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Joint Resource Allocation and Trajectory Control for UAV-Enabled Vehicular Communications

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ABSTRACT In this paper, aiming at the emergency coverage for vehicular network, we consider the problem of resource allocation for unmanned-aerial-vehicle (UAV) enabled vehicular communications, where UAV work as a temporary cellular base station. Our objective is to maximize the sum achievable rate of vehicle-to-infrastructure (V2I) communications and ensure the reliability of vehicle-to-vehicle (V2V) communications by dynamic coverage provided by UAV. Firstly, through theoretical analysis, optimal transmission power expressions for cellular users (CUEs) and device-to-device users (DUEs) are given, respectively. Secondly, by utilizing 3-partite graph matching and Hungarian algorithm, we present two graph-based methods for spectrum sharing and resource block assignment of UAV enabled vehicular network. Moreover, considering the mobility of UAV, we adopt the Q-Learning algorithm to control the trajectory of UAV in order to adapt to the time-varying channel. Finally, the feasibility of the presented schemes are verified by simulation and compared to randomized matching scheme. The simulation results show that the sum achievable rate of V2I links increases with the increase of the maximum transmission power of CUEs and the interruption probability of V2V links, and decreases with the increase of the ratio of DUEs to CUEs and the minimum capacity requirement of single V2I link. Moreover, the sum achievable rate of V2I links is enhanced by controlling the trajectory of UAV in real time.

INDEX TERMS Resource allocation, vehicular communications, UAV, graph theory, D2D, Q-learning.

I. INTRODUCTION

In some emergent events, e.g., earthquake and typhoon, vehicles cannot communicate with the base station directly after disaster. At this time, unmanned-aerial-vehicle (UAV) can play the role of a temporary base station in a wireless communications system to service the vehicles [1]. UAV is superior to the existing terrestrial base stations in terms of convenient deployment, easy control, and variability of coverage area [2]. According to discussions about connected UAV in 3GPP Release15 [3], a 100% line-of-sight (LOS) probability is assumed when UAV flies above a given height, which can provide better signal quality and greater throughput. Due to diverse application requirements of intelligent-transport-system (ITS), both vehicle-to-infrastructure (V2I) communications and vehicle-to-vehicle (V2V) communications need to be supported. V2I link can maintain stable

communications of vehicles [4], whereas V2V communications can reduce the costs for transmission over cellular network [5], and V2V link is more suitable for safety-critical applications. The existing technical solutions for vehicle-to-everything (V2X) communications include ad-hoc communications based on IEEE 802.11p standards and LTE-V2X communications based on LTE network. However, these two solutions need to be further improved to better meet the strict quality-of-service(Qos) requirements of vehicular communications [6]–[8]. By introducing device-to-device(D2D) technology into vehicular communications, the hop gain of D2D communications meets the low latency requirement of V2X communications, and the proximity gain of D2D communications meets the high reliability requirement of V2X communications [9]. In addition, considering UAV enabled vehicular communications, the establishment of D2D link can extend the coverage of UAV [10].

Although there are many studies of UAV in wireless communication, e.g., UAV as base station [11], UAV as relay [12],

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and UAV as terminal [13]. As far as we know, little is known about UAV enabled vehicular communications except for the recent studies on vehicular ad hoc network (VANET) against smart jamming and routing protocol of UAV enabled vehicular network [14], [15]. For instance, Xiao *et al.* [14] utilized UAV to relay the message of an onboard unit (OBU) and improve the communications performance of VANET against smart jammers, where the proposed scheme was proved to reduce the bit error rate of the OBU message effectively. Seliem *et al.* [15] proposed a routing protocol that used the infrastructure UAV for boosting VANET communications to achieve a minimum vehicle-to-UAV packet delivery delay, and the closed-form expression for the probability distribution of the vehicle-to-UAV packet delivery delay on a two-way highway was also given. Different from the studies of above two papers, we mainly consider the problem of joint resource allocation and trajectory control in UAV enabled vehicular communications.

Graph theory has been utilized to solve the resource allocation problem in wireless communications [16]–[19]. In [16], interference relationships among different D2D and cellular communications links were formulated as a newly designed interference graph, and an interference graph-based resource allocation scheme was proposed to obtain a near optimal solution at the base station with low computational complexity. In [17], the problem of cooperative communications for scheduling in vehicular networks was formulated as a problem of bipartite graph matching, and Kuhn-Munkres algorithm was adopted to achieve maximum weighted matching. In [18], by modeling constrained radio broadcast scheduling into a constrained maximum weighted bipartite matching problem, this paper propose a branch-and-bound algorithm to solve the resource allocation problem in radio broadcast scheduling. By formulating the spectrum sharing problem as a weighted 3-D matching problem, Liang *et al.* [19] proposed a baseline graph-based resource allocation algorithm, a greedy resource allocation algorithm, and a randomized resource allocation algorithm to achieve the performance-complexity tradeoffs. In this paper, we will also utilize the knowledge of graph theory to solve the problem of resource allocation.

In this paper, joint optimization of uplink resource allocation and trajectory control in UAV enabled vehicular network is studied, where UAV acts as a flying base station. Meanwhile, D2D technology is applied to V2V link to ensure reliable communication. UAV provides communications services for the vehicles with the help of resources of the adjacent cell. Adopting the concept of almost blank subframe in LTE [20], data of vehicular communications transmits in these blank subframes. It is almost impossible to track fast changing channels in the vehicular network. Therefore, resource management is based on slow fading parameters and channel statistics rather than instantaneous channel state information (CSI) [21]. To support high bandwidth applications, we maximize the capacity of V2I links. And in order to achieve reliable communication between vehicles, the V2V

link interruption probability is considered as a constraint. We formulate spectrum sharing and resource block assignment as a 3-partite graph matching problem. By utilizing k-partite graph matching theory proposed in [22], and the Local Ratio algorithm proposed in [23], the 3-partite graph matching problem can be solved. Besides, without considering the selection of resource block, the problem of V2I link multiplexing V2V link can be modeled as a bipartite graph matching problem, and Hungarian algorithm can be adopted to solve the problem. Moreover, mobility of UAV is exploited to further improve the sum achievable rate of V2I links. But we only consider four flight directions of UAV at a fixed height for convenience of description in this paper. Considering high propulsion power consumption and communications power consumption of UAV, tethered multi-rotor UAV is capable to provide communications guarantee for disaster areas to support long-time hovering [24]. The main contributions of this paper can be summarized as follows:

1) The resource allocation problem in UAV enabled vehicular network is studied for the first time. Referring to baseline graph-based resource allocation algorithm proposed by L. Liang *et al.* [19], the problems of spectrum sharing and resource block assignment are modeled as a 3-partite graph matching problem and solved by k-partite graph matching theory and Local Ratio algorithm in this paper.

