Throughput Optimization in Heterogeneous Swarms of Unmanned Aircraft Systems for Advanced Aerial Mobility

Jian Wang, Yongxin Liu, Shuteng Niu, Weipeng Jing, and Houbing Song, *Senior Member, IEEE*

***Abstract*—The ubiquitous deployment of 5G New Radio (5G NR) stimulates Unmanned Aircraft Systems (UAS) swarm networking to evolve to achieve more imminent progress. The heterogeneous collaboration between UAS swarm enhances the complexity and the efficiency of mission complement that requires robustness, flexibility, and sustainability of throughput in UAS swarm networking. The conventional approaches mainly are based on the hierarchical architectures that are limited to satisfy the challenges of UAS swarm with high dynamics on a large scale. In this paper, we propose an optimal cell wall paradigm to enhance the throughput in heterogeneous UAS swarm networking. With the weight adjustment of each link, we map the optimization into a polyhedron scheduling problem and formula the problem into Max-min Throughput Fair Scheduling (MTFS). Further, we propose a max-min throughput algorithm to optimize the minimum throughput of cell wall paradigm. With the optimal max-min throughput, we optimize the schedule with edge-coloring to achieve global MTFS solving. The normalized MTFS shows our algorithm can achieve over 40% improvement of MTFS globally. In terms of MTFS solving, our algorithms have promising potential to improve the throughput and mitigate the incidents for multiple beams enabling of UAS in cell wall communication. With the throughput enhancement, the advanced aerial mobility of UAS swarm networking can be escalated on a large scale.**

***Index Terms*—Intelligent Transportation Systems (ITS), Heterogeneous Swarms, Unmanned Aircraft Systems (UAS), Advanced Aerial Mobility.**

I. Introduction

THE ubiquitous deployment of 5G New Radio (5G NR) accelerates the evolution of techniques in many fields [1], [2] that enlarges the scale of diverse implementations significantly. The prominent advantages (ultra low latency [3], experienced throughput [4], and networking efficiency [5]) of 5G NR provide progress to the collaborations and cooperation between the heterogeneous devices and platforms. The collaborations and cooperations, in real-time, play pivotal roles in Unmanned Aircraft Systems (UAS) swarm deployment on a large scale [6], [7]. With the enhancement of 5G NR, the UAS swarm can complete the missions which are more challenging on complexity and accuracy. The complexity and accuracy of mission complement pose a challenge to the capacities of heterogeneous UAS swarm networking. The shared information and collaborated intrusions need to be delivered to the specific UAS so that the specific sub-missions can be achieved in unambiguous time and positions. Consequently, the complement of sub-missions affects the achievement of the whole project. The high capacities of 5G NR can provide the UAS swarm networking powerful support to extend the deployment on a large scale.

Heterogeneous UAS swarm networking requires robust, flexible, and reduced interference connections to improve the throughput of UAS swarm networking [8]. The high and robust throughput between multiple UAS swarms can enhance the controllability, mission complement, and flight efficiency of UAS swarms. 5G enabled heterogeneous UAS swarm networking can enable UAS in the swarm to select optimal hops for the next delivery which can reduce the interference and increase the spectrum efficiency with sustainable throughput. Beamforming, as one of the main technologies of 5G NR, can enable UAS control communication more accurately which enables UAS to deliver packets to the specific destinations directionally. The beamforming enabled UAS networking can reduce energy consumption and interference remarkably [9] which improves the compatibility of UAS networking to the mobility of UAS crucially. The optimal direction pointing enables the multiple connections can be constructed simultaneously. The low divergence angle allows the beamforming to transmit beams with lower intervals for each hop comparing with Omni-directional transmitting. The high spectrum efficiency of 5G NR enables the heterogeneous UAS swarms to achieve robust connections and reliable throughput between different UAS swarms. The conventional UAS swarms are based on the hierarchical architectures which need to deploy a high capacity of UAS to afford the communication between heterogeneous UAS swarms. The hierarchical architectures are efficient in the management of UAS swarms which lacks resilience and flexibility of controllability for heterogeneous UAS swarms on a large scale. The excellent points of beamforming provide sufficient freedom for communication between UAS swarms more locally. The local optimized characteristics of the beamforming process the robustness of decentralization of UAS swarm networking. The conventional approaches can not extend the UAS swarm networking on a large scale in real time, and are also vulnerable to the dynamics of UAS swarms topology. A decentralized and distributed architecture is required to satisfy the requirement of the flexibility and mobility of UAS swarm networking.

