization model to obtain reliable data transmission scheduling solutions for the platooning vehicles as follows

$$\boldsymbol{q}^*\left(\boldsymbol{s}^*\right)\in\arg\max_{\boldsymbol{q}}:\ \phi_{\text{platoon}}(\boldsymbol{q};\boldsymbol{s}^*)\quad\text{s.t. }\boldsymbol{q}_j\in\mathcal{Q}_j, j\in\mathcal{N}.\tag{15}$$

It is remarked from (15) that the vehicular data transmission scheduling is driven by the platoon mobility. Once an optimal scheduling solution $\boldsymbol{q}^*\left(\boldsymbol{s}^*\right)$ is obtained, depending on the specific platoon mobility $\boldsymbol{s}^*$, the platooning vehicles can offload their massive data to the computing edge (i.e., the roadside infrastructure) for remote processing, such that more onboard computing power is saved and allocated to locally execute other tasks and applications like the real-time car-following coordination based on the obtained control inputs $\{a_j^*(t),\forall j,t\}$. Therefore, in such an implicit closed-loop paradigm, the performance of the platoon system is improved in terms of control and communication.

IV. Analytical Scheduling Solution

To facilitate the implementation of data transmission scheduling, we further derive a special analytical solution based on (15). In the following analysis, we treat $\boldsymbol{q}^*$ as $\boldsymbol{q}^*(\boldsymbol{s}^*)$ and also $\phi_{\text{platoon}}(\boldsymbol{q})$ as $\phi_{\text{platoon}}(\boldsymbol{q};\boldsymbol{s}^*)$ for notation simplicity. Given $\boldsymbol{s}^*$ and $L_j^*(t)$ for all j and t, solving an optimal $\boldsymbol{q}^*$ from (15) boils down to solving the minimization problem

$$\min_{\boldsymbol{q}}:\ U(\boldsymbol{q})=\sum_{j=0}^{N}\sum_{t=1}^{T_j}\frac{\left(L_j^*(t)\right)^\gamma 2^{\frac{(M+N+1)q_j(t)}{B\Delta\tau}}}{\omega_j}\quad\text{s.t. }\boldsymbol{q}_j\in\mathcal{Q}_j, j\in\mathcal{N}.\tag{16}$$

The proof of its convexity can be found in Appendix B. Now, from (16) we have the following lemma.

Lemma 1: For two different time slots, $t' \neq t''$, it holds that

$$\left(L_j^*(t')\right)^{\gamma} 2^{\beta q_j^*(t')} = \left(L_j^*(t'')\right)^{\gamma} 2^{\beta q_j^*(t'')} \tag{17}$$

for $j \in \mathcal{N}$, where β is defined as $\beta = \frac{(M+N+1)}{B\Delta\tau}$ for simplicity, and $q_j^*(t')$, $q_j^*(t'')$ are two positive optimal data partitions, i.e., $q_j^*(t') > 0$ and $q_j^*(t'') > 0$.

Proof: According to the first-order optimality theory, we formulate the Lagrangian function of (16) as follows

$$\begin{aligned}\mathcal{L}(\boldsymbol{q}, \boldsymbol{\lambda}, \boldsymbol{\delta}) = & U(\boldsymbol{q}) - \sum_{j=0}^{N}\sum_{t=1}^{T_j} \lambda_j(t) q_j(t) \\ & - \sum_{j=0}^{N} \delta_j \left(\sum_{t=1}^{T_j} q_j(t) - Q_j\right),\end{aligned} \tag{18}$$

where $\boldsymbol{\lambda}$ is the collection of the nonnegative Lagrangian multipliers associated with the lower-bound constraints in (16), $\boldsymbol{\lambda} = \mathrm{col}\{\lambda_j(t) \in \mathbb{R}_{\geq 0}, \forall j, t\}$, and $\boldsymbol{\delta}$ is the collection of the Lagrangian multipliers associated with the equality constraints in (16), $\boldsymbol{\delta} = \mathrm{col}\{\delta_j \in \mathbb{R}, \forall j\}$. Hence, the Karush-Kuhn-Tucker (KKT) conditions that an optimal data transmission scheduling solution must satisfy are given by

$$\begin{cases} \frac{\partial U(\boldsymbol{q})}{\partial q_j(t)}\Big|_{q_j(t)=q_j^*(t)} - \delta_j - \lambda_j(t) = 0, \forall j, t; \\ \lambda_j(t) q_j^*(t) = 0, \forall j, t; \\ \lambda_j(t) \geq 0, \forall j, t; \\ \boldsymbol{q}^* \in \mathcal{Q}_j, \forall j. \end{cases} \tag{19}$$

In (19), the first item is the gradient condition, the second indicates the complementary slackness, and the third denotes the nonnegative constraint on the Lagrangian multipliers associated with the inequalities. The last item represents the feasibility of the optimal solution.

According to the complementary slackness, when two different data partitions of $j \in \mathcal{N}$ are positive, e.g., $q_j^*(t') > 0$ and $q_j^*(t'') > 0$, it must hold that $\lambda_j(t') = \lambda_j(t'') = 0$. In this situation, from the gradient condition in (19), we further get

$$\delta_j = \frac{\partial U(\boldsymbol{q})}{\partial q_j(t')}\Big|_{q_j(t')=q_j^*(t')} = \frac{\partial U(\boldsymbol{q})}{\partial q_j(t'')}\Big|_{q_j(t'')=q_j^*(t'')}, \tag{20}$$

which immediately results in (17). ■

Lemma 1 mathematically characterizes the fact that each vehicle $j \in \mathcal{N}$ should increase the number of data bits per time slot to be transmitted, $q_j(t)$, when the relative transmission distance, $L_j(t)$, decreases. On the contrary, the platooning vehicles need to reduce the number of data bits served in a time slot to guarantee the probability of success in data transmissions, when they moves far away from the infrastructure. Using Lemma 1, we obtain the results:

Theorem 1: Suppose that there exist an optimal data transmission scheduling solution $\boldsymbol{q}_j^*$ for each $j \in \mathcal{N}$ that is an interior point of the feasible region $\mathcal{Q}_j$, i.e., $\boldsymbol{q}_j^* \in \mathrm{Int}(\mathcal{Q}_j)$. The optimal scheduling solution $\boldsymbol{q}_j^*$ can be expressed in a closed form as follows

$$q_j^*(t) = \frac{Q_j}{T_j} + \frac{\gamma}{\beta T_j}\left[\left(\sum_{\ell=1}^{T_j} \log_2\left(L_j^*(\ell)\right)\right) - T_j \log_2\left(L_j^*(t)\right)\right] \tag{21}$$

for $t = 1, 2, \ldots, T_j$ and $j \in \mathcal{N}$. The optimal V2I communication reliability of the overall platoon is given by

$$\phi^*_{\text{platoon}}(\boldsymbol{q}^*) = \exp\left(\sum_{j=0}^{N}\sum_{t=1}^{T_j}\left[\frac{\left(L_j^*(t)\right)^{\gamma}}{\omega_j} - \frac{2^{\beta Q_j}\prod_{\ell=1}^{T_j}\left(L_j^*(\ell)\right)^{\frac{\gamma}{T_j}}}{\omega_j}\right]\right), \tag{22}$$

where $\boldsymbol{q}^* = \mathrm{col}\{\boldsymbol{q}_j^*, j \in \mathcal{N}\}$.