2) Considering the mobility of UAV, Q-Learning algorithm is introduced to control the trajectory of UAV in real time when the sum achievable rate of V2I links is regarded as a reward. And the trajectory of UAV is explored by simulation results by setting up a reasonable scenario.

The remainder of this paper is organized as follows. Section II summarizes the related works on joint optimization of resource allocation and trajectory design. Section III provides a brief description of the system model and formulates the resource allocation problem. Graph-based schemes for resource allocation and Q-Learning algorithm for trajectory control of UAV are proposed in Section IV. In Section V, simulation results are presented and discussed. Finally, Section VI concludes this paper.

II. RELATED WORKS

There are some advanced works considering the issue of joint resource allocation and trajectory control for UAV enabled communications are presented by researchers [25]–[27]. In [25], Li *et al.* decoupled the joint optimization problem into two subproblems, i.e., the optimal resource allocation for a given UAV trajectory and the trajectory optimization of UAV for a given resource allocation policy. The authors transformed the first subproblem into Lagrange dual problem to solve it, and obtain a suboptimal solution for the second subproblem by utilizing the difference of convex programming. Cui *et al.* [26] proposed a double-loop algorithm to solve joint optimization problem for NOMA based UAV communication systems with the aid of penalty dual decomposition technique. In the inner loops, the

transformed augmented Lagrangian problem was solved via block coordinate descent method. In the outer loops, dual variable and penalty coefficient are updated according to the equality constraint violation. Sun *et al.* [27] investigated the resource allocation and trajectory design for multicarrier solar-powered UAV communication systems. The authors considered two cases, i.e., optimal offline resource allocation design by assuming non-causal knowledge of the channel gains and online resource allocation design which only requires causal CSI. The offline resource allocation problem was rewritten as a monotonic optimization problem, and solved by sequential polyblock approximation algorithm. For online resource allocation problem, the authors proposed a iterative suboptimal algorithm based on the successive convex approximation to strike a balance between computational complexity and optimality. These three papers are all about downlink resource allocation. Different from these three papers, this paper considers resource allocation of uplink and the users are vehicles. The paper divides the joint optimization problem into resource allocation and trajectory control. Besides, resource allocation subproblem is solved in two steps. The case of a single RB, a single V2I link, and a single V2V link is first considered, and we can get optimal transmission power of CUE and DUE. Then we adopt two graph-based algorithm, i.e., 3-partite graph matching and Hungarian algorithm, to solve the resource allocation problem with the case of multiple RBs, multiple V2I links, and multiple V2V links in polynomial time. When the UAV moves in any of four directions we defined, the distances between UAV and vehicles will be changed, which will affect the achievable rate of a single V2I link and the result of matching will changed accordingly. Therefore, the value of the sum achievable rate of V2I links will also be changed. We adopt Q learning algorithm to control the trajectory of UAV with the goal of getting bigger sum achievable rate of V2I links. But in order to balance exploration and exploitation, we eventually adopted ϵ-greedy policy.

III. SYSTEM MODEL

As shown in Fig. 1, UAV is not only the user of cell 1, but also the service base station of UAV cell where the vehicles locate. We assume that cell 1 can provide enough resources required by the UAV cell. M vehicles establish V2I links (links between vehicles and UAV), which are recorded as CUEs (cellular users). And K pairs of vehicles constitute K V2V links, which are recorded as DUEs (D2D users). we denote the set of CUEs as $\varphi = \{1, 2, \cdots, M\}$ and the set of DUEs as $\psi = \{1, 2, \cdots, K\}$. The total number of resource block(RB) is F, and the set of RB is denoted as $\zeta = \{1, 2, \cdots, F\}$. CUE_m represents the m-th CUE in the V2I link. DUE_k represents k-th DUE in a V2V link. RB_f represents f-th RB. The uplink resource by orthogonal allocation for CUEs, i.e., those RBs, are reused by DUEs, which can increase spectral efficiency and reduce the burden of cell 1. A centralized resource allocation is performed by UAV, and the statistical characteristics of small-scale fading
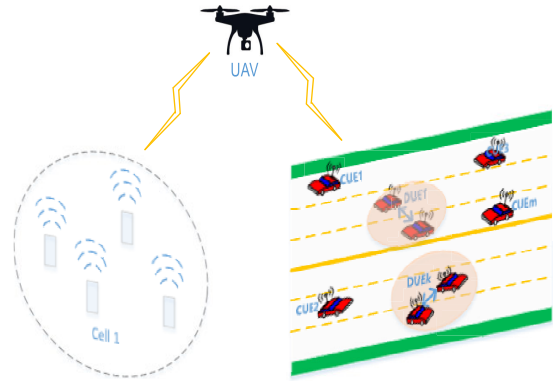

FIGURE 1. UAV-enabled vehicular communication for both V2I and V2V links.

TABLE 1. Key mathematical symbols.

Symbol	Definition
$h_{m,f}^{\text{C2U}}$	channel coefficient from CUE_m to UAV over RB_f
$h_{k,f}^{\text{D2U}}$	channel coefficient from DUE_k to UAV over RB_f
$h_{m,k,f}^{\text{C2D}}$	channel coefficient from CUE_m to DUE_k over RB_f
$h_{k,f}^{\text{D2D}}$	channel coefficient between DUE_k pair over RB_f
$\eta_{m,f}^{\text{C}}$	SINR of CUE_m at UAV over RB_f
$\eta_{k,f}^{\text{D}}$	SINR of DUE_k at the receiver of V2V link over RB_f

parameters are assumed to be known through periodical feedback or channel estimation. The notation of key mathematical symbols are given in Table 1.

The channel coefficient, $h_{m,f}^{\text{C2U}}$, which defines the channel from CUE_m to UAV over RB_f, is written as

$$h_{m,f}^{\text{C2U}} = g_{m,U,f} \beta_{m,U} L d_{m,U}^{-\alpha}, \qquad (1)$$

where $g_{m,U,f}$ stands for fast fading factor obeying an exponential distribution with parameter of 1, $\beta_{m,U}$ is a random variable of shadow fading obeying log-normal distribution, L is the path loss constant, d is the distance between CUE_m and UAV, α is the path-loss exponent factor. Symbol $\gamma_{m,U}$ is used to indicate the large-scale fading effects, i.e.,

$$\gamma_{m,U} = \beta_{m,U} L d_{m,U}^{-\alpha}. \qquad (2)$$

Correspondingly, $h_{k,f}^{\text{D2U}}$, $h_{m,k,f}^{\text{C2D}}$, $h_{k,f}^{\text{D2D}}$ are defined similarly. $h_{k,f}^{\text{D2U}}$ is the interference channel coefficient from DUE_k to UAV over RB_f. $h_{m,k,f}^{\text{C2D}}$ is the interference channel coefficient from CUE_m to DUE_k over RB_f. $h_{k,f}^{\text{D2D}}$ is the channel coefficient between DUE_k vehicles over RB_f. Then the SINR of V2I link for CUE_m at UAV can be written as

