# Joint Optimization of Resource Scheduling and Mobility for UAV-Assisted Vehicle Platoons

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***Abstract*—In the era of the Internet of Everything, autonomous driving has put forward a higher ambition for data transmission capabilities. This paper studies joint scheduling of computation and communication resources in the collaborative networking of unmanned aerial vehicles (UAVs) and platooning vehicles in mobile edge computing (MEC) framework to maximize the energy efficiency. Considering the movement characteristics of vehicles, we integrate mobility, communication, computation, and energy consumption to establish a collective optimization problem. Since this multivariate coupled model is non-convex, we further propose a joint optimization method (JOM) algorithm based on the convex approximation theory, particularly quadratic programming. Experimental results verify that this algorithm converges quickly within a dozen iterations and proves to be superior to several other benchmark schemes.**

***Index Terms*—Mobile edge computing (MEC), unmanned aerial vehicle (UAV), connected and autonomous vehicle (CAV), vehicle platooning, convex approximation**

## I. Introduction

Nowadays, tremendous applications and envisioned novel information system architectures, such as connected vehicles, mobile edge computing (MEC), Internet of Things, etc., are heavily dependent on well-established wireless ad hoc networks. Data has exploded with the rapid development of technologies like artificial intelligence, big data, beyond fifth-generation (B5G) and sixth-generation (6G). MEC enables data to be processed quickly near the source. Its advantages of ultralow delay, highbandwidth, and direct access to real-time network information can better satisfy unmanned driving and other intelligence scenes which demand to perform latency-critical and computation-intensive tasks [1].

The unmanned aerial vehicle (UAV), as a fleetly moving and low-cost server carrier, is not restricted by geographical constraints. Free from expensive construction and complex deployment, it can be employed as a supplementary resource under emergencies. Research on the UAV-assisted MEC systems mainly involves that when ground users need external assistance to calculate intensive tasks or their remaining available computing capacity is insufficient, they offload the tasks to UAVs. Then UAVs, as an edge computing server, can collect, calculate, and return the offloaded tasks, especially when there are absent or destroyed wireless infrastructures. Currently, scholars have adopted diverse approaches to address the UAV-aid MEC system optimization problems [2–6].

However, the prevailing research principally focuses on the fixed position of ground terminals and adjusts the UAV trajectory to achieve the optimization goal [2, 3, 7]. And the existing literature concerned with vehicle mobility only involves one single node [8] and lacks advanced study on the multi-vehicle situation. When applying the UAV-assisted MEC system to traffic scenarios, it is necessary to consider the high-speed movement characteristics of ground vehicles because the communication links vary with the related distance at different times. Therefore, the mobility of both UAVs and ground users is essential to be taken into account.

This paper establishes a platooning vehicles-UAV collaborative networking scenario, where the UAV assists the moving vehicles with computation capacity. We introduce the intelligent driver model (IDM) and innovatively combine mobility, communication, computation, and energy consumption into the system model. To solve the complicated problem, we devise an algorithm based on the convex approximation theory to maximize the UAV energy efficiency. The experiment results prove that the proposed algorithm performs well.

## II. System Model

We consider a general UAV-aid MEC system in Fig. 1, where a UAV and a platoon of $I$ mobile vehicles are moving in a two-dimensional plane. The UAV flies along the road at a fixed altitude of $H$ with a steady velocity of $v_{\mathrm{UAV}}$. The total time spent on the UAV serving the platooning vehicles is equally divided into $K$ time slots. A time slot lasts for $\tau$. We have the set $\mathcal{I} = \{1, ..., I\}$ and the set $\mathcal{K} = \{1, ..., K\}$.