Proof: According to the condition and Lemma 1, we can derive from the gradient conditions in (19)

$$q_j^*(t) = \frac{1}{\beta}\log_2\left(\frac{\omega_j \delta_j}{\left(L_j^*(t)\right)^{\gamma}(\ln 2)\beta}\right), \forall j, t. \tag{23}$$

Substituting (23) into the equality constraint $\sum_{\ell=1}^{T_j} q_j^*(\ell) = Q_j$ can get the equation with respect to δ_j as follows

$$\sum_{\ell=1}^{T_j}\log_2\left(\frac{\omega_j \delta_j}{\left(L_j^*(\ell)\right)^{\gamma}(\ln 2)\beta}\right) = \beta Q_j, j \in \mathcal{N}. \tag{24}$$

Solving (24) can derive the explicit expression of δ_j as follows

$$\delta_j = \frac{1}{\omega_j} 2^{\frac{\beta Q_j}{T_j}}\left[\prod_{\ell=1}^{T_j}\left(\left(L_j^*(\ell)\right)^{\gamma}(\ln 2)\beta\right)\right]^{\frac{1}{T_j}}, j \in \mathcal{N}. \tag{25}$$

Substituting (25) back into (23) can immediately derive the closed-form expression in (21). Moreover, substituting (21) into the definition (14) can also obtain (22). At this point, the theorem is proven. ■

Furthermore, when the optimal scheduling solution $\boldsymbol{q}_j^*$ is a boundary point of the feasible region $\mathcal{Q}_j$ for $j \in \mathcal{N}$, i.e., $\boldsymbol{q}_j^* \in \partial(\mathcal{Q}_j)$ where there exists at least one zero component in $\boldsymbol{q}_j^*$, i.e., $\exists t \in \{1, 2, \ldots, T_j\}$, $q_j^*(t) = 0$, the results in Theorem 1 may not be applicable. Hence, we extend the closed-form results of Theorem 1 to a more general situation as follows.

For notation simplicity, let $\mathcal{T}_j = \{1, 2, \ldots, T_j\}$ for each $j \in \mathcal{N}$. Let the index set of the platoon vehicles that will not transmit data bits in some certain time slots be $\mathcal{M}$, i.e., $\mathcal{M} \subset \mathcal{N}$ and $\mathcal{M} \neq \emptyset$. For each $j \in \mathcal{M}$, we further denote by $\mathcal{T}_{j,\text{inactive}}$ the index set of time slots in which vehicle j keeps silent, and $\mathcal{T}_{j,\text{active}}$ the index set of time slots in which vehicle j transmits data bits. For $j \in \mathcal{M}$, we have $\mathcal{T}_{j,\text{inactive}} \neq \emptyset$ and $\mathcal{T}_{j,\text{inactive}} \cup \mathcal{T}_{j,\text{active}} = \mathcal{T}_j$. For vehicle $j \in \mathcal{N} \setminus \mathcal{M}$ that is always active in each time slot, we can simply let $\mathcal{T}_{j,\text{inactive}} = \emptyset$ and $\mathcal{T}_{j,\text{active}} = \mathcal{T}_j$.

We define $G_j(t)$ for $j \in \mathcal{N}$ and $t \in \mathcal{T}_j$ according to (21),

$$G_j(t) = \frac{Q_j}{T_j} + \frac{\gamma}{\beta T_j}\left[\left(\sum_{\ell=1}^{T_j}\log_2\left(L_j^*(\ell)\right)\right) - T_j \log_2\left(L_j^*(t)\right)\right]. \tag{26}$$

In the above situation where $\boldsymbol{q}_j^* \in \partial(\mathcal{Q}_j)$, $\exists j \in \mathcal{N}$, we derive more general results in the following theorem.

Theorem 2: Suppose that $\exists j \in \mathcal{N}$ $\boldsymbol{q}_j^*$ is a boundary point of the feasible region $\mathcal{Q}_j$, i.e., $\boldsymbol{q}_j^* \in \partial(\mathcal{Q}_j)$. The index set $\mathcal{M}$ can be constructed by

$$\mathcal{M} = \arg_j\left\{G_j(t) \leq 0, t \in \mathcal{T}_j, j \in \mathcal{N}\right\}. \tag{27}$$

For $j \in \mathcal{M}$, the index sets $\mathcal{T}_{j,\text{inactive}}$ and $\mathcal{T}_{j,\text{active}}$ can be constructed by

$$\begin{aligned} \mathcal{T}_{j,\text{inactive}} &= \arg_t \left\{ G_j(t) \leq 0, t \in \mathcal{T}_j \right\}, \\ \mathcal{T}_{j,\text{active}} &= \mathcal{T}_j \setminus \mathcal{T}_{j,\text{inactive}}. \end{aligned} \tag{28}$$

For $\ell \in \mathcal{T}_{i,\text{active}}$, $i \in \mathcal{N} \setminus \mathcal{M}$ and for $\ell \in \mathcal{T}_{i,\text{active}}$, $i \in \mathcal{M}$, the positive (nonzero) optimal component, $q_i^*(\ell) > 0$, can be expressed in a closed form as follows

$$\begin{aligned} q_i^*(\ell) =& \frac{Q_i}{|\mathcal{T}_{i,\text{active}}|} \\ &+ \frac{\gamma}{\beta\, |\mathcal{T}_{i,\text{active}}|} \left[\begin{array}{c} \left(\displaystyle\sum_{k \in \mathcal{T}_{i,\text{active}}} \log_2 \left(L_i^*(k) \right) \right) \\ - |\mathcal{T}_{i,\text{active}}| \log_2 \left(L_i^*(\ell) \right) \end{array} \right]. \end{aligned} \tag{29}$$

The optimal V2I communication reliability of the overall platoon is given by

$$\begin{aligned} &\phi_{\text{platoon}}^*(\boldsymbol{q}^*) = \\ &\exp \left(\sum_{j=0}^{N} \sum_{t=1}^{T_j} \frac{(L_j^*(t))^\gamma}{\omega_j} - W\left(\mathcal{T}_{j,\text{active}}, j \in \mathcal{N}\right) \right), \end{aligned} \tag{30}$$

where $W\left(\mathcal{T}_{j,\text{active}}, j \in \mathcal{N}\right)$ is defined by

$$\begin{aligned} W\left(\mathcal{T}_{j,\text{active}}, j \in \mathcal{N}\right) =& \sum_{j \in \mathcal{N}, \mathcal{T}_{j,\text{active}} = \emptyset} \ \sum_{\ell \in \mathcal{T}_{j,\text{inactive}}} \frac{(L_j^*(\ell))^\gamma}{\omega_j} \\ &+ \sum_{j \in \mathcal{N}, \mathcal{T}_{j,\text{active}} \neq \emptyset} \ \sum_{\ell \in \mathcal{T}_{j,\text{active}}} \frac{2^{\beta Q_j} \displaystyle\prod_{k \in \mathcal{T}_{j,\text{active}}} \left(L_j^*(k) \right)^{\frac{\gamma}{|\mathcal{T}_{j,\text{active}}|}}}{\omega_j}. \end{aligned} \tag{31}$$

Proof: As indicated in the condition, we have $\mathcal{M} \subset \mathcal{N}$, $\mathcal{M} \neq \emptyset$, and $\mathcal{T}_{j,\text{inactive}} \subset \mathcal{T}_j$, $\mathcal{T}_{j,\text{inactive}} \neq \emptyset$ for $j \in \mathcal{M}$. Besides, we have $q_j^*(t) = 0$ for $t \in \mathcal{T}_{j,\text{inactive}}$ and $j \in \mathcal{M}$.

According to the complementary slackness as in Lemma 1 and due to the fact that $q_j^*(t') = 0$ for $j \in \mathcal{M}$ and $t' \in \mathcal{T}_{j,\text{inactive}}$, the Lagrangian multiplier $\lambda_j(t')$ may not be zero. But, with the nonnegative constraints, $\lambda_j(t')$ always meets $\lambda_j(t') \geq 0$. Thus, using the gradient condition, we have

$$\left. \frac{\partial U(\boldsymbol{q})}{\partial q_j(t')} \right|_{q_j(t') = q_j^*(t')} = \delta_j + \lambda_j(t') \geq \delta_j \tag{32}$$

for $j \in \mathcal{M}$ and $t' \in \mathcal{T}_{j,\text{inactive}}$.

On the other side, according to Lemma 1, we have

$$\left. \frac{\partial U(\boldsymbol{q})}{\partial q_j(t'')} \right|_{q_j(t'') = q_j^*(t'')} = \delta_j \tag{33}$$

for $j \in \mathcal{M}$ and $t'' \in \mathcal{T}_{j,\text{active}}$, since $\lambda_j(t'') = 0$ under the condition $q_j^*(t'') > 0$.