$$\eta_{m,f}^{\text{C}} = \frac{P_{m,f}^{\text{C}} h_{m,f}^{\text{C2U}}}{\sigma^2 + \sum_k I_{m,k} P_{k,f}^{\text{D}} h_{k,f}^{\text{D2U}}}, \qquad (3)$$

and the SINR of DUE_k at the receiver of V2V link is given as

$$\eta_{k,f}^{D} = \frac{P_{k,f}^{D} h_{k,f}^{D2D}}{\sigma^2 + \sum_m I_{m,f} P_{m,f}^{C} h_{m,k,f}^{C2D}} \quad (4)$$

where $P_{m,f}^{C}$ is the transmission power of CUE_m over RB_f, and $P_{k,f}^{D}$ is transmission power of DUE_k over RB_f. $I_{m,f}$ and $I_{m,k}$ are indicator factors. $I_{m,f}$ indicates that whether CUE_m occupies RB_f, and $I_{m,k}$ indicates that whether DUE_k reuses CUE_m resources. σ^2 is noise power.

The QoS requirements of V2I link is different from V2V link. V2I link requires large system capacity, and reliable communications between vehicles. Therefore, we maximize the sum achievable rate of all V2I links, and ensure the reliability of V2V links by setting the SINR threshold and the threshold of interruption probability. In addition, the achievable rate of a single V2I link also should satisfy the threshold requirement. Therefore, the optimization problem can be formulated as

$$\max_{\substack{\{I_{m,f}, I_{m,k}\} \\ P_{m,f}^{C}, P_{k,f}^{D}\}}} \sum_m \sum_f I_{m,f} \log_2\left(1 + \eta_{m,f}^{C}\right)$$

$$s.t. \quad C_1: \ \Pr\left\{\eta_{k,f}^{D} \leq \eta_0^{D}\right\} \leq p_0, \ \forall k, f$$

$$C_2: \ \log_2\left(1 + \eta_{m,f}^{C}\right) \geq r_0^{C}, \ \forall m, f$$

$$C_3: \ 0 \leq P_{m,f}^{C} \leq P_{\max}^{C}, \ \forall m, f$$

$$C_4: \ 0 \leq P_{k,f}^{D} \leq P_{\max}^{D}, \ \forall k, f$$

$$C_5: \ \sum_m I_{m,f} \leq 1, \ \forall f$$

$$C_6: \ \sum_f I_{m,f} = 1, \ \forall m$$

$$C_7: \ \sum_m I_{m,k} = 1, \ \forall k$$

$$C_8: \ \sum_k I_{m,k} \leq 1, \ \forall m$$

$$C_9: \ I_{m,f}, I_{m,k} \in \{0, 1\}. \ \forall m, k, f, \quad (5)$$

where η_0^{D}, p_0 are the minimum SINR and interruption probability threshold for DUEs to establish reliable V2V links, respectively, r_0^{C} is the minimum achievable rate requirement for a single V2I link, $P_{\max}^{C}$, $P_{\max}^{D}$ are the maximum transmission power of CUE and DUE, respectively. The constraint C_5 indicates that a RB can be occupied by one CUE at most, and C_6 indicates that each CUE will occupy one RB. C_7 indicates that a V2V link will reuse the uplink resource of one V2I link. C_8 indicates that V2I link can allow only one V2V link to sharing resource. Both $I_{m,f}$ and $I_{m,k}$ take value from 0 or 1. If the value of $I_{m,f}$ is 1, it means CUE_m will occupy RB_f. If the value of $I_{m,k}$ is 1, it means CUE_k will share resource block with DUE_k.

IV. RESOURCE ALLOCATION SOLUTIONS

Firstly, we consider the case of a single RB, a single V2I link, and a single V2V link. And the problem of resource allocation

is simplified as

$$\max_{\{P_{m,f}^{C}, P_{k,f}^{D}\}} \log_2\left(1 + \eta_{m,f}^{C}\right)$$

$$s.t. \quad C_1: \ \Pr\left\{\eta_{k,f}^{D} \leq \eta_0^{D}\right\} \leq p_0,$$

$$C_2: \ \log_2\left(1 + \eta_{m,f}^{C}\right) \geq r_0^{C},$$

$$C_3: \ 0 \leq P_{m,f}^{C} \leq P_{\max}^{C},$$

$$C_4: \ 0 \leq P_{k,f}^{D} \leq P_{\max}^{D}. \quad (6)$$

For C_1, it can be further derived as

$$\Pr\left\{\eta_{k,f}^{D} \leq \eta_0^{D}\right\}$$

$$= \Pr\left\{\frac{P_{k,f}^{D} g_{k,f} \gamma_k}{\sigma^2 + P_{m,f}^{C} g_{m,k,f} \gamma_{m,k}} \leq \eta_0^{D}\right\}$$

$$= \Pr\left\{g_{k,f} \leq \frac{\eta_0^{D}\left(\sigma^2 + P_{m,f}^{C} g_{m,k,f} \gamma_{m,k}\right)}{P_{k,f}^{D} \gamma_k}\right\}$$

$$= \int_0^{\infty}\left[\int_0^{\lambda} e^{-g_{k,f}} dg_{k,f}\right] e^{-g_{m,k,f}} dg_{m,k,f}$$

$$= 1 - \frac{P_{k,f}^{D} \gamma_k e^{-\frac{\eta_0^{D} \sigma^2}{P_{k,f}^{D} \gamma_k}}}{P_{k,f}^{D} \gamma_k + \eta_0^{D} P_{m,f}^{C} \gamma_{m,k}} \leq p_0. \quad (7)$$

where

$$\lambda = \frac{\eta_0^{D}\left(\sigma^2 + P_{m,f}^{C} g_{m,k,f} \gamma_{m,k}\right)}{P_{k,f}^{D} \gamma_k}. \quad (8)$$

Equation (7) shows that there exists a certain constraint relationship between the transmission power of CUE and DUE in order to meet the reliability requirements of V2V links. For ease of expression, let

$$E = e^{-\frac{\eta_0^{D} \sigma^2}{P_{k,f}^{D} \gamma_k}}, \quad (9)$$

$$F_m = g_{m,U,f} \gamma_{m,U}, \quad (10)$$

$$F_k = g_{k,U,f} \gamma_{k,U}. \quad (11)$$

Taking the predefined threshold as the interruption probability, we can get an equation relationship of the transmission power of CUE and DUE.