In this system, the UAV is equipped with a computing processor, a MEC server, and an onboard communication circuit. Each mobile vehicle is set up with a local computing processor and a communication circuit. On the one hand, to refrain from the interference among the platooning vehicles, the time division multiple access (TDMA) protocol is engaged, where

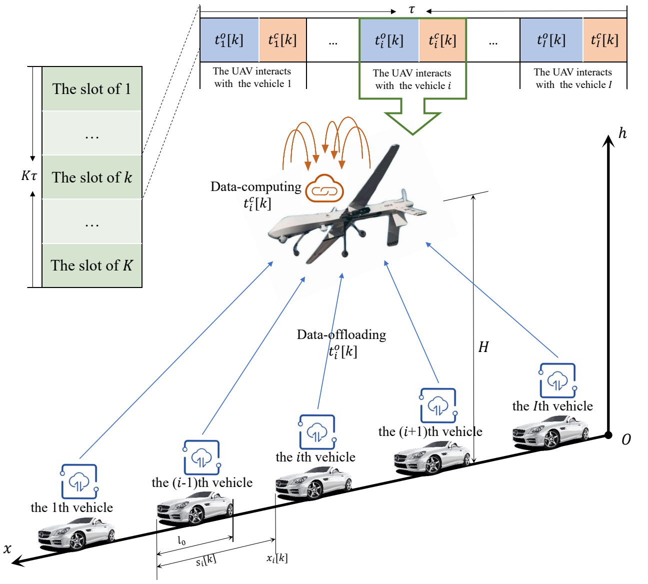


Fig. 1. A UAV and platooning vehicles moving in a two-dimensional plane and communicating in a manner of TDMA.

each vehicle interacts with the UAV orderly and independently in time dimensionality. To be specific, at the $k$th ($k \in \mathcal{K}$) slot, the $i$th ($i \in \mathcal{I}$) vehicle offloads data to the UAV within the duration of $t_i^o[k]$, then the UAV calculates the offloaded data within $t_i^c[k]$ and downloads it back to the $i$th vehicle. Then the next vehicle interacts with the UAV at the same slot until the last vehicle. Like [5], the downloading time of the UAV is neglected due to the little bits of the computation result. On the other hand, in space dimensionality, the position coordinate of the $i$th vehicle at the $k$th slot is denoted by $\mathbf{s}_i[k] = [x_i[k], 0]$, where $x_i[k]$ signifies the horizontal position and 0 represents the vertical altitude. Similarly, the position coordinate of the UAV at the $k$th slot is denoted by $\mathbf{s}_{\text{UAV}}[k] = [x_{\text{UAV}}[k], H]$.

The IDM is a widely cited classic car-following model to characterize the movement relationship between the platooning vehicles in continuous time [9]. According to the IDM, the acceleration of the $i$th vehicle $a_i$ is determined by its velocity $v_i$, the relative velocity $\Delta v_i$, and the space $s_i$ from the preceding vehicle. The motion state of the platooning vehicles be described by the following equation set for $i \in \mathcal{I}$

$$a_i = a_{\max}\left[1-\left(\frac{v_i}{v_{\max}}\right)^{\delta}-\left(\frac{s^*(v_i,\Delta v_i)}{s_i}\right)^2\right], \tag{1a}$$

$$s^*(v_i,\Delta v_i) = s_{\min} + t_0 v_i + \frac{v_i \Delta v_i}{2\sqrt{a_{\max} b_{\max}}}, \tag{1b}$$

$$\Delta v_i = v_i - v_{i-1}, \tag{1c}$$

$$s_i = x_{i-1} - x_i - l_0. \tag{1d}$$

In Eq. (1), $x_i$ and $v_i$ respectively denote the horizontal position and the velocity of the $i$th vehicle. In Eq. (1a), $a_{\max}$ signifies the platooning vehicles' maximum acceleration, and $v_{\max}$ shows the desired velocity in a free flow. The acceleration exponent value $\delta$ is usually set from 1 to 5 [9]. The parameters in Eq. (1b) are the minimum net distance $s_{\min}$, the reaction time $t_0$, and the maximum deceleration $b_{\max}$ ($b_{\max} > 0$). And $l_0$ in Eq. (1d) stands for the body length of a vehicle.