Combining (32) and (33), we get the following inequality

$$\left. \frac{\partial U(\boldsymbol{q})}{\partial q_j(t'')} \right|_{q_j(t'') = q_j^*(t'')} \leq \left. \frac{\partial U(\boldsymbol{q})}{\partial q_j(t')} \right|_{q_j(t') = q_j^*(t')} \tag{34}$$

for $j \in \mathcal{M}$, $t' \in \mathcal{T}_{j,\text{inactive}}$ and $t'' \in \mathcal{T}_{j,\text{active}}$. With the expression of $U(\boldsymbol{q}^*)$, (34) directly results in

$$\left(L_j^*(t'') \right)^\gamma 2^{\beta q_j^*(t'')} \leq \left(L_j^*(t') \right)^\gamma 2^{\beta q_j^*(t')} = \left(L_j^*(t') \right)^\gamma \tag{35}$$

for $j \in \mathcal{M}$, $t' \in \mathcal{T}_{j,\text{inactive}}$ and $t'' \in \mathcal{T}_{j,\text{active}}$.

From (35), we further have

$$\sum_{t''=1}^{T_j} \log_2 \left(\left(L_j^*(t'') \right)^\gamma \right) + \sum_{t''=1}^{T_j} \beta q_j^*(t'') \leq \sum_{t''=1}^{T_j} \log_2 \left(\left(L_j^*(t') \right)^\gamma \right). \tag{36}$$

Recalling $\sum_{t''=1}^{T_j} q_j^*(t'') = Q_j$, (36) is equivalent to

$$\gamma \sum_{t''=1}^{T_j} \log_2 \left(\left(L_j^*(t'') \right) \right) + \beta Q_j \leq T_j \gamma \log_2 \left(\left(L_j^*(t') \right) \right). \tag{37}$$

Now, combining (37) and (26) can get the following inequality

$$\frac{Q_j}{T_j} + \frac{\gamma}{\beta T_j} \left[\left(\sum_{t''=1}^{T_j} \log_2 \left(L_j^*(t'') \right) \right) - T_j \log_2 \left(L_j^*(t') \right) \right] \leq 0, \tag{38}$$

which indicates $G_j(t') \leq 0$ for $j \in \mathcal{M}$, $t' \in \mathcal{T}_{j,\text{inactive}}$.

On the contrary, for $q_j^*(t') = 0$ and $q_j^*(t'') > 0$ where $t' \in \mathcal{T}_{j,\text{inactive}}$, $t'' \in \mathcal{T}_{j,\text{active}}$ and $j \in \mathcal{N}$, using the same logic above and Lemma 1, we can obtain

$$\left(L_j^*(t') \right)^\gamma \geq \left(L_j^*(t'') \right)^\gamma 2^{\beta q_j^*(t'')} > \left(L_j^*(t'') \right)^\gamma, \tag{39}$$

which leads to

$$\gamma \sum_{\ell=1}^{T_j} \log_2 \left(\left(L_j^*(\ell) \right) \right) + \beta Q_j > T_j \gamma \log_2 \left(\left(L_j^*(t'') \right) \right). \tag{40}$$

(40) further indicates

$$\frac{Q_j}{T_j} + \frac{\gamma}{\beta T_j} \left[\left(\sum_{\ell=1}^{T_j} \log_2 \left(L_j^*(\ell) \right) \right) - T_j \log_2 \left(L_j^*(t'') \right) \right] > 0. \tag{41}$$

In this case, we can see $G_j(t'') > 0$ for $q_j^*(t'') > 0$ where $t'' \in \mathcal{T}_{j,\text{active}}$ and $j \in \mathcal{N}$.

Combining (38) and (41), we have the following results

$$\begin{cases} G_j(t') \leq 0, \ t' \in \mathcal{T}_{j,\text{inactive}}; \\ G_j(t'') > 0, \ t'' \in \mathcal{T}_{j,\text{active}}, \end{cases} \tag{42}$$

for $j \in \mathcal{N}$. As indicated by (42), we can check the sign of $G_j(t)$ to determine which vehicle in $\mathcal{N}$ does not alway transmit data bits, and in which time slots no data transmissions occur. Thus, we can have (27) and (28).

Furthermore, once we determine the index sets $\mathcal{M}$ and $\mathcal{T}_{j,\text{active}}$ for $j \in \mathcal{M}$, we can rewrite the data transmission integrity constraint as follows

$$\begin{aligned} \sum_{t \in \mathcal{T}_j} q_j^*(t) &= \sum_{\ell \in \mathcal{T}_{j,\text{inactive}}} q_j^*(\ell) + \sum_{\ell \in \mathcal{T}_{j,\text{active}}} q_j^*(\ell) \\ &= \sum_{\ell \in \mathcal{T}_{j,\text{active}}} q_j^*(\ell) = Q_j \end{aligned} \tag{43}$$

for $j \in \mathcal{N}$, since $q_j^*(\ell) = 0$ for $\ell \in \mathcal{T}_{j,\text{inactive}}$, $j \in \mathcal{N}$. Thus, using the same logic in Theorem 1, we can immediately derive the closed-form expressions for the positive optimal scheduling components, $\left\{ q_j^*(\ell) > 0, \ell \in \mathcal{T}_{j,\text{active}}, j \in \mathcal{M} \right\}$, and for the optimal V2I communication reliability of the platoon as in (29) and (30), respectively. Then, the theorem is proven. ■

It is remarked that using Theorems 1 and 2 we can analytically calculate the reliability-optimal data transmission

TABLE I
PARAMETER SETTINGS.

Symbol	Definition	Value
T_j	number of time slots	300
Q_j	application data volume	30 Mbit
$\Delta\tau$	duration per time slot	0.1 s
τ	desired time headway	1 s
l_{j-1}	desired inter-vehicle spacing	8 m
$\alpha_{1,j}$, $\alpha_{2,j}$	controller gains	0.3, 0.7
$[v_{\min}, v_{\max}]$	velocity bounds	$[0, 33]\,\mathrm{m/s}$
$[a_{\min}, a_{\max}]$	acceleration bounds	$[-3, 3]\,\mathrm{m/s^2}$
β_{j0}, β_{j1}	parameters for (7)	8, 1.09 [79], [91]
β_{j2}, β_{j3}	parameters for (7)	0.0052, 0.0007 [79], [91]
B	available bandwidth	10 MHz [92]
γ	path loss exponent	2.75 [92]
P_T	transmission power	33 dBm [92]
N_0	average background noise	−95 dBm [92]

scheduling solution, $\boldsymbol{q}_j^*$, $j \in \mathcal{N}$, for the platooning vehicles when the temporal-spatial information, $\boldsymbol{s}_j^*$, $j \in \mathcal{N}$, is given from the platoon coordination layer. This essentially enables the computation offloading of the vehicles via V2I communication to adaptively response to the coordinated platoon mobility. Additionally, the optimal V2I communication reliability of the platoon in the theorems provides an upper bound of the reliability performance. It takes into account the channel characteristics and the integrity and delay requirements besides the mobility. The closed-form expression provides a deep insight into how these aforementioned factors are coupled, thus being helpful to the system design of MEC-enabled CVIS. Another benefit of Theorems 1 and 2 is that the closed-form expressions provided can be used to obtain the optimal data transmission scheduling solution directly. We do not need to perform a sequence of algorithmic iterations. At this point, the computational complexity in solving the minimization problem (16) is quite low, which can be in the order of $\mathcal{O}(1)$.

V. PERFORMANCE EVALUATION

In this section, we present the simulation experiments to validate our proposed model and method and compare the performance with other schemes.

A. Parameter Settings

We consider a platoon system with one leader vehicle and four following vehicles in the simulations. The initial acceleration of the vehicles is $0\,\mathrm{m/s^2}$, and the initial velocity is $20\,\mathrm{m/s}$. The leader is initially located at $100\,\mathrm{m}$, and the inter-vehicle distance is initialized to $10\,\mathrm{m}$. s_{I} is set to $300\,\mathrm{m}$ and L is set to $10\,\mathrm{m}$. We also let $M = 40$ to simulate the effect of channel contention. The main simulation parameters of our control protocol, fuel consumption model and V2I communication model are configured based on the recent literature as summarized in Table I. More insights for simulation implementation are detailed in Appendix C in the online supplementary material.