$$P_{m,f}^{C} = \frac{\gamma_k \left[E - (1 - p_0)\right]}{\gamma_{m,k}(1 - p_0)\eta_0^{D}} P_{k,f}^{D}. \quad (12)$$

When k-th V2V link reuse m-th V2I link resources over RB_f, the corresponding achievable rate of CUE_m is recorded as $C_{m,k,f}$, i.e.,

$$C_{m,k,f} = \log_2\left(1 + \frac{P_{m,f}^{C} h_{m,f}^{C2U}}{\sigma^2 + P_{k,f}^{D} h_{k,f}^{D2U}}\right). \quad (13)$$

By substituting (12) into (13), then get

$$C_{m,k,f} = \log_2 \left\{ 1 + \frac{F_m \left[\gamma_k E - (1-P_0) \gamma_k \right]}{\left(\frac{\sigma^2}{P_{k,f}^D} + F_k \right)(1-P_0)\eta_0^D \gamma_{m,k}} \right\}. \quad (14)$$

Equation (14) shows that the sum achievable rate of V2I links increases with the transmission power of DUE on the premise of satisfying the reliability requirements of V2V links. Intuitively speaking, when the transmission power of CUE increases, the achievable rate of V2I link will increase. Considering the constraints of the maximum transmission power, the above analysis shows that the optimal transmission power of CUE and DUE are

$$P_{m,f}^{*C} = min \left(P_{max}^C, P_{m,f}^{C(D_{max})} \right), \quad (15)$$

$$P_{k,f}^{*D} = min \left(P_{max}^D, P_{k,f}^{D(C_{max})} \right), \quad (16)$$

respectively. where $P_{m,f}^{C(D_{max})}$ is the transmission power of a CUE that satisfies (12) when the transmission power of the DUE is maximized. $P_{k,f}^{D(C_{max})}$ is the transmission power of a DUE that satisfies (12) when the transmission power of the CUE is maximized. If the transmission power of CUE and DUE are optimal, the corresponding achievable rate of V2I link will also get optimal value.

Based on the above analysis and derivation, the resource allocation problem in the case of multiple RBs, multiple V2I links, and multiple V2V links can be formulated as follows:

$$\max_{\{I_{m,f}, I_{m,k}\}} \sum_m \sum_f \sum_k I_{m,f} I_{m,k} C_{m,k,f}^*$$

$$s.t. \quad \mathcal{C}_2: \log_2 \left(1 + \eta_{m,f}^C \right) \geq r_0^C, \quad \forall m, f$$

$$\mathcal{C}_5: \sum_m I_{m,f} \leq 1, \ \forall f$$

$$\mathcal{C}_6: \sum_f I_{m,f} = 1, \ \forall m$$

$$\mathcal{C}_7: \sum_m I_{m,k} = 1, \ \forall k$$

$$\mathcal{C}_8: \sum_k I_{m,k} \leq 1, \ \forall m$$

$$\mathcal{C}_9: I_{m,f}, I_{m,k} \in \{0, 1\}, \ \forall m, k, f \quad (17)$$

where $C_{m,k,f}^*$ denotes optimum.

Next, we will consider the sharing of resource block for V2I links and V2V links. The hypergraph matching theory will be adopted to solve the problem, and we need to relax the equality constraints, i.e, $\mathcal{C}_6$ and $\mathcal{C}_7$, before matching.

$$\mathcal{C}_6: \sum_f I_{m,f} \leq 1, \quad \forall m$$

$$\mathcal{C}_7: \sum_m I_{m,k} \leq 1, \quad \forall k \quad (18)$$

The linear programming problem for the weighted hypergraph matching problem is formulated as

$$\max \sum_{e \in E} w_e x_e$$

$$s.t. \quad x(\delta(v)) \leq 1, \quad \forall v \in V$$

$$x_e \geq 0, \quad \forall e \in E \quad (19)$$

where w_e is the weight of hyperedge $e \in E$. $\delta(v)$ is the hyperedge set which containing vertex v.

By graph theory, we construct φ, ψ, and ζ into three parts of a 3-partite graph. If the value of $I_{m,f}$ is 1, there is a connection between CUE$_m$ and RB$_f$. If the value of $I_{m,k}$ is 1, there is a connection between CUE$_m$ and DUE$_k$. 3-partite graph matching is based on hypergraph matching theory. There are three vertices in a hyperedge. If RB$_f$, CUE$_m$, DUE$_k$ constitute a hyperedge, then the corresponding weight of the hyperedge is $C_{m,k,f}^*$. V2I link occupies different RB and V2V link reuse the resource of different V2I link, which will form different hyperedge, and the corresponding hyperedge weight is therefore not equal. Our goal is to achieve the maximum weighted matching under the constraints of $\mathcal{C}_5$-$\mathcal{C}_9$. Assuming that $H = (V, E)$ represents a 3-partite hypergraph, V is the vertex set of the hypergraph and E is the edge set.

Algorithm 1 3-partite Graph Matching Algorithm

Find an optimal extreme point solution x to (19).
Remove every hyperedge e with $x_e = 0$.
Initialize $G \leftarrow \phi$.
for i from 1 to $|E|$ **do**
    (a) Find a hyperedge e with $\sum_{e \in N[e]} x_e \leq 2$.
    (b) Set $e_i \leftarrow e$ and mark e with i.
    (c) $G = G \cup \{e_i\}$.
    (d) Remove e from $|E|$.
end for
$M \leftarrow$ **Local Ratio**(G, w), where w is the weight vector of the hyperedges.
return M
Local Ratio Algorithm:
Remove from G all hyperedges with non-positive weights.

Choose the hyperedge e from G with the smallest index.
Decompose the weight vector $w = w_1 + w_2$ where

$$w_1(e_1) = \begin{cases} w(e) & if \ e_1 \in N[e] \\ 0 & otherwise \end{cases}$$

$M_1 \leftarrow$ **Local Ratio**(G, w_2)
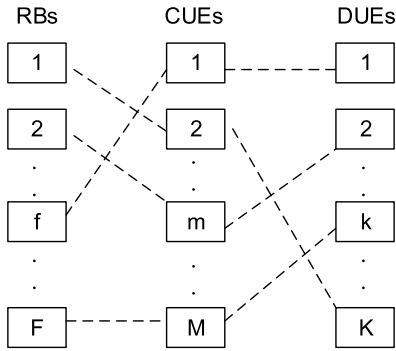**if** $M_1 \cup \{e\}$ is a matching **then**
    $M = M_1 \cup \{e\}$.
else
    $M = M_1$.
end if
return M

FIGURE 2. Assignment representation for resource allocation in the vehicular network.

The 3-partite graph matching algorithm is summarized in Algorithm 1. $N(e)$ denotes the set of hyperedges that intersect hyperedge e.