Jian Wang, Yongxin Liu, Shuteng Niu, and Houbing Song are with the Security and Optimization for Networked Globe Laboratory (SONG Lab), Embry-riddle Aeronautical University, Daytona Beach, FL 32114 USA

Weipeng Jing is with the College of Information and Computer Engineering, Northeast Forestry University, Harbin, Heilongjiang 150040 China

Manuscript received on January 10, 2021, XXXX; revised XX XX, XXXX.

In this paper, we propose an optimal cell wall paradigm for heterogeneous UAS swarm networking. Enhanced with beamforming of 5G NR, each UAS in the swarm can leverage beamforming to optimize the connections to achieve better delivery efficiency. Within the transmission range of beamforming, the cell wall of each UAS swarm can be constructed to share information and intrusions of collaborations and mission complement. With geographical measurement, the UAS that detects other swarms can build connections to members of the other UAS swarms within the transmission range. The goal of this paper is to design a cell wall paradigm to enhance the throughput of heterogeneous UAS swarm networking. By re-mapping the connections between heterogeneous UAS swarms, we construct a cell wall for communication between heterogeneous UAS swarm networking. With adjustment of weight of each link derived from the cell wall, we map the optimization of throughput into a polyhedron scheduling problem and formula the problem into MTFS. Further, we propose a max-min throughput algorithm to optimize the throughput of heterogeneous UAS swarm networking. With optimal max-min throughput derived from the max-min algorithm, we optimize the weight of the schedule to achieve global MTFS solving. The evaluation shows the optimal cell paradigms can improve the throughput of UAS swarm networking largely and achieve more capacity for cell wall construction. The normalized MTFS shows our algorithm can achieve over 40% improvement of MTFS globally.

The paper is organized as follows: Section I illustrates our motivation and contributions. Section II presents the related work of UAS swarm networking. Section III depicts the system model. Section IV describes cell wall construction and modeling for heterogeneous UAS swarm networking. Section V depicts throughput optimization for fair scheduling for cell wall construction. Section VI presents the evaluation. Section VI concludes the paper.

II. Related Work

To achieve a better throughput between UAS and ground terminals with subjections to power allocation and UAS trajectories, in [10], an optimization problem is decomposed into two sub optimizations which obtain 1) communication scheduling and power allocation 2) trajectory optimization. A similar thought is presented in [11] which focuses on the optimal adjustment of trajectory generation and speed control. By applying the alternating optimization and successive convex programming, the local optimization of throughput for UAS and ground users can be achieved [12]. The optimal trajectory of mobile relaying can enhance the throughput for UAS networking. With the fixed trajectory of relaying, the optimization of power allocation is proposed to extend the throughput maximization. Further, based on the allocated power, the trajectory is optimized to achieve the maximum throughput [13]. Aiming to maximize the uplink throughput between UAS and ground users, a trajectory optimization is proposed to maximize the throughput with constraints of limit flight time of UAS and users' neutral energy [14]. Better performances are achieved in [15] which optimize UAS trajectories, scheduling for uplinks and downlinks [16], and uplink power allocations jointly. With block coordinate descent and successive convex approximation, the throughput of networking can be enhanced [17]. The optimal trajectory can enable UAS to obtain good channel states and energy saving so that the UAS can achieve better throughput with ground devices. The main flaw of these approaches is limited to the mobility of UAS which is at low flexibility.

Enhancement for the achievable rate of Multiple Input and Multiple Output (MIMO) cognitive radio systems [18] relayed by UAS is required. The constraint with power allocation, the energy consumption of relay, and channel interference, power optimization for MIMO cognitive radio system relayed by UAS can improve the throughput between UAS and ground users (Primary and Secondary) [19], [20]. To achieve resilience of UAS swarm networking, a deep Q learning based approach to deploy UAS in the swarm to rescue the broken links dynamically. The deployment of relay nodes is optimized based on Quality-of-Service (QoS) and link conditions. Fueled by deep Q learning, efficient throughput can be achieved in [21]. With a strategy of amplification and forwarding, a power splitting-based relaying protocol for packets forwarding is proposed in [22]. Joint optimization of bandwidth allocation, power consumption, and trajectories of UAS, in [23], can improve the spectrum efficiency and the average end-to-end throughput. With the optimization of resource allocations, UAS can achieve extensive performance on the MIMO scenarios and QoS which enable more complicated implementation possible. However, the machine learning enabled approaches still can not enlarge the scaling of deployment of UAS swarm networking which requires much more computational support in real time.