B. Model Validation

Fig. 3 shows that the platoon leader decelerates in the first few seconds and then increases its acceleration to boost

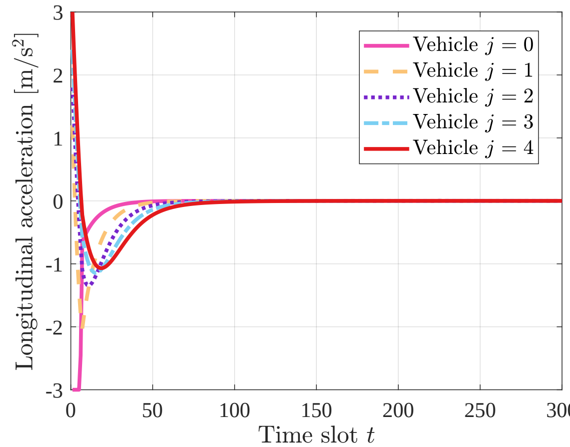

Fig. 3. The optimal accelerations of the platooning vehicles.

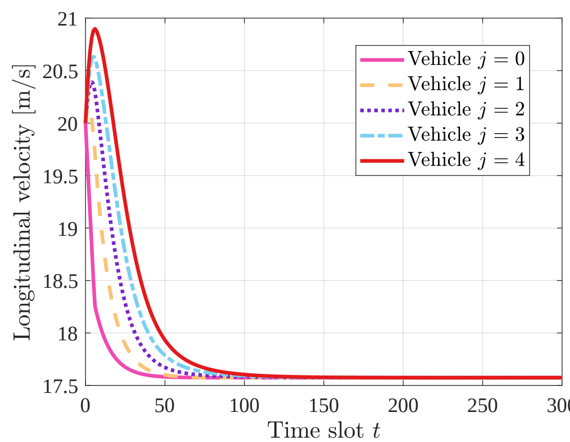

Fig. 4. The optimal velocities of the platooning vehicles.

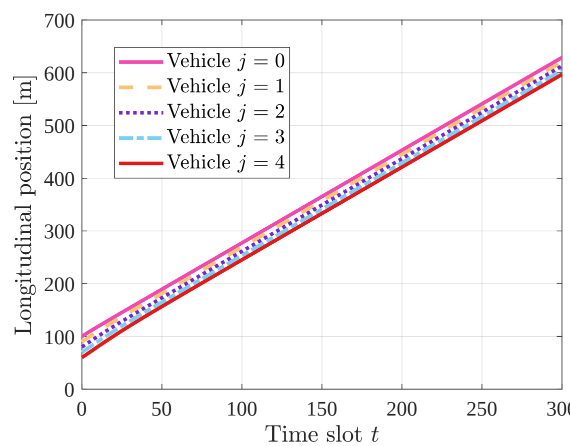

Fig. 5. The optimal trajectories of the platooning vehicles.

the velocity. Due to the car-following control, the following vehicles also react to the leader's behavior by reducing their accelerations at the beginning. After about $100 \times 0.1 = 10$ seconds, the vehicles can stably converge to the uniform motion state. As shown in Fig. 4, the velocity of the leader decreases to about $17.58\,\mathrm{m/s}$ while the following vehicles can finally reach the stable velocity state as that of the leader. In this way, the

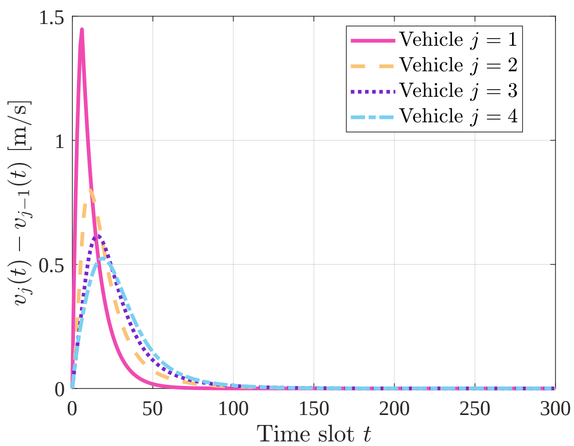

Fig. 6. The car-following velocity errors.

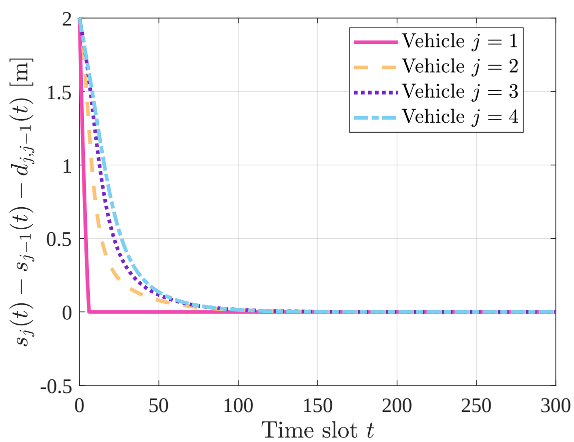

Fig. 7. The car-following position errors.

velocities of the platooning vehicles are optimized to save fuel consumption meanwhile achieving platoon consensus. Fig. 5 illustrates the temporal-spatial trajectories of the platooning vehicles, indicating that the vehicles guarantee the motion smoothness under the control. In Fig. 6, the inter-vehicle velocity error between any two platooning vehicles is stabilized, i.e., $(v_j(t) - v_{j-1}(t))$ arriving at zero for $j = 1, 2, 3, 4$. Similarly, the position error, $(-s_i(t) + s_0(t) - i \times l_0)$ for $j = 1, 2, 3, 4$, can also reach zero after about 10 seconds as shown in Fig. 7. The results indicate that the proposed fuel-efficient optimization solution with the car-following control can stably coordinate the whole platoon.

Fig. 8 illustrates each vehicle's reliability-optimal data transmission scheduling. The platooning vehicles increase the number of data bits served in the time slots when approaching the roadside infrastructure and when the V2I communication link can support increasing data load. On the contrary, the vehicles reduce their data bits to guarantee the probability of success in data transmissions when they are moving far away from the infrastructure. The increasing or decreasing rate of each vehicle's data allocation depends on its moving velocity relative to the infrastructure. In this fashion, the vehicles can adapt data transmissions according to their mobility. Additionally, we also compare the analytical scheduling solutions with those

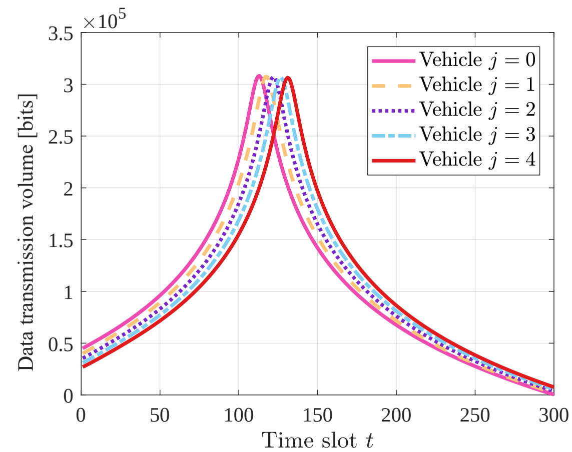

Fig. 8. The optimal V2I data scheduling solution of each vehicle.

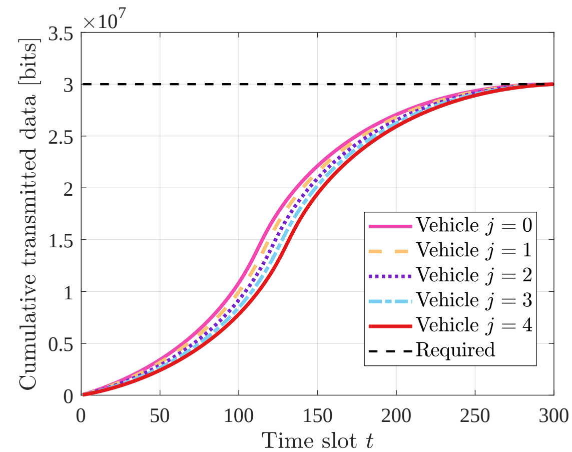

Fig. 9. The cumulative transmitted data bits of each vehicle.