In Algorithm 1, step 1 and step 2 intend to find out the edges that can constitute the hyperedges of 3-partite graph and mark them with a serial number. The Local Ratio algorithm started in step 3 is a proximity search algorithm, based on the sequence number of the hyperedges provided by step 2. The output of Local Ratio algorithm is a 2-approximate solution of 3-partite graph matching, and the cost of matching is at least 1/2 of the optimal matching [22]. In other words, the Local Ratio algorithm does not achieve optimal matching, or even maximum matching. It is a NP problem to solve 3-partite graph optimal matching directly, whereas the Local Ratio algorithm can implement a 3-partite graph matching in polynomial time. However, in order to apply Local Ratio algorithm to the resource allocation problem above, it motivates us to make some modifications to the algorithm.

As Fig. 2 shows, this is a diagram of the resource allocation problem. If second V2I link occupys first RB, meanwhile, the K-th V2V link reuses the resource of second V2I link. Then RB_1, CUE_2 and DUE_K form a hyperedge, and the weight of hyperedge is $C_{2,K}^{*1}$. It is necessary to ensure that all V2I links are allocated, and all V2V links reuses the uplink resources of V2I links. Based on the matching found by the Local Ratio algorithm, the hyperedges with weights greater than the set threshold w_0 from G are added to the matching until all CUE and DUE vertices are saturated. And we improve the value of weight threshold when the maximum maching is ensured in order to approach closer to optimal matching.

The mobility of UAV can be exploited to enhance the channel conditions so as to make full use of the resources provided. We assume that UAV is floating on a fixed height H and has four flight directions. Two directions are parallel to the road, and another two directions are perpendicular to the road. When UAV moves in any direction, it will affect the channel power gain, which will further affect the achievable rate of the corresponding link and the result of resource matching. Therefore, Q-Learning algorithm is adopted to work out the optimal trajectory of UAV. Here, we adopt

Q learning algorithm based on time difference. Four directions of UAV are considered as the action set, and recorded as $A = \{a_1, a_2, a_3, a_4\}$. The position of UAV is denoted as the state value, and the state at i timestep is recorded as $s_i = (x_i, y_i, H)$. The sum achievable rate of V2I links is regarded as the reward value R. And in order to balance exploration and exploitation, we consider $\epsilon-greedy$ policy, i.e.,

$$\pi(a|s) = \begin{cases} \epsilon/|A| + 1 - \epsilon, & if, a = argmax\ Q(s, a) \\ \epsilon/|A|, & otherwise \end{cases} \quad (20)$$

If the generated random number is less than ϵ, a greedy strategy is adopted, i.e., UAV always chooses the action that can get the maximum reward value. Otherwise, UAV will select one of the four actions randomly. Q(s, a) denotes the expected maximum benefit of taking action a under state s, while R denotes the immediate benefit.

The formula for updating Q value based on time difference is

$$Q(s, a) \leftarrow Q(s, a) + \alpha[R + \gamma\ maxQ(s', a') - Q(s, a)] \quad (21)$$

In this paper, we set the value α to 1. Therefore, the updated formula of Q value is simplified to

$$Q(s, a) \leftarrow R + \gamma\ maxQ(s', a') \quad (22)$$

where s is the current state, and a is the current action. s' is the next state, and a' is the next action. γ is reward decay factor, and we set the value of γ to 0.9 in this paper.

The Q learning algorithm is summarized in Algorithm 2. s_0 is the initial position of UAV.

Algorithm 2 Q-Learning Algorithm

Initialize $s = s_0$, and Initialize $Q(s, a) = 0$.
Set the value of ϵ to 0.9.
Loop
Generate a random number *num*.
if $num > \epsilon$ **then**
    UAV chooses an action from the action set randomly.
else
    UAV chooses the action which can get the largest Q value from action set.
end if
update Q value:
    $Q(s, a) \leftarrow R + \gamma\ maxQ(s', a')$.
update state:
    $s \leftarrow s'$.
end Loop.

Without considering resource block, the resource allocation problem can be modeled as bipartite graph matching problem, which can be solved by Hungarian algorithm. Hungarian algorithm is a combinatorial optimization algorithm for solving task assignment problem in polynomial time, and detailed algorithm refers to [28]. This is to say, only V2V link

multiplexing V2I link will be considered. Then the problem of resource allocation can be formulated as

$$\max_{\{I_{m,k}, P_m^C, P_k^D\}} \log_2\left(1 + \eta_m^C\right)$$

$$s.t. \quad Pr\left\{\eta_k^D \leq \eta_0^D\right\} \leq p_0, \quad \forall k$$

$$log_2\left(1 + \eta_m^C\right) \geq r_0^C, \quad \forall m$$

$$0 \leq P_m^C \leq P_{\max}^C, \quad \forall m$$

$$0 \leq P_k^D \leq P_{\max}^D, \quad \forall k$$

$$\sum_m I_{m,k} = 1, \quad \forall k$$

$$\sum_k I_{m,k} \leq 1, \quad \forall m$$

$$I_{m,k} \in \{0, 1\}. \quad \forall m, k \qquad (23)$$

The derivation and analysis process similar to the 3-partite graph can be applied to the bipartite graph matching by referring to [28], and we omit the detailed derivation and analysis process here.

Next, we will analyze the complexity of of two resource allocation algorithm, i.e., 3-partite graph matching algorithm and Hungarian algorithm. First, we need to calculate the optimal power of CUE and DUE to get the optimal achievable rate of single V2I link for all CUEs. For 3-partite graph matching algorithm, these steps will take $\mathcal{O}(FMK)$. For Hungarian algorithm, these steps will take $\mathcal{O}(MK)$. For the convenience of analysis, let us assume that F = K = M. As for 3-partite graph matching algorithm, it will take polynomial time to find optimal extreme point solution to (19). Assume that we adopt binary tree to store hyperedges. When constructing matrix G, it will take $\mathcal{O}(M)$ time to iterate over the set of hyperedges. In each iteration, we need to find the hyperedges that satisfies $x_e \leq 2$, and add the hyperedges to the set of G as well as delete the hyperedges in set of E, which will take $\mathcal{O}(M^2 logM)$. So the time complexity to construct matrix G is $\mathcal{O}(M^3 logM)$. In Local Ratio algorithm, we need to iterate over the set of hyperedges and decompose the weight function, which will take $\mathcal{O}(M^3)$. At last, to search for hyperedges whose weight greater than w_0 based on the matching found by the Local Ratio algorithm, the time complexity is $\mathcal{O}(M)$. Therefore, the total complexity of 3-partite graph matching algorithm is $\mathcal{O}(M^3 logM)$. As for Hungarian algorithm, it will take $\mathcal{O}(M^3)$ time to solve the bipartite graph matching problem in the worst case.