Then, we apply a double integration scheme to discretize the continuous-time model to adapt to our platooning vehicles under discrete time slots for $i \in \mathcal{I}$ and $k \in \mathcal{K}$

$$\begin{cases} v_i[k+1] = v_i[k] + a_i[k]\tau, \\ x_i[k+1] = x_i[k] + v_i[k]\tau + \dfrac{1}{2}a_i[k]\tau^2. \end{cases} \tag{2}$$

According to the principle of minimizing the sum of the distance between the UAV and each vehicle, we determine the horizontal position of the UAV $x_{\text{UAV}}[k]$. Referring to [2, 10], we obtain the energy consumption of the UAV mobility based on its acceleration and velocity. For any $k \in \mathcal{K}$, we have

$$\begin{cases} v_{\text{UAV}}[k] = \dfrac{x_{\text{UAV}}[k] - x_{\text{UAV}}[n-1]}{\tau}, \\ a_{\text{UAV}}[k] = \dfrac{v_{\text{UAV}}[k] - v_{\text{UAV}}[n-1]}{\tau}, \\ E^s_{\text{UAV}}[k] = \gamma_1 v^3_{\text{UAV}}[k] + \dfrac{\gamma_2}{v_{\text{UAV}}[k]}\left(1+\dfrac{a^2_{\text{UAV}}[k]}{g^2}\right), \end{cases} \tag{3}$$

where $\gamma_1$ and $\gamma_2$ are parameters dependent on the UAV's hardware and surrounding environment. And the parameter $g$ signifies the gravitational acceleration.

Thus, the relative distance between the vehicle $i$ and the UAV at the $k$th slot can be signified as $d_i[k] = ||\mathbf{s}_{\text{UAV}}[k] - \mathbf{s}_i[k]||$. Like [2, 3, 5, 10], the channel power gain between the UAV and the vehicle is given as

$$\rho_i[k] = \rho_0 d_i[k]^{-\kappa} = \frac{\rho_0}{||\mathbf{s}_{\text{UAV}}[k] - \mathbf{s}_i[k]||^{\kappa}}, \quad i \in \mathcal{I}, \quad k \in \mathcal{K}, \tag{4}$$

where $\rho_0$ is the channel power gain at a reference distance $d_0 = 1$ m, and $\kappa$ is the path loss exponent that depends on the dominated wireless channel model. Since our system mainly operates in open areas, we assume that the wireless channel is dominated by line-of-sight and take the value $\kappa = 2$.

We apply the block fading channel model assuming that the channel keeps static in each slot. Namely, communication bandwidth $B$ and noise power $N_0$ are stable during the whole process. Based on Shannon's theorem, the data-offloading transmission rate $R_i^o[k]$ is formulated as follows [5, 6]

$$R_i^o[k] = B\log_2\left(1+\frac{P_i^o[k]\rho_i[k]}{N_0}\right), i \in \mathcal{I}, \quad k \in \mathcal{K}, \tag{5}$$

where $P_i^o[k]$ denotes the offloading transmission power of the $i$th vehicle to the UAV at the $k$th slot. Since the energy consumption on receiving offloaded data is concerned with the relative distance, we multiply the channel gain $g_i[k]$ in Eq. (6) to calculate the UAV receiving energy consumption [5, 7]

$$E^o_{\text{UAV}}[k] = \sum_{i=1}^{I} P_i^o[k]\rho_i[k]t_i^o[k], \quad k \in \mathcal{K}. \tag{6}$$

The UAV calculates tasks with the central processing unit (CPU) frequency $f$. Denote the number of CPU cycles for computing one bit of raw data by $C$. The UAV local computation rate is defined as $R^c_{\text{UAV}} = \frac{f}{C}$ [5, 7]. Since the offloaded data from the $i$th vehicle equals the raw data to be computed at the UAV at this slot, we can have

$$R^o_i[k]t^o_i[k] = R^c_{\text{UAV}} t^c_i[k], \quad i \in \mathcal{I}, \quad k \in \mathcal{K}. \tag{7}$$

Besides, the CPU frequency $f$ also determines the UAV local execution energy consumption. Similar to [4, 5], the UAV energy expended on calculating data is described as

$$E^c_{\text{UAV}}[k] = \sum_{i=1}^{I} \lambda_c f^3 t^c_i[k], \quad k \in \mathcal{K}, \tag{8}$$

where $\lambda_c$ is an effective capacitance coefficient related to the UAV processor chip architecture.