For cognitive UAS networking, an optimization of three-dimensional location and spectrum sensing duration of UAS, in [24], divides the problem into two convex sub-problems to improve the throughput [25] weighted sum and location weighted sum to solve the non-convex problem. The optimized time slots for each communication can achieve maximum throughput for networking support of disaster-affected area [26] and multiple areas services in [27]. To achieve a balance between maximizing the throughput in a set of areas and Grid-connected Micro Generation (GMG) energy consumption at ground sites, an optimization model maximizes the profit of UAS networking which contains mission plans, action associations, and optimal balance between GMG and UAS [28]. Additional parameters obtaining uplink power control, and resource allocation for the wireless energy transfer and wireless information transfer are considered in Wireless Powered Communication Networking (WPCN) system to achieve the efficiency of WPCN [29], [30]. The evaluation in [23], shows the cyclical time division multiple access schemes can keep throughput between UAS and users stable as the delay tolerance increases. With the reduction of latency between the ground devices [31] and UAS in the flight, the networking can be extended to a larger scale which is still a constraint within dozens. The merits of the delay tolerance can improve the access of UAS and ground devices to UAS swarm networking which can execute multiple missions simultaneously.

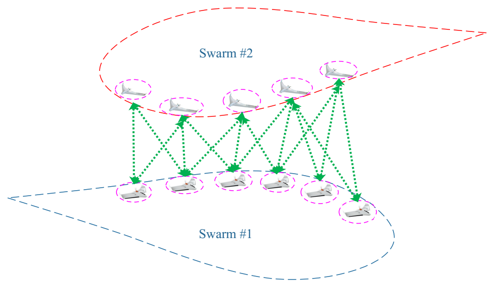

Fig. 1. Collaboration between heterogeneous UAS swarm networking

Joint optimization of time allocation, reflection coefficient, and UAS trajectories, in [32], is proposed to maximize the system throughput backscatter device with UAS harvesting. To extend the communication coverage and system performance, a power control algorithm, in [33], can improve the throughput for UAS relaying networking for secondary users in UAS-assisted cellular networking. An investigation about throughput optimization of cache-enabled UAS is presented in [34], and an optimization proposed in this research work can improve the throughput between UAS and Internet of Things (IoT) devices which obtains deployment optimization of UAS and probabilistic caching placement optimization of IoT devices [34]. To achieve the maximization of system throughput on the UAS investigation, the Markov chain is implemented to decide the mode of nodes and optimize the trajectory of UAS with a greedy algorithm in [35]. Multiple targets optimization can enable UAS swarm networking to achieve optimization globally with the sacrifice of time consumption and computational support which is hard to deploy UAS on a large scale in real time.

The optimal trajectory, the optimal resource allocation, and the multiple targets optimization can improve the throughput of UAS swarm networking from different aspects. However, these approaches are not feasible to improve the throughput of UAS swarm networking on large scale with the requirement of collaboration and corporation in real time. The throughput of UAS networking focuses on the enhancement of UAS networking and ground devices which rarely contain throughput between the heterogeneous UAS swarms on a large scale. The previous research on UAS networking can be a useful reference for the extending of research on the throughput of UAS swarm networking on a large scale. The hierarchical architectures of UAS swarms can help the ground terminal achieve efficient controllability with the sacrifice of resilience and flexibility of UAS swarm networking. Based on the fluid characteristics of UAS swarms, a more compatible communication paradigm for heterogeneous UAS swarm networking is needed.

III. System Model

We consider the system model consists of a heterogeneous UAS swarm networking which contains two heterogeneous UAS swarms. Each UAS in the swarm is equipped with multiple mmWave RF beams which is depicted as Fig. 1.