V. SIMULATION
A. SIMULATION PARAMETERS
In this section, the presented resource allocation algorithms in UAV enabled vehicular network will be validated by computational simulation.The LOS transmission model in WINNER+B1 [29] will be used as the path loss model of V2V link, and the LOS model in RMA-AV scenario of TR 38.901 [3] will be used as the path loss model of V2I link. Vehicle-related parameters will be referred to freeway case in

TABLE 2. Simulation parameters.

Parameter	Value
Radius of UAV cell	500 m
UAV height	12 m
UAV antenna gain	8 dBi
UAV receiver noise figure	5 dB
UAV speed	180 km/h
Vehicle height	1.5 m
Vehicle antenna gain	3 dBi
Vehicle receiver noise figure	9 dB
Vehicle speed	70 km/h
Inter-vehicle distance	2.5s * vehicle speed
Noise power σ^2	-114 dBm
Carrier frequency	2 GHz
Bandwidth	10 MHz

TABLE 3. Channel model.

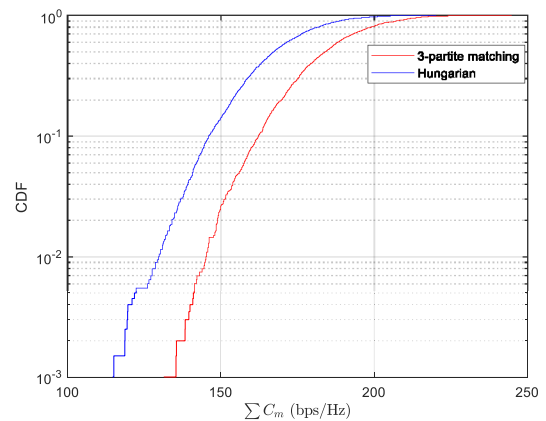|	Pathloss model	Fast fading
V2I link	PL=max(23.9-1.8*lgh,20)*lgd +20lg(40*pi*fc/3)	Rayleigh fading
V2V link	WINNER+B1 [?]	Rayleigh fading

FIGURE 3. CDF of sum achievable rate of V2I links with M = 10, K = 10 using 3-partite graph matching algorithm.

TR 36.885 [30], and UAV-related parameters will be referred to TR 38.901 [3].

B. SIMULATION RESULTS
Fig. 3 shows the CDF of sum achievable rate of V2I links for 3-partite matching algorithm and Hungarian algorithm. Fig. 4 shows that the sum achievable rate of V2I links decrease if SINR threshold at the receiver of V2V link increases. This is because the increase of SINR threshold at the receiver of V2V link limits the transmission power of CUEs. In Fig. 5 we can observe that the sum achievable rate of V2I links get larger when the interrupt probability threshold of V2V links increases, which is due to the fact that V2V links are more tolerant of interference from V2I links with
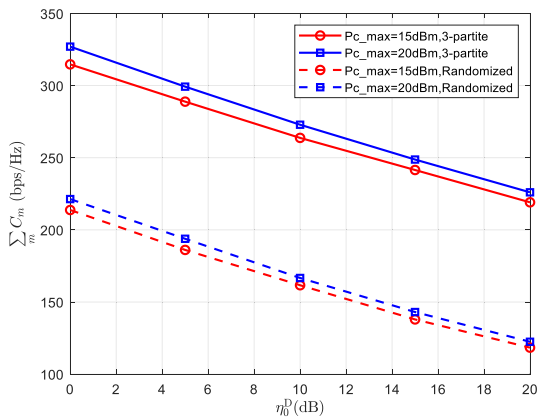
FIGURE 4. Sum achievable rate of V2I links with varying η_0^D using 3-partite graph matching algorithm.
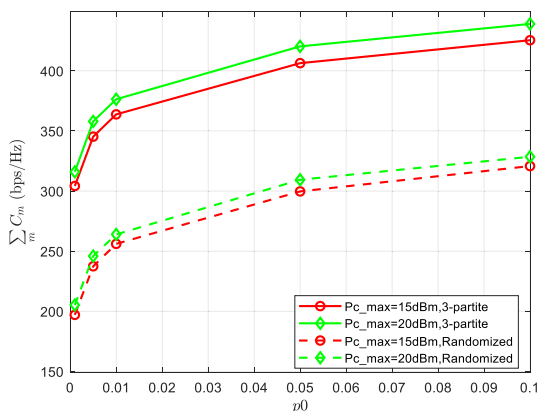

FIGURE 6. Sum achievable rate of V2I links with varying P_{max}^C using Hungarian algorithm.

FIGURE 5. Sum achievable rate of V2I links with varying p_0 using 3-partite graph matching algorithm.

FIGURE 7. Sum achievable rate of V2I links with varying DUE ratio using Hungarian algorithm.

FIGURE 8. Sum achievable rate of V2I links with varying DUE ratio using hungarian algorithm.

higher interrupt probability threshold. Moreover, it can be seen from Fig. 4 and Fig. 5 that the sum achievable rate of V2I links increases as the maximum transmission power of CUE increases, because of larger allowed transmission power of CUE. Besides, it can also be seen from Fig. 4 and Fig. 5 that the sum achievable rate of V2I links with 3-partite matching algorithm is higher than randomized matching. And the result of comparison also shows the effectiveness of 3-partite matching algorithm.