## III. Convex Approximation Based JOM Algorithm

### A. Problem Formulation

The energy efficiency $\theta(\mathbf{X})$ is denoted by the ratio of system transmission throughput and UAV energy consumption sum in Eq. (9), where the independent variable is defined as $\mathbf{X} = \text{col}\{P^o_i[k],\ t^o_i[k]\},\ i \in \mathcal{I},\ k \in \mathcal{K}$

$$\theta(\mathbf{X}) = \sum_{k=1}^{K} \frac{\sum_{i=1}^{I} R^o_i[k]t^o_i[k]}{E^o_{\text{UAV}}[k] + E^c_{\text{UAV}}[k] + E^s_{\text{UAV}}[k]}. \tag{9}$$

Integrating mobility, communication, computation, and energy consumption, we formulate the system optimization problem in a standard form as $\mathbf{P}_1$. Eq. (10b) is the equality constraint on interaction time, and Eq. (10d) and Eq. (10e) are the boundary constraints on independent variables.

$$\begin{aligned}
\mathbf{P}_1 : \min_{\mathbf{X}} \ & f(\mathbf{X}) = \frac{1}{\theta(\mathbf{X})} && \text{(10a)}\\
\text{s.t.} \ & \sum_{i=1}^{I} (t^o_i[k] + t^c_i[k]) = \tau, && \text{(10b)}\\
& R^o_i[k]t^o_i[k] = R^c_{\text{UAV}} t^c_i[k], && \text{(10c)}\\
& 0 \leqslant P^o_i[k] \leqslant P_{\max}, && \text{(10d)}\\
& 0 \leqslant t^o_i[k] \leqslant \tau, && \text{(10e)}\\
& i \in \mathcal{I}, \quad k \in \mathcal{K}. && \text{(10f)}
\end{aligned}$$

### B. Convex Quadratic Program Algorithm

The objective function $f(\mathbf{X})$ is a twice continuously differentiable function, and its Hesse matrix is not semi-positive definite. Since the variables are coupled nonlinearly, the problem $\mathbf{P}_1$ is non-convex [11], which is difficult to figure out the globally optimal solution. In this paper, we employ the convex quadratic programming to find the optimal solution of the original non-convex problem by iteratively solving a series of convex approximation problems. The proposed joint optimization method (JOM) on communication resource and computation resource is summarized in Algorithm 1.

In Algorithm 1, the underlying idea is to approximate the original model $\mathbf{P}_1$ at each iterate $r$ by using a convex quadratic programming model and to solve a feasible search direction $\mathbf{d}_r$ from the sub-model. To be specific, we denote the Lagrangian function of $f(\mathbf{X})$ by $L(\mathbf{X}, \lambda)$, where $\lambda$ is the Lagrange multiplier vector. Define the Hesse matrix $\mathbf{U}$ as the positive definite approximation of $\nabla^2_{\mathbf{X}} L(\mathbf{X}, \lambda)$. Set the descent search direction vector $\mathbf{d} = \mathbf{X}_{r+1} - \mathbf{X}_r$ at the $r$th iteration. According to the second-order Taylor expansion, we establish a convex quadratic function, $f(\mathbf{X}_r) + \nabla f(\mathbf{X}_r)^{\text{T}}\mathbf{d} + \frac{1}{2}\mathbf{d}^{\text{T}}\mathbf{U}_r\mathbf{d}$, to approximate $f(\mathbf{X})$ at $r$. The first-order Taylor expansion is used to linearize the nonlinear constraints, i.e. $C(\mathbf{X}) \approx C(\mathbf{X}_r) + \nabla C(\mathbf{X}_r)^{\text{T}}\mathbf{d}$. Then, we can formulate the quadratic programming model at $r$ by $\mathbf{P}_2$ as follows