An UAS in swarm together with many peers of the other swarm in a heterogeneous Time Division Multiple Access (TDMA) cellular networking. The UAS of the cell wall in each swarm is considered as the backhaul gateway for the UAS of the cell wall in the other swarm. In terms of 5G NR interference, each UAS in the swarm with R mmWave RF beams enable R links to connect to the other UAS simultaneously. We leverage directed graphs to model the links between different nodes in the networking.

Let $G = (\nu,\ \varepsilon)$ be a directed graph with the vertex (node) set ν and edge (link) set ε. The capacity of each ε in G is denoted as c_ε. Based on wireless communication theory, each c_ε is formulated as $c_\varepsilon = g_\varepsilon log(1 + \frac{p_\varepsilon}{10^{PL_\varepsilon/10}\sigma^2})$ and $c_\varepsilon > 0$, where g_ε is direct gain of channel, p_ε is transmission power of ε, and σ is Gaussian noise distributed with zero mean. PL_ε is the path loss of ε in line-of-sight which is given by $PL_\varepsilon = 20log_{10}(d_\varepsilon) + 20log_{10}(f_\varepsilon) - 147.55$, where d_ε is the distance for ε and f_ε is the frequency of ε adopts.

For the heterogeneous UAS swarm networking, connection time is not static which may vary according to mission assignment. In this paper, our goal is to achieve an optimal throughput for collaboration between heterogeneous UAS swarm networking in each connection frame. The connection time consists of multiple connection frames. During collaboration, the communication time, denoted as $\mathcal{T}$, can be divided into the multiple connection frame, denoted as $\mathcal{F}$, which can be divided into a unit time scale, 1. The unit time scale can be scheduled into N slots t, where $N \geq 1$. The i_{th} slot is defined as t_i which follows the constraint: $\sum_{i=1}^{N} t_i = 1$ and $1 \geq t_i \geq 0$. Further, in a i_{th} slot, a set of links $\varepsilon_i \subseteq \varepsilon$ are active for the information exchange.

IV. Cell Wall Construction

Due to the dynamics and flexibility of UAS in a swarm, we consider a UAS swarm as a cell that is an analogy to the biological cell. The cell obtains a cell wall for the communication between heterogeneous UAS swarms. For communication, the two communication cells require to provide two cell walls to construct connections between heterogeneous UAS swarm networking. As Fig. 1 depicted, swarm #1 and swarm #2 are denoted as S_1 and S_2 respectively. The UAS, in S_1, is selected as cell wall, $U_{(S_1,\ n)} \in S_1$. Similar to S_1, the UAS, in S_2, is selected as cell wall, $U_{(S_2,\ m)} \in S_2$.

With broadcast packets derived from Automatic Dependent Surveillance-Broadcast (ADS-B), the UAS, in the peripheral distribution of S_1, calculate the distance to the UAS in S_2 and send a request once the distance is within the valid connection range. The carriers of ADS-B are 978MHz and 1090MHz which is far away from the carriers of 5G NR devices. The interference between 5G NR devices and ADS-B can be ignored. Once the UAS in S_1 receives the ACK from S_2, the UAS of S_1 will broadcast its connections to its peers in S_1 and be marked as $U_{(S_1,\ n)}$. The selection of $U_{(S_2,\ m)}$ from S_2 is similar to $U_{(S_1,\ n)}$. When the desired throughput requirement is satisfied, the cell wall construction processing will be finished. A set of links is constructed between S_1 and S_2 and their capacity is denoted as c_i, $c_i \in c_\varepsilon$. The c_ε forms a reliable tunnel for the information exchange between two heterogeneous swarm networking. Once packets arrive at the

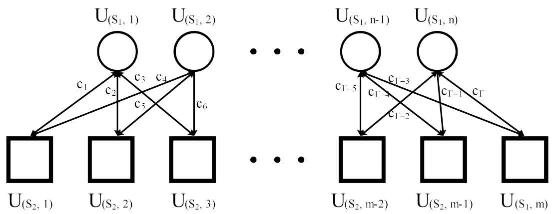

Fig. 2. Cell wall construction with multiple beams

UAS in the cell wall, the packets will be delivered to the other UAS swarms directly.