As shown in Fig. 6, the numerical results further illustrates the relationship between the sum achievable rate of V2I links and maximum transmission power of CUEs. The results in both Fig. 6 and Fig. 7 show that the sum achievable rate of V2I links decreases as *Ratio* increases, where *Ratio* refers to the ratio of the number of DUEs to the number of CUEs. The reason is that the interference caused by V2V links will increase if the number of CUEs increase relatively. The curves of Fig. 7 seem to indicate that when the achievable rate threshold for a single V2I link increase, the sum achievable rate of V2I links will increase. In Fig. 8, however, this does not seem to be the case. This is because the sum achievable rate of a single V2I link is relatively large when UAV acts as a base station. If achievable rate threshold is set small, the result
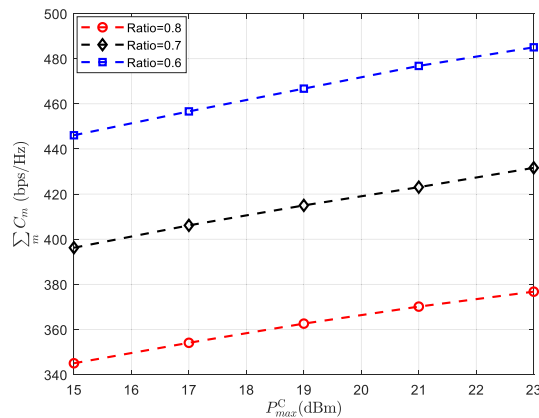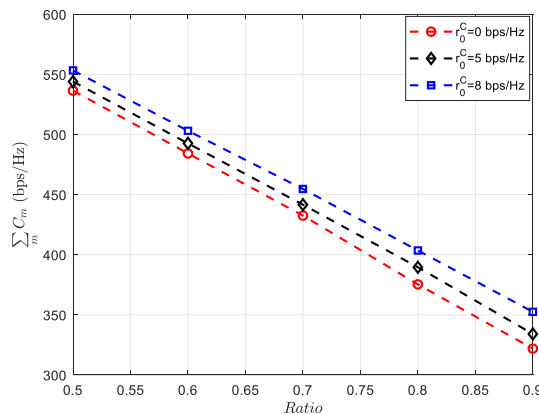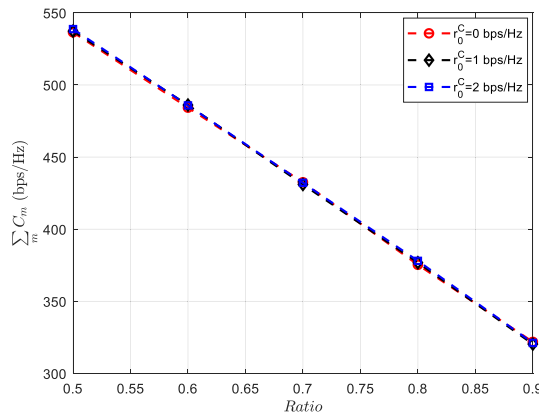
of matching and sum achievable rate of V2I links will not be affected by raising threshold for the achievable rate of single V2I link.

We set up a simple but reasonable simulation scenario to explore the trajectory of UAV using Q-learning algorithm in Fig. 9, and the simulation result is shown in Fig. 10.
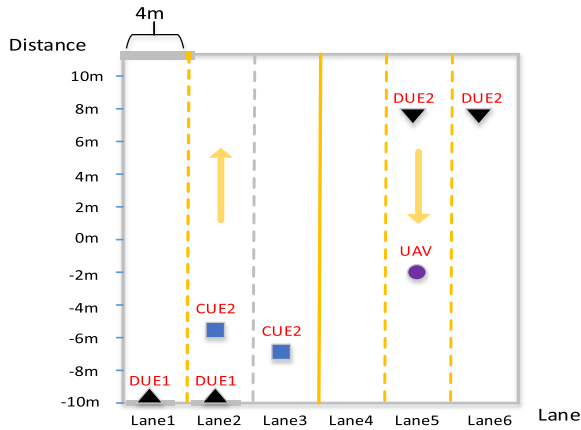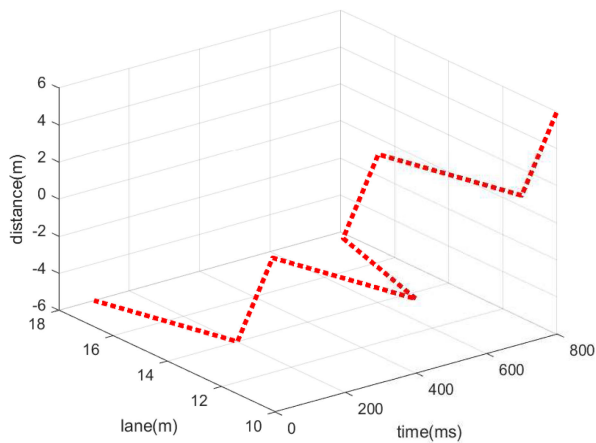
FIGURE 9. Simple scenario: M = 2, K = 2.

FIGURE 10. The trajectory of UAV when M = 2, K = 2.

TABLE 4. Performance comparison in two cases.

	Sum Achievable Rate CUEs=20 DUEs=20	Sum Achievable Rate CUEs=20 DUEs=18	Sum Achievable Rate CUEs=20 DUEs=16
UAV (control trajectory)	292.0043 (bps/Hz)	320.1847 (bps/Hz)	354.2079 (bps/Hz)
UAV (without control)	263.9974 (bps/Hz)	306.8584 (bps/Hz)	318.8437 (bps/Hz)
Gain	10.6%	4.3%	11.1%

In order to better observe the trajectory of UAV, the number of vehicles in two directions on the freeway is set differently. From Fig. 10, we can see that the UAV will change its position when the vehicle moves.

To further illustrate that the real-time trajectory control of UAV is beneficial, we compare the performance of UAV enabled vehicular network in two cases, i.e., controlling the trajectory of UAV according to real-time communications conditions and UAV hovering at a fixed height. We assume that the positions of vehicles obey poisson distribution. The simulation results are recorded in Table 4.

Through observation, we can find that the sum achievable rate of V2I links in the case that the trajectory of UAV was controlled is larger than the case that UAV hovered at a fixed position. In other words, the result shows the effectiveness of the trajectory controlling for UAV.

VI. CONCLUSION

This paper considers UAV as a temporary base station in disasters to restore vehicular communications. The mobility of UAV is exploited to enhance the channel conditions. Whereas the power consumption of UAV is a challenge. The propulsion power consumption of UAV is usually higher than communications power consumption (e.g., hundred of watts versus a few watts) [31]. Although there is a tethered UAV, it limits the mobility of UAV to a certain extent. Therefore, energy-efficient UAV-enabled system design is desirable. And the 3-partite graph matching algorithm can be further extended in this paper. Our algorithm only achieve a maximum weighted matching for 3-partite graph, but not optimal.

REFERENCES

[1] A. Merwaday and I. Guvenc, "UAV assisted heterogeneous networks for public safety communications," in *Proc. IEEE Wireless Commun. Netw. Conf. Workshops (WCNCW)*, New Orleans, LA, USA, Mar. 2015, pp. 329–334.

[2] M. Mozaffari, W. Saad, Y.-H. Nam, M. Debbah, and M. Bennis, "A tutorial on UAVs for wireless networks: Applications, challenges, and open problems," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2334–2360, 3rd Quart., 2019.

[3] *Technical Specification Group Radio Access Network: Study on Channel Model for Frequencies From 0.5 to 100 GHz: (Release 14)*, document 3GPP TR 38.901 V2.0.0, 3rd Generation Partnership Project, Jun. 2018.

[4] X. Cheng, L. Yang, and X. Shen, "D2D for intelligent transportation systems: A feasibility study," *IEEE Trans. Intell. Trans. Syst.*, vol. 16, no. 4, pp. 1784–1793, Jan. 2015.

[5] A. Bazzi and B. M. Masini, "Taking advantage of V2V communications for traffic management," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Baden-Baden, Germany, Jun. 2011, pp. 504–509.