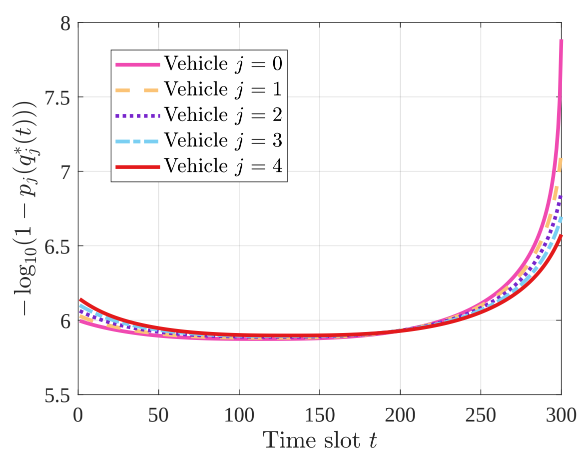

Fig. 10. The optimal V2I communication reliability of each vehicle.

obtained by performing numerical optimization in Appendix D in the online supplementary material. The analytical results match the numerical results, thus validating Theorems 1 and 2 derived in our paper. From Fig. 9, we see that the vehicles can complete the transmission of their required data volume (i.e., $30\,\mathrm{Mbit}$) by the given deadline. This result indicates that the

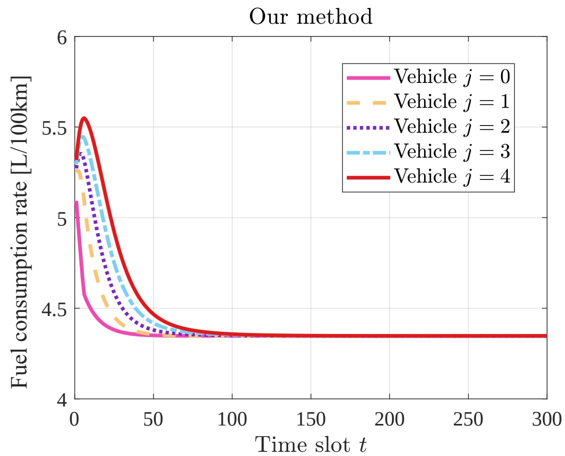

Fig. 11. The variation of each vehicle's fuel consumption under our method using fuel-efficient optimization.

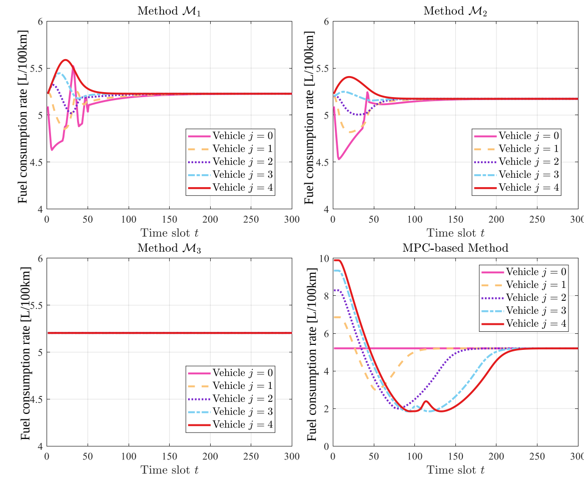

Fig. 12. The variation of each vehicle's fuel consumption under the other compared methods.

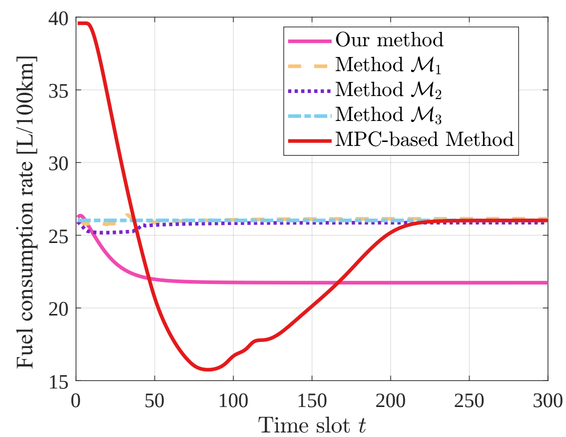

Fig. 13. The time-varying fuel consumption of the whole platoon under different methods.

optimal scheduling solution satisfies the transmission integrity and delay-limit requirements.

To facilitate the comparison of the communication reliability, we let $p_j(q_j^*(t)) = 1 - 10^{-n_j(t)}$ where we call $n_j(t)$ *the reliability exponent* that can be uniquely determined by the reliability $p_j(q_j^*(t))$. That is, we calculate the reliability exponent by $n_j(t) = -\log_{10}\left(1 - p_j(q_j^*(t))\right)$, which is an increasing function of $p_j(q_j^*(t))$. Fig. 10 shows the reliability exponent of each vehicle in each time slot. It is seen that the communication reliability of the platooning vehicles slightly decreases from the beginning to about 12.5 seconds when they significantly increase the transmitted data load. By comparison, even when they are moving far away from the infrastructure, they can increase the communication reliability by reducing the data load in the last 15 seconds. Moreover, note that the application of 3GPP Ultra-Reliability and Low-Latency Communication (URLLC) in 5G generally requires that the transmission reliability for transmitting a data packet of 32 bytes with the user-plane latency of 1 ms should achieve at least $99.999\% = 1 - 10^{-5}$. From Fig. 10, it is seen that the reliability exponent of the platooning vehicles is guaranteed above 5, i.e., $n_j(t) > 5$ for all j and t, implying that $p_j(q_j^*(t)) > 1 - 10^{-5}$ for all j and t. This means that the optimal data transmission scheduling solution can significantly improve the transmission reliability over the level required by URLLC. Additionally, the URLLC requires that the average data transmission rate with the reliability of 99.999% should be $32 \times 8 \times 0.1 \times 10^3 \times 10^{-6} = 0.0256\,\mathrm{Mbit/slot}$. From Fig. 8, it is also seen that the average amount of data bits transmitted in most of time slots (e.g., $t \in [0, 250]$) is higher than the URLLC-required level, $0.0256\,\mathrm{Mbit/slot}$. Therefore, these results indicate that our proposed method can deal with more data load with greatly satisfying URLLC requirements.

C. Performance Comparison

We further compare our joint method with several baselines that are based on different platoon control and uniform data scheduling schemes. In these baselines, the data volume Q_j for each vehicle j is evenly distributed across the time slots, ensuring that each time slot receives an equal share of the data volume. This uniform distribution provides a consistent baseline, allowing for a fair evaluation of the effectiveness of our more advanced scheduling strategy. Specifically, we consider two representative car-following control protocols in the platoon coordination layer, the predecessor-following (PF) method (denoted by $\mathcal{M}_1$) and the bidirectional (BD) method (denoted by $\mathcal{M}_2$), which have also been widely adopted in the current literature [93]. The key difference between our platoon coordination and these two methods lies in the inter-vehicle information flow topology. The PL control method uses only the state-feedback information from the predecessor of each following vehicle to construct the control input, while the BD method uses the state-feedback information from both the preceding and rear vehicles of an individual to construct the control input. We also consider the uniform-motion scheme (denoted by $\mathcal{M}_3$) as a baseline, in which the vehicles are always moving at the given initial velocity. The compared methods, $\mathcal{M}_l$ for $l = 1, 2, 3$, uniformly schedule application or task data in each time slot. We also implement a decentralized MPC-based ACC for vehicle platooning to validate

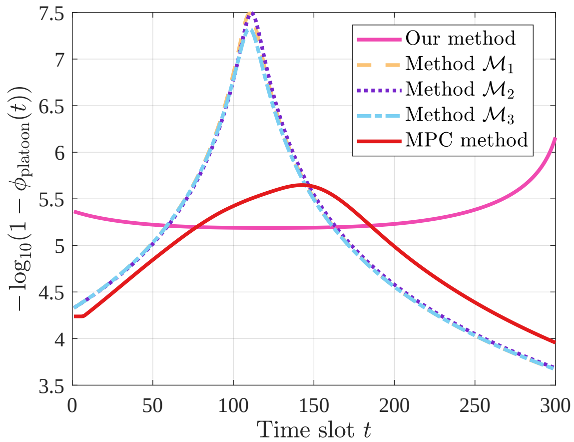

Fig. 14. The communication reliability per time slot under different methods.