As Fig. 2 shows, we suppose that a set of links ε is scheduled in the i_{th} slot, and $\varepsilon_i,\ \varepsilon_j \in \varepsilon$ are two different links. The ε_i and ε_j can not share a common UAS in S_1 and S_2 with avoidance of incident between different beams. Based on the above constraints, we can assure that the active links in each slot are corresponding to matching in the expanded graph. In the graph, the optimal matching is defined as a set of edges that share no common vertex. Each scheduled link in ε is defined to be active in the range $t_e \in (0,\ 1]$. For the active links, we define the active time of links set is t, $t = \{t_e | \forall e \in \varepsilon\}$. Based on the optimal matching of polyhedron P, each vertex in P can be mapped into every active t.

Definition 1. (Schedule Polyhedron) Given a graph $G = (\nu, \varepsilon)$, the schedule polyhedron G is defined as a set of link time t that satisfy the following linear constraints:

$$\sum_{e\in\delta(\zeta)} t_e \leq 1 \qquad \forall \zeta \in \nu \tag{1a}$$

$$t_e \geq 0 \qquad \forall e \in \varepsilon \tag{1b}$$

Where $\delta(\zeta)$ is the set of links incidents to ν.

Lemma 1. (1) Each point in the polyhedron P is a feasible link time t, and (2) each feasible link time t is a point in P.

Proof. Based on the proof work presented in [36], we simplified the model of the scenario. With Edmonds' matching polyhedron theorem, a feasible schedule $\mathcal{S}$ consists of $N \geq 1$ slots. In each slot, a set of links is active for the schedule $\mathcal{S}$ from the G which is corresponding to a vertex of matching polyhedron Q. In Q, each edge is corresponding to the selection of links in P. The value of vertex in Q is binary, active $\{1\}$, or inactive $\{0\}$. Therefore, we can have linear constraints for Q is the following:

$$\sum_{e\in\delta(\zeta)} x_e \leq 1 \qquad \forall \zeta \in \nu \tag{2a}$$

$$x_e \geq 0 \qquad \forall e \in \varepsilon \tag{2b}$$

In the matching polyhedron Q, each link x_e has the state x_e^i in i^{th} slot and $\sum_{i=1}^{N} t_i \leq 1$. In each schedule $\mathcal{S}$, we have:

$$\sum_{e\in\delta(\zeta)} x_e \sum_{i=1}^{N} t_i \leq \sum_{i=1}^{N} t_i \leq 1 \qquad \forall \zeta \in \nu \tag{3a}$$

$$\sum_{i=1}^{N} x_e t_i = t_e \geq 0 \qquad \forall e \in \varepsilon \tag{3b}$$

The above shows the each feasible link time t is a point in P. We suppose the schedule polyhedron P obtains K vertexes $X = \{x_k | k \in K\}$ in the schedule $\mathcal{S}$ which contains K slots $\Gamma = \{\tau_k | k \in K\}$. For the feasible time t, we can have:

$$t = X\Gamma = \sum_{i=1}^{K} x_k \tau_k \tag{4}$$

Here, the scheduled link sets ε are corresponding to x_k which is matching, and ε are scheduled in k^{th} slot. □

V. Throughput Optimization For Fair Scheduling

Based on the cell wall constructed between S_1 and S_2, we mapped it into a polyhedron optimization problem, thereafter we will maximize the throughput for the polyhedron P in the schedule $\mathcal{S}$ which can be concluded as the problem of Maximum Throughput Fair Scheduling (MTFS). The goal of MTFS is to achieve max-min fairness in throughput for the cell wall connections.

Definition 2. (MTFS) Given the cell wall network G and a schedule $\mathcal{S}$ in unit time 1. We define the throughput of $\mathcal{S}$ is $\mathcal{H}_{\mathcal{S}} = \{h_{(\nu,\ \mathcal{S})} |\ \nu \in R\}$, where $h_{(\nu,\ \mathcal{S})}$ denotes the throughput of UAS, ν, in the cell wall. The throughput in practice can not be negative.

(I) We consider the max-min throughput for schedule $\mathcal{S}$ as the following criteria: If the feasible schedule $\mathcal{S}_f$ satisfy $\min_{\nu\in R} h_{(\nu,\ \mathcal{S}_f)} \geq \min_{\nu\in R} h_{(\nu,\ \mathcal{S})}$ for any feasible unit time in the schedule $\mathcal{S}$.