$$\begin{aligned}
\mathbf{P}_2 : \min_{\mathbf{d}} \ & \nabla f(\mathbf{X}_r)^{\text{T}}\mathbf{d} + \frac{1}{2}\mathbf{d}^{\text{T}}\mathbf{U}_r\mathbf{d} && \text{(11a)}\\
\text{s.t.} \ & C_m(\mathbf{X}_r) + \nabla C_m(\mathbf{X}_r)^{\text{T}}\mathbf{d} = 0, \quad m \in \mathcal{M}, && \text{(11b)}\\
& C_n(\mathbf{X}_r) + \nabla C_n(\mathbf{X}_r)^{\text{T}}\mathbf{d} \geqslant 0, \quad n \in \mathcal{N}, && \text{(11c)}
\end{aligned}$$

where $C_m(\mathbf{X}) =$

$$\begin{cases} \sum_{i=1}^{I} (t^o_i[k] + t^c_i[k]) - \tau, & m = 1, ..., K, \\ R^o_i[k]t^o_i[k] - R^c_{\text{UAV}} t^c_i[k], & m = K+1, ..., K+IK, \end{cases} \tag{12}$$

$$\text{and } C_n(\mathbf{X}) = \begin{cases} t^o_i[k], & n = 1, ..., IK, \\ \tau - t^o_i[k], & n = IK+1, ..., 2IK, \\ P^o_i[k], & j = 2IK+1, ..., 3IK, \\ P_{\max} - P^o_i[k], & j = 3IK+1, ..., 4IK. \end{cases} \tag{13}$$

Another important step of Algorithm 1 is to exploit a simple line search approach with quadratic interpolation steps to calculate the step size $\alpha_r$ [12]. Besides, we adopt the Broyden-Fletcher-Goldfarb-Shanno (BFGS) method [13] to update $\mathbf{U}_r$ at each iterate as well. The BFGS method is considered as one of the most effective quasi-Newton methods for solving unconstrained optimization problems. It uses an approximation to calculate the Hessian of the Lagrange function for the original model $\mathbf{P}_1$ and such an approximate Hessian guarantees the quadratic subproblem to remain convex at each iterate.

## IV. Performance Evaluation

### A. Basic Simulation Settings and Motion State Trajectory

The simulation parameters on the physical-layer communication like bandwidth $B$, noise power $N_0$, and channel power gain $g_0$ are given based on [3, 5]. In terms of the UAV's processor computation parameters, we take UAV's maximum CPU frequency $f$ according to Phantom 4 of SZ DJI Technology Co., Ltd. Also, we refer to [3, 5] to adopt the number of CPU cycles $C$ and effective capacitance coefficient $\lambda_c$. The power boundary $P_{\max}$ is 100 mW [2]. The motion state parameters of the IDM are recommended in [14]. To sum up, the simulation parameters are presented in Table I.

In our vehicle mobility model, we set the leading vehicle's initial velocity at 15 m/s and its initial acceleration at 0 m/s$^2$. At the first slot, the vehicle positions are stochastically assigned obeying the rule that the distance between two adjacent vehicles (head to head) is set from 10 to 100 m.

**Algorithm 1:** The JOM algorithm for solving the joint optimization problem $\mathbf{P}_1$

Initialize $k = 1$.
**for** $k \leqslant K$ **do**
  Initialize $\mathbf{X}_1[k]$, $\mathbf{U}_1[k]$, and set $\xi > 0$, $r = 1$.
  Transform $\mathbf{P}_1$ into $\mathbf{P}_2$ at the $k$th slot.
  **repeat**
    Solve $\mathbf{P}_2$ to obtain $\mathbf{d}_r[k]$ and $\lambda_r[k]$.
    Determine $\alpha_r$ by a line search approach.
    Set $\mathbf{X}_{r+1}[k] = \mathbf{X}_r[k] + \alpha_r \mathbf{d}_r[k]$.
    **if** $||\nabla_{\mathbf{X}} L(\mathbf{X}_{r+1}[k], \lambda)|| > \xi$ **then**
      Update $\mathbf{U}_{r+1}[k]$ based on the BFGS.
      Update $r = r + 1$.
  **until** $||\nabla_{\mathbf{X}} L(\mathbf{X}_{r+1}[k], \lambda)|| \leqslant \xi$
  Output $\mathbf{X}^*[k] = \mathbf{X}_{r+1}[k]$.
  Update $k = k + 1$.
Output the optimal solution $\mathbf{X}^*$.