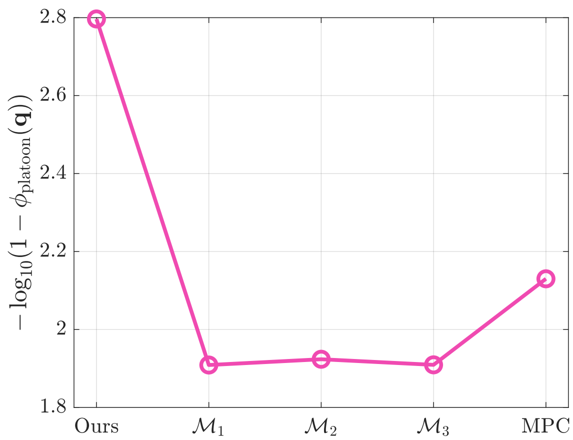

Fig. 15. The platoon communication reliability under different methods.

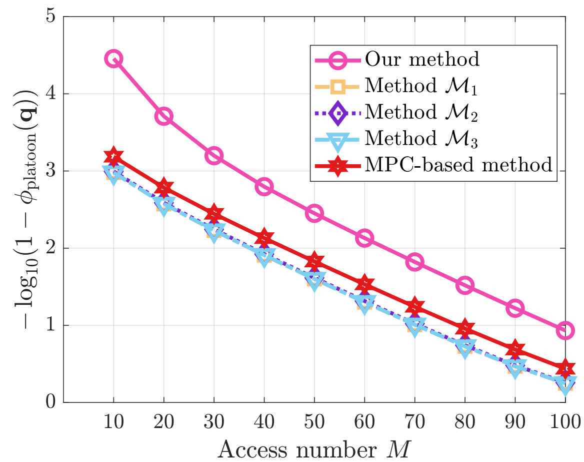

Fig. 16. The comparison of platoon communication reliability under different channel access numbers.

our method's superior performance. This MPC-based method uses vehicular real-time radar measurements and enables each following vehicle in a platoon to adapt its inter-spacing and velocity relative to its predecessor. The MPC-based method belongs to the optimization-based control paradigm, considered a state-of-the-art control technique for various control systems. Considerable works have also applied such a method to platoon systems, such as [50], [58], [78], [93]. For performance comparison, the above compared methods do not jointly realize platoon coordination and transmission reliability optimization.

From Fig. 11 and Fig. 12, it is seen that our method drives each platoon vehicle to converge to a lower fuel consumption level in a consensus manner. By comparison, methods $\mathcal{M}_1$ and $\mathcal{M}_2$ converge to a similar fuel consumption level, even though they adopt different platoon control protocols. Since $\mathcal{M}_3$ follows the uniform motion mode, it consumes the same fuel volume in different time slots. The MPC-based method can drive the following vehicles to converge to the same fuel consumption level as that of the leader since the ACC controller ensures that the vehicles follow the leader's velocity while keeping a safe inter-spacing. Recalling that (7) estimates the individual fuel consumption based on the time-varying velocity, the fuel consumption profiles in Figs. 11 and 12 also reflect the convergence behaviors of the vehicles under different platooning methods. We also provide additional figures to show the velocity profiles of the vehicles and their real-time relative distances to the roadside infrastructure under different platoon coordination controllers in Appendix D in the supplementary material. The supplementary results show that all the platoon controllers can stabilize the vehicles and guarantee stability and safety. Even though all the methods can coordinate the platooning vehicles, our method enables the platoon to reach the most fuel-efficient mobility. The essential reason is that our platoon coordination control incorporates fuel efficiency optimization and drives the vehicles to converge to a fuel-efficiency steady velocity.

Fig. 13 shows the aggregate fuel consumption from the platoon perspective under different methods. We can see that the whole platoon consumes less fuel per time slot when the vehicles reach the stable state under our proposed method. This reduction in fuel consumption is achieved because our method optimizes vehicle dynamics through the LPF control architecture, minimizing unnecessary acceleration and taking advantage of aerodynamic benefits within the platoon. Our method reduces the fuel consumption per time slot of the platoon by about 16.4% on average, compared to the other methods. Meanwhile, Fig. 14 illustrates the communication reliability of the platoon under different methods, showing that our method is able to maintain the communication reliability over all the time slots. Specifically, the communication reliability of the platoon with our joint data transmission scheduling scheme is alway greater $1-10^{-5}$ since our reliability exponent is always guaranteed above 5, while the other three methods, $\mathcal{M}_1$, $\mathcal{M}_2$ and $\mathcal{M}_3$, can satisfy the URLLC requirement only when the vehicles are close enough to the roadside infrastructure, e.g., when $t \in [50, 170]$. The MPC-based method can provide the URLLC performance only when $t \in [75, 200]$. When the vehicles are moving far away from the road infrastructure, the communication reliability obviously decreases under the other methods. Interestingly, even in this situation, our method can slightly improve the reliability. The main reason is that our method adaptively schedules the transmission data across different time slots. When the relative distance between the vehicles and the roadside infrastructure decreases, i.e., the channel quality becomes better, more application or task data are transmitted to the infrastructure. When the channel becomes worse, less data remains to be transmitted. In this way, our method adaptively boosts the probability of success in data transmission according to the vehicle mobility. In Fig. 15, the global communication reliability of the platoon is compared. It is shown that our method achieves the best communication reliability, with the reliability exponent being about 42.43% higher than that of the other methods on average.

We further conduct different simulations under different numbers of nodes contending the channel and different data loads. Fig. 16 shows the communication reliability of the platoon with increasing the number of contending nodes. It is observed that increasing the channel access number makes the channel become worse and thus results in worse communication reliability. Even in this case, our method outperforms the other methods, making the reliability exponent about 81.19% higher than that of the other methods on average. In particular, our method gets a 50.51% increase in the reliability exponent on average when compared to the MPC-based method. In Fig. 17, we compare the communication reliability of the platoon under different data loads. It is shown that our method provides the highest communication reliability in all the data load situations. From Fig. 17, the communication reliability of our method is about 1.31 times higher than that of the other methods on average. In particular, even when the data load of each vehicle is relatively large, e.g., at $Q_j = 80\,\text{Mbit}$ for all j, our method can achieve the communication reliability of about $1 - 10^{0.5277} \approx 70.33\%$, while the communication reliability of the other methods is only about 14.47% on average. Combining all the above figures, it is seen that our method greatly benefits the platoon system by improving the fuel efficiency and communication reliability of the vehicles.

VI. Conclusion and Future Work

This paper investigates the joint implementation of platoon coordination and data transmission scheduling for MEC-enabled CVISs. Specifically, we develop a two-tier hierarchical framework. It integrates a fuel-efficient optimization model with a car-following platoon control protocol and a V2I communication reliability optimization model. We derive a closed-form expression for the reliability-optimal data transmission scheduling solution that characterizes platoon mobility, channel characteristics, transmission integrity, and delay-limit requirements of vehicles' applications or tasks. The proposed joint method enables platooning vehicles to adaptively schedule their transmission data across different time slots according to the platoon's mobility. Simulation results show that our method outperforms traditional methods regarding fuel efficiency and communication reliability. We expect to consider heterogeneous vehicular networking in future work. We will also optimize the control robustness of the platooning vehicles by extending the joint framework to different information topologies.

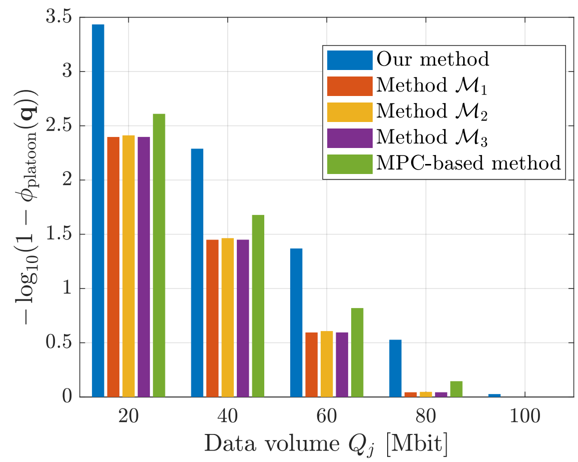

Fig. 17. The comparison of platoon communication reliability under different transmission data loads.