(II) A feasible schedule $\hat{\mathcal{S}}$ is the solution to MTFS that if $\hat{\mathcal{S}}$ obtains the maximum throughput $\sum_{\nu\in R} h_{(\nu,\ \mathcal{S})}$ among all feasible schedule $\mathcal{S}_f$, in which satisfies the max-min criteria in (I).

Definition 3. (Capacity Matching) Based on the given graph G defined in section IV, we supposed there are $K \geq 1$ matching in G. Thereafter, the node matching matrix $\mathcal{A} = \{a_{(i,j)} | i, j \in K\}$. Each element in $\mathcal{A}$ is correspondent to the capacity of each link ε_i constructed between node i and j in G, $a_{(i,j)} = c$. All elements in $\mathcal{A}$ is non-negative, $\forall a_{(i,j)} \geq 0$.

Let $\mathcal{A}$ be the node capacity matching matrix, and K nodes are matching in each slot of the schedule $\mathcal{S}$. Thus, the K nodes corresponding the submatrix, $\mathcal{A}^R$, which contains R links between S_1 and S_2. In each schedule $\mathcal{S}$, we define $t^{\mathcal{S}}$ as a $K \times 1$ slot length for each schedule. Let the minimum throughput of UAS in the cell wall be σ. MTFS problem is a linear problem that optimizes the throughput with the involvement of scheduling. To solve the MTFS problem, we divide it into two steps: (1) obtaining a maximum σ. (2) based on max-min throughput σ in (1), we optimize the schedule $\hat{\mathcal{S}}$.

To solve step (1), we formulate step (1) in the following constraints:

$$maximize \quad \sigma \tag{5a}$$

$$subject\ to\ \mathcal{A}^R t^{\mathcal{S}} \geq \sigma 1 \tag{5b}$$

$$1^\top t^{\mathcal{S}} = 1 \ \ and \ \ t^{\mathcal{S}} \geq 0 \tag{5c}$$

Where 1 and 0 denotes a column vector obtains all ones or all zeros separately. (5b) is the constraint for each node in the schedule which is supposed to have the least throughput σ. (5c) is the schedule length constraint which is supposed to equal the unit time, and each time slot is a non-empty set. With all possible matchings, the feasibility of the schedule can be satisfied with the above formulation.

Next, based on the least throughput of σ for each UAS in the cell wall, we formulate step (2) for each UAS in the following constraint:

$$maximize \quad c^\top t^{\mathcal{S}} \tag{6a}$$

$$subject \quad to \quad (5c) \quad and \quad (5b) \tag{6b}$$

Here, c is the capacity of element c_i is the capacity of S_1-to-S_2 links in the i^{th} matching.

To optimize σ, an initial basic feasible solution for step (1) is required. With a constructed cell wall between S_1 and S_2, we perform a Breath First Search (BFS) from S_1. The result is a tree ξ which has R edges. The initial schedule $\mathcal{S}_0$ has R slots and each slot obtains one link in ξ. The initial throughput for each UAS in the cell wall is equal and the schedule performs in the unit time 1. To be simple, we convert step (2) into a general form by adding a negligible variable s_i in the following constraints:

$$maximize \quad -f^\top x \tag{7a}$$

$$subject \quad to \quad Ux = g \quad and \quad x \geq 0 \tag{7b}$$

where $U = [U^1|U^2|U^3] = \begin{bmatrix} \mathcal{A}^R & -1 & -I \\ 1^\top & 0 & 0^\top \end{bmatrix}$, $f^\top = [0^\top|-1|0^\top]$, $x^\top = [(t^{\mathcal{S}})^\top|\sigma|s^\top]$, and $g^\top = [0^\top|1^\top]$. The detail pesudocode is shown as Algorithm 1.

Algorithm 1: Render the max-min throughput σ

Initial $B = B_0$ with BFS for Initial Schedule $\mathcal{S}$
while *True* **do**
  Calculate $p^\top = f_B^\top B^{-1}$;
  Weight setting for links $(v_i,\ v_j)$ of G:
  $w_{(v_i,\ v_j)} = c_{