[6] M. Botsov, M. Klügel, W. Kellerer, and P. Fertl, "Location dependent resource allocation for mobile device-to-device communications," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Istanbul, Turkey, Apr. 2014, pp. 1679–1684.

[7] W. Sun, E. G. Ström, Y. Sui, K. Cheong Sou, and F. Brännström, "D2D-based V2V communications with latency and reliability constraints," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, Austin, TX, USA, Dec. 2014, pp. 1414–1419.

[8] X. Shen, X. Cheng, R. Zhang, B. Jiao, and Y. Yang, "Distributed congestion control approaches for the IEEE 802.11p vehicular networks," *IEEE Intell. Transp. Syst. Mag.*, vol. 5, no. 4, pp. 50–61, Oct. 2013.

[9] W. Sun, D. Yuan, F. Brännström, and E. G. Ström, "Cluster-based radio resource management for D2D-supported safety-critical V2X communications," *IEEE Trans. Wireless Commun.*, vol. 15, no. 4, pp. 2756–2769, Apr. 2016.

[10] X. Liu, Z. Li, W. Meng, G. Gui, Y. Chen, F. Adachi, and N. Zhao, "Transceiver design and multihop D2D for UAV IoT coverage in disasters," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 1803–1815, Apr. 2019.

[11] Q. Wu, Y. Zeng, and R. Zhang, "Joint trajectory and communication design for UAV-enabled multiple access," in *Proc. GLOBECOM IEEE Global Commun. Conf.*, Singapore, Dec. 2017, pp. 1–6.

[12] F. Ono, H. Ochiai, and R. Miura, "A wireless relay network based on unmanned aircraft system with rate optimization," *IEEE Trans. Wireless Commun.*, vol. 15, no. 11, pp. 7699–7708, Nov. 2016.

[13] I. Cermakova and J. Komarkova, "Modelling a process of UAV data collection and processing," in *Proc. Int. Conf. Inf. Soc. (i-Society)*, Dublin, Ireland, 2016, pp. 161–164.

[14] L. Xiao, X. Lu, D. Xu, Y. Tang, L. Wang, and W. Zhuang, "UAV relay in VANETs against smart jamming with reinforcement learning," *IEEE Trans. Veh. Technol.*, vol. 67, no. 5, pp. 4087–4097, May 2018.

[15] H. Seliem, R. Shahidi, M. H. Ahmed, and M. S. Shehata, "Drone-based highway-VANET and DAS service," *IEEE Access*, vol. 6, pp. 20125–20137, 2018.

[16] R. Zhang, X. Cheng, L. Yang, and B. Jiao, "Interference graph-based resource allocation (InGRA) for D2D communications underlaying cellular networks," *IEEE Trans. Veh. Technol.*, vol. 64, no. 8, pp. 3844–3850, Aug. 2015.

[17] K. Zheng, F. Liu, Q. Zheng, W. Xiang, and W. Wang, "A graph-based cooperative scheduling scheme for vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 62, no. 4, pp. 1450–1458, May 2013.

[18] S. Wang, T. Wu, D. Bu, S. Cai, and Y. Yao, "Constrained maximum weighted bipartite matching: A novel approach to radio broadcast scheduling," *Sci. China Inf. Sci.*, vol. 62, no. 7, p. 72102, 2019. doi: 10.1007/s11432-017-9324-0.

[19] L. Liang, S. Xie, G. Y. Li, Z. Ding, and X. Yu, "Graph-based resource sharing in vehicular communication," *IEEE Trans. Wireless Commun.*, vol. 17, no. 7, pp. 4579–4592, Jul. 2018.

[20] S. Xu, Z. Wei, and Z. Feng, "A novel algorithm of UAV-mounted base station placement and frequency allocation," in *Proc. Int. Conf. 5G Future Wireless Netw.* Cham, Switzerland: Springer, 2017, pp. 182–193.

[21] L. Liang, G. Y. Li, and W. Xu, "Resource allocation for D2D-enabled vehicular communications," *IEEE Trans. Commun.*, vol. 65, no. 7, pp. 3186–3197, Jul. 2017.

[22] Y. H. Chan and L. C. Lau, "On linear and semidefinite programming relaxations for hypergraph matching," *Math. Program.*, vol. 135, nos. 1–2, pp. 123–148, 2012.

[23] A. Bar-Noy, R. Bar-Yehuda, A. Freund, J. Naor, and B. Schieber, "A unified approach to approximating resource allocation and scheduling," *J. ACM*, vol. 48, no. 5, pp. 1069–1090, 2001.

[24] L. Zikou, C. Papachristos, and A. Tzes, "The power-over-tether system for powering small UAVs: Tethering-line tension control synthesis," in *Proc. 23rd Medit. Conf. Control Autom. (MED)*, Torremolinos, Spain, 2015, pp. 681–687.

[25] R. Li, D. Xu, D. W. K. Ng, N. Yang, J. Yuan, J. An, and L. Yang, "Joint trajectory and resource allocation design for UAV communication systems," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, Abu Dhabi, United Arab Emirates, Dec. 2018, pp. 1–6.

[26] F. Cui, Y. Cai, M. Zhao, G. Y. Li, and Z. Qin, "Joint trajectory design and power allocation for UAV-enabled non-orthogonal multiple access systems," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Abu Dhabi, United Arab Emirates, Dec. 2018, pp. 1–6.

[27] Y. Sun, D. Xu, D. W. K. Ng, L. Dai, and R. Schober, "Optimal 3D-trajectory design and resource allocation for solar-powered UAV communication systems," *IEEE Trans. Commun.*, vol. 67, no. 6, pp. 4281–4298, Jun. 2019.

[28] H. W. Kuhn, "The Hungarian method for the assignment problem," *Naval Res. Logistics Quart.*, vol. 2, nos. 1–2, pp. 83–97, 1955.

[29] J. Meinilä, P. Kyösti, L. Hentilä, and T. Jämsä, "WINNER II channel models," in *Radio Technologies and Concepts for IMT-Advanced*. Hoboken, NJ, USA: Wiley, 2009, pp. 39–92.

[30] *Technical Specification Group Radio Access Network: Study LTE-Based V2X Services: (Release 14)*, document 3GPP TR 36.885 V2.0.0, 3rd Generation Partnership Project, Jun. 2016.

[31] Y. Zeng and R. Zhang, "Energy-efficient UAV communication with trajectory optimization," *IEEE Trans. Wireless Commun.*, vol. 16, no. 6, pp. 3747–3760, Jun. 2017.

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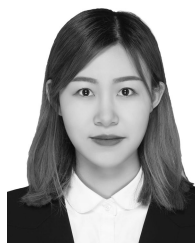
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