TABLE I
EXPERIMENTAL PARAMETERS

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $i$ | 5 | $\gamma_1$ | 0.0037 |
| $K$ | 500 | $\gamma_2$ | 500.206 |
| $v_{\max}$ | 30 m/s | $g$ | 9.8 m/s$^2$ |
| $a_{\max}$ | 0.73 m/s$^2$ | $B$ | $4 \times 10^7$ Hz |
| $b_{\max}$ | 1.67 m/s$^2$ | $N_0$ | $10^{-9}$ W |
| $t_0$ | 1.5 s | $\rho_0$ | -50 dB |
| $s_{\min}$ | 2 m | $f$ | $2 \times 10^9$ cyc/s |
| $\delta$ | 4 | $C$ | $10^3$ cyc/bit |
| $l_0$ | 5 m | $\lambda_c$ | $10^{-28}$ |

The initial velocity of the platooning vehicles ranges from 13 to 17 m/s. Moreover, the motion energy consumption-related parameters like $\gamma_1$ and $\gamma_2$ are set according to [2]. Fig. 2 clearly shows the motion state curves of the platooning vehicles and the UAV over the time slot $k$.

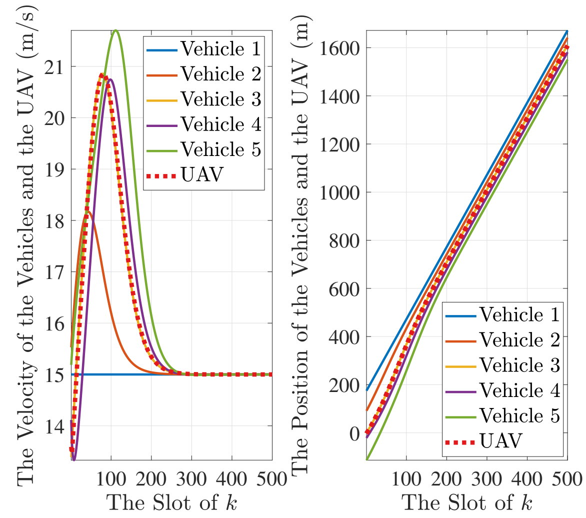


Fig. 2. The motion state trajectory over the time slot $k$.

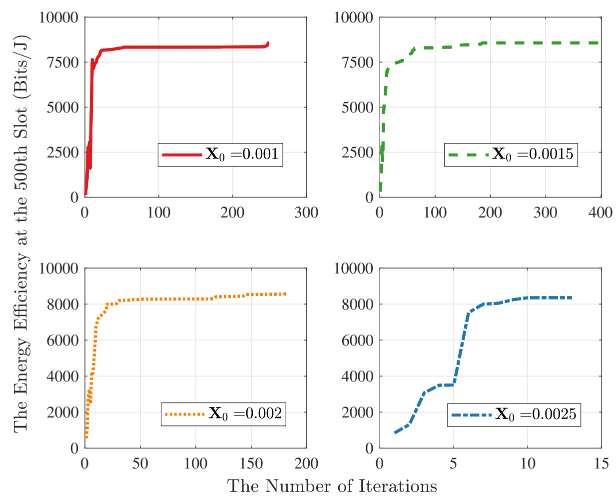


Fig. 3. The energy efficiency at the 500th slot against iterations.

## *B. Convergence Analysis and Performance Comparison*

Under diverse initial values of the independent variable $\mathbf{X}_0$, the diagrams of the energy efficiency at the 500th slot against iterations are given in Fig. 3. As is shown, the curves climb gradually with the increasing iterations and tend to be roughly stable, which convincingly verifies the convergence of our proposed algorithm. Under the condition of $\mathbf{X}_0 = 0.0025$, there is a fast convergence performance within 15 iterations.