Future work will focus on two key areas. First, we will investigate the optimization of data transmission and fuel efficiency during vehicle platoon handovers between different MECs. Second, we will incorporate the effects of braking energy recovery, particularly for hybrid and electric vehicles.

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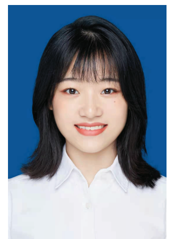

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Supplementary Material for Joint Fuel-Efficient Vehicle Platooning and Data Transmission Scheduling for MEC-Enabled Cooperative Vehicle-Infrastructure Systems

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APPENDIX A
ADDITIONAL LITERATURE REVIEW

It can be recognized from the recent survey papers, such as [1]–[6], that numerous studies are focusing on platoon control for connected and autonomous vehicles (CAVs). As summarized in [3], a general platoon system of CAVs consists of four components: node dynamics, information flow network, distributed controller, and formation geometry. Modifications or improvements in different components of the platoon system can lead to a new control design. Many advanced control methods and architectures have been proposed from the control theory perspective. In particular, researchers propose many advanced robust control solutions to deal with different impacts arising from platoon-based sensing, wireless communication, human factors, and information-aware controllers [1]. The representative robust platoon control solutions include robust model predictive control (MPC) [7], sliding mode control [8], and H-Infinity methods [9]. Besides, platoon-based communication and control co-design has also received increasing attention. For example, [10] combines relay-based communication with MPC-based platoon controllers to reduce the position errors of platooning vehicles. [11] jointly optimizes the LTE resource allocation among platooning vehicles and their control parameters using graph matching and heuristic gradient descent-based algorithms. In [12], radio resource allocation and platoon control are jointly designed to reduce tracking errors of platooning vehicles. [13] develops a joint network access scheduling and platoon control framework to mitigate access conflicts meanwhile guaranteeing platoon stability. Many other advanced co-design solutions can also be found in the context of networked control systems [14]–[16]. Even though a wide variety of communication and control solutions for CAV platoons have been proposed in the above existing literature, how to join integrity- and delay-constrained vehicle-to-infrastructure (V2I) data transmission scheduling into a platooning framework to optimize two system goals simultaneously, the fuel efficiency and transmission reliability of platooning vehicles, remains to be explored.

In this paper, we focus on a mobile edge computing (MEC)-enabled cooperative vehicle-infrastructure system where a vehicle platoon aims to offload computation to a roadside infrastructure, i.e., an edge computing node [1]. In this application scenario, computation offloading based on a reliable data transmission scheduling strategy can promote platoon-based connected vehicles by expanding their onboard task processing capacity. Computation offloading with guaranteed reliability enables autonomous vehicles to leverage edge computing power to process their sensor data like massive camera and LiDAR data. Edge computing helps connected vehicles achieve situational awareness by combining information collected and processed at the edge and applying computation-intensive algorithms like AI and machine learning to facilitate autonomous driving or platoon control applications. On the other side, the design of a data transmission scheduling strategy relies on not only the channel characteristics but also the platooning vehicles' mobility and real-time trajectories. In other words, platoon control or car-following dynamics can impact computation offloading performance. Motivated by the two sides mentioned above, we aim to develop a joint platoon coordination and data transmission scheduling framework. Our framework integrates fuel-efficient optimization and reliable data transmission scheduling into a platoon system. The essential difference between our work and the existing literature lies in two aspects:

i) We propose a fuel efficiency optimization model and combine it with a car-following control protocol. Thus, we

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[1] Our study specifically focuses on the data transmission process and the energy consumption of platooning vehicles within the MEC framework. We did not include MEC's computational energy consumption in our analysis, since it can be regarded as a separate research direction.

can enable fuel-efficient car-following control for platoon coordination.

ii) We model the platoon-based V2I communication reliability considering fuel-efficient car-following dynamics, V2I channel characteristics, and upper-layer application constraints. Moreover, we derive analytical solutions for reliability-optimal data transmission scheduling for platooning vehicles under fuel-efficient car-following control.

We enable vehicles' data offloading to adapt to platoon mobility under fuel-efficient car-following coordination and satisfy data integrity and delay constraints. Our method provides new insight into implementing platoon-based cooperative vehicle-infrastructure systems in terms of Eco-driving and reliable V2I communication.

Appendix B
Convexity Proof of $U(\mathbf{q})$

In this appendix, we provide a detailed proof of the convexity of the function $U(\mathbf{q})$ as defined in the manuscript.

The function $U(\mathbf{q})$ is given by

$$U(\mathbf{q}) = \sum_{j=0}^{N} \sum_{t=1}^{T_j} \frac{\left(L_j^*(t)\right)^\gamma 2^{\frac{(M+N+1)q_j(t)}{B\Delta\tau}}}{\omega_j}. \quad (1)$$

To determine the convexity, we analyze the second-order properties of the function. We compute the second derivative of the individual terms within the double sum. For a fixed j and t, the term is:

$$f(q_j(t)) = \frac{(L_j^*(t))^\gamma 2^{\frac{(M+N+1)q_j(t)}{B\Delta\tau}}}{\omega_j}. \quad (2)$$

The first derivative of $f(q_j(t))$ is

$$f'(q_j(t)) = \frac{(L_j^*(t))^\gamma 2^{\frac{(M+N+1)q_j(t)}{B\Delta\tau}} \ln(2) \cdot \frac{(M+N+1)}{B\Delta\tau}}{\omega_j}. \quad (3)$$

And the second derivative of $f(q_j(t))$ is

$$f''(q_j(t)) = \frac{(L_j^*(t))^\gamma 2^{\frac{(M+N+1)q_j(t)}{B\Delta\tau}} (\ln(2))^2 \left(\frac{(M+N+1)}{B\Delta\tau}\right)^2}{\omega_j}. \quad (4)$$

It is evident that the second derivative $f''(q_j(t))$ is positive because

- $(L_j^*(t))^\gamma > 0$;
- $2^{\frac{(M+N+1)q_j(t)}{B\Delta\tau}} > 0$;
- $(\ln(2))^2 > 0$;
- $\left(\frac{(M+N+1)}{B\Delta\tau}\right)^2 > 0$;
- $\omega_j > 0$.

Since all terms are positive, $f''(q_j(t)) > 0$. Therefore, $f(q_j(t))$ is convex for each j and t. The function $U(\mathbf{q})$ is a sum of the convex functions $f(q_j(t))$. The sum of convex functions is also convex. Thus, the function $U(\mathbf{q})$ is convex.

This step-by-step proof demonstrates that by analyzing the second derivative of each term in the sum and establishing its convexity, we can conclude that the overall function $U(\mathbf{q})$ is convex.

Appendix C
Insights for Simulation Implementation

1) Simulation platform and vehicle mobility model: We implement the proposed fuel-efficiency car-following mobility optimization and the data transmission scheduling solution with MATLAB on a computer with four-core processor: Intel(R) Core(TM) i7-8750H CPU @ 2.20 GHz-2.21 GHz and RAM: 24 GB. In the simulation experiment, we focus on one-dimensional vehicle platooning scenarios as in the existing literature [7], [9], [10], [17]–[22], and exploit the discrete-time longitudinal dynamics model (2) to simulate the mobility of each platooning vehicle. This model has been well investigated and widely accepted for longitudinal platoon control design and simulation in the literature, such as [10], [18], [19]. The initial state of the platoon is given as follows: the leader is located at $s_0(0) = 100\,\mathrm{m}$ while $s_{j-1}(0) - s_j(0) = 10\,\mathrm{m}$ for $j = 1, 2, 3, 4$ initially; the velocity of the vehicles is initialized to $v_j(0) = 20\,\mathrm{m/s}$ and their acceleration is initialized to $a_j(0) = 0\,\mathrm{m/s^2}$ for all j. The access point of the edge cloud is located at $[300, 10]^{\mathrm{T}}$ (m).

2) Fuel efficiency optimization and car-following control: In the simulation, we set up the fuel-efficient car-following mobility optimization model in the upper layer of the proposed hierarchical framework by using a nonlinear optimization modeling and algorithmic differentiation framework with flexible interfaces to MATLAB, CasADi [23], and exploit a widely-used interior point solver, IPOPT [24], to obtain the optimal fuel-efficient control input for the platoon leader. The parameter settings for the fuel efficiency optimization are detailed in Table I, which are given according to [25], [26]. The control input of the other followers in the platoon is calculated based on the car-following control protocol (4). The vehicle-to-vehicle (V2V) information flow topology follows the well-known decentralized control structure, predecessor-leader-follower (PLF) [2], [3].