In contrast with other approaches including the stochastic power method (SPM) and uniform time method (UTM), the performance comparison is plotted, which shows the improvement of our proposed JOM algorithm. Fig. 4 plots the variation of the optimal energy efficiency sum with the height of the UAV under the time slot length $\tau = 0.2$ s. The optimal value declines as the UAV flying height increases. We can infer that the flight altitude affects the communication quality, and too high flight altitude will have a negative impact on the energy efficiency of the UAV. Obviously, the optimal function values of our proposed method are always higher than the other methods. Under the five flight heights, JOM improved an average of 2.65% over SPM and 6.34% over UTM. It can be seen that our algorithm has a significant advantage.

Fig. 5 draws the variation of the optimal energy efficiency sum with the length of a slot under the height of the UAV $H = 10$ m. We can see that the function value is positively correlated with the slot length. It indicates that the longer the slot is, the more time can be allocated for the platooning vehicles and UAV to offload and calculate, which is more beneficial to the improvement of UAV's energy efficiency. Similarly, JOM is superior to the others approaches. During the 500 slots, the optimal energy efficiency sum of JOM is $1.120 \times 10^5$ Bits/J higher than SPM and $2.117 \times 10^5$ Bits/J higher than UTM. The above experiment results demonstrate the availability and efficiency of our designed algorithm.

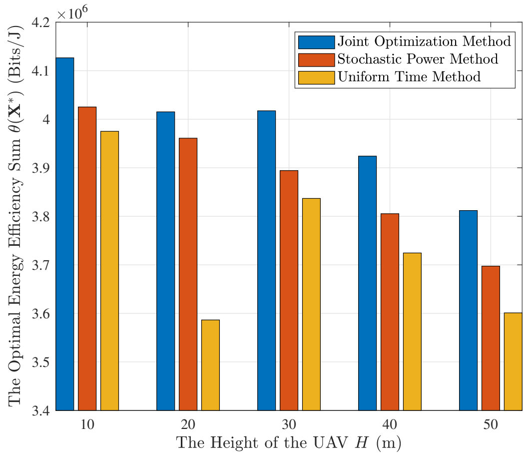


Fig. 4. The optimal energy efficiency sum $\theta(\mathbf{X}^*)$ versus the height of the UAV $H$ under the slot length $\tau = 0.2$ s.

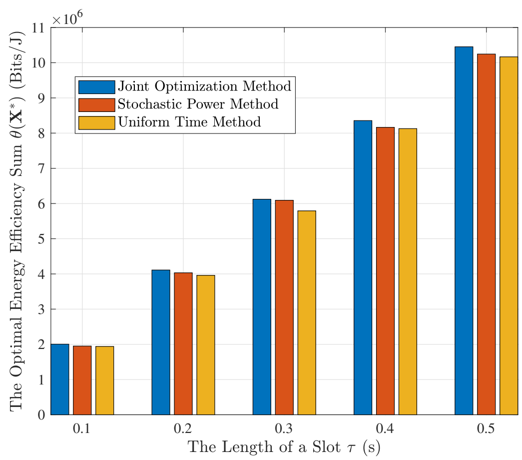


Fig. 5. The optimal energy efficiency sum $\theta(\mathbf{X}^*)$ versus the length of a slot $\tau$ under the heigth of the UAV $H = 10$ m.

## V. Conclusion

In this paper, we have investigated that the UAV, as a mobile edge server, offers computation resources to platooning vehicles, especially when there are no or few wireless infrastructures. We build a joint optimization system model integrating mobility, communication, computation, and energy consumption to maximize the UAV's energy efficiency sum during the whole process. To address the model con-convexity, we devise the JOM algorithm based on the convex approximation theory. Experimental results prove that this algorithm can converge quickly. And compared with other benchmark approaches, this algorithm can efficiently improve the UAV energy efficiency. The scheme and algorithm proposed in this paper will provide a theoretical basis for the further application of 6G technology and the Internet of Things technology.


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