3) Vehicle-to-infrastructure communication model: Since the vehicle-to-infrastructure (V2I) channel fading is characterized by the Rayleigh distribution model and the transmission performance is analytically described by mathematical models (9) to (12), we are allowed to simulate the V2I communication performance by using the analytical models. In the communication models, the time-varying transmitter-receiver distance is calculated based on the vehicles' position relative to that of the edge cloud. The channel characteristics parameters, such as the bandwidth, the transmission power, the average background noise, and the path loss exponent, are given in Table I according to the MATLAB simulation configuration on the LTE-based cellular vehicle-to-everything (C-V2X) in Mode 3 in [21]. Each vehicle's data transmission scheduling solution in the lower layer of the proposed hierarchical framework is calculated using our proposed closed-form expressions as given in Theorems 1 and 2. Here, we remark that the communication performance is evaluated by using parameterized mathematical models instead of following a discrete event-based simulation approach. The model-based simulation approach is widely adopted for the simulation of various communication systems in current literature, such as

C-V2X network simulation in Mode 3 and Mode 4 [21], [22], UAV-assisted air-to-ground (A2G) communication simulation [27], MIMO beamforming and channel estimation [28], [29], Intelligent Reflecting Surface (IRS)-assisted and relay-based communication simulation [30]. Furthermore, it is recognized that the existing studies [21], [22], [27]–[30] also implement their system models and algorithms with MATLAB. Therefore, according to the literature, we implement our simulation experiment with MATLAB using the model-based approach. Implementing the system model with other programming frameworks and discrete event-based network simulators, such as Veins [31], will require additional efforts in developing and integrating numerical computing, optimization, and control functionalities and modules, which is left as an important direction of our future work.

Appendix D
Supplementary Simulation Results

4) Method Validation: In Fig. 1, the number of data bits allocated by each vehicle in different time slots varies according to the relative distance between the vehicle and the roadside infrastructure. When the vehicle is closer to the edge node, it offloads more data since the channel quality is better. On the contrary, the vehicles reduce the data load when the channel quality worsens. Hence, our method enables the platooning vehicles to adapt their data allocation according to the channel condition. More importantly, our method guarantees that the vehicles successfully offload all the required data by the deadline. Fig. 1 also compares the optimal data transmission scheduling solution of each platooning vehicle using our analytical model with that obtained by a numerical optimization approach. It is seen that the theoretical results match the numerical results, thus validating the derived analytical solution given in Theorems 1 and 2.

5) Relative Distance to Infrastructure and Velocity Profile: In Fig. 2 and Fig. 3, we show the time-varying relative distance to the roadside infrastructure and velocity profile of each platooning vehicle under different controllers, respectively. Fig. 2 demonstrates that the platooning vehicles have a similar position trajectory under car-following coordination. The relative distance to the infrastructure decreases when the vehicles approach the infrastructure, while the distance increases when the vehicles move away from the infrastructure. In addition, since our method and the other methods, $\mathcal{M}_1$, $\mathcal{M}_2$ and $\mathcal{M}_3$, follow the same control paradigm that is based on car-following dynamics and have the same initial configurations, the relative distance profiles resulting from the car-following controllers are similar to each other. The model predictive control (MPC)-based method falls into another control paradigm, i.e., using a constrained optimization technique. The MPC-based method can handle vehicles with different initial velocities and has relative distance profiles different from the car-following methods'. In Fig. 3, we can see that each control method can enable the convergence of the platooning vehicles to a stable state, guaranteeing platoon stability and safety. However, the steady velocity of the platoon under our method is different from that under the other controllers. Since our car-following platoon coordination is based on fuel-efficiency optimization, our method can find the fuel efficiency-optimal steady velocity, about $17.58\,\mathrm{m/s}$, for the platoon system and then drive the vehicles to converge to this fuel-efficient velocity. Recalling the fuel consumption evaluation model (7) in the main text, the fuel consumption level of each vehicle is evaluated based on its real-time velocity [25], [26]. Nevertheless, fuel consumption is not a monotone function of a vehicle's velocity, so simply reducing it may not save fuel energy. Our method incorporates a fuel efficiency optimization model with the car-following controller, improving the fuel efficiency of the entire platoon under car-following control.

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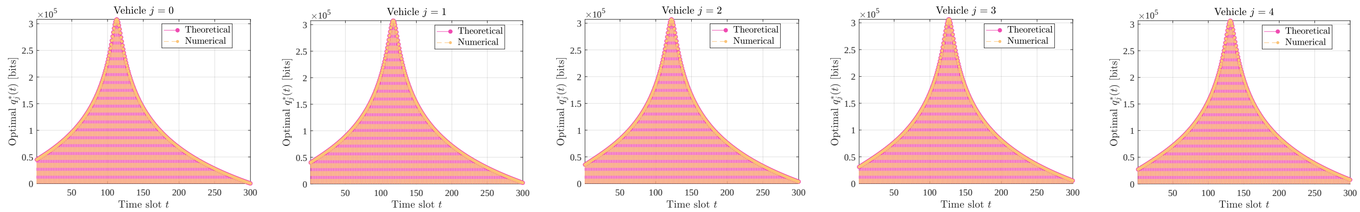
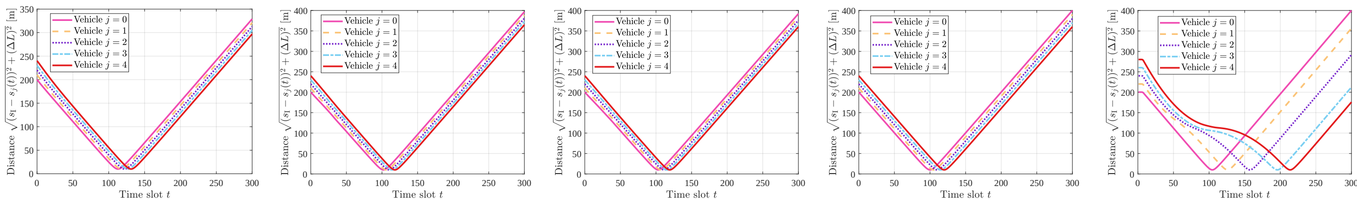


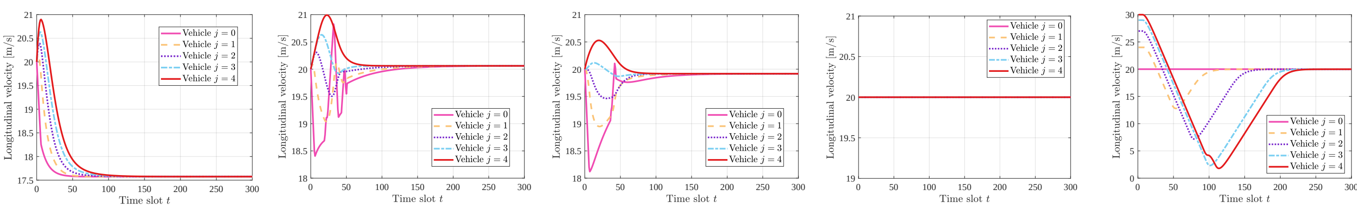
(a) Vehicle $j = 0$ (b) Vehicle $j = 1$ (c) Vehicle $j = 2$ (d) Vehicle $j = 3$ (e) Vehicle $j = 4$

Fig. 1. The optimal V2I data scheduling solution obtained under the analytical model and the numerical optimization approach.



(a) Our method (b) Method $\mathcal{M}_1$ (c) Method $\mathcal{M}_2$ (d) Method $\mathcal{M}_3$ (e) MPC-based Method

Fig. 2. The time-varying relative distance to the infrastructure of the vehicles under different platoon controllers.



(a) Our method (b) Method $\mathcal{M}_1$ (c) Method $\mathcal{M}_2$ (d) Method $\mathcal{M}_3$ (e) MPC-based Method

Fig. 3. The velocity profiles of the vehicles under different platoon controllers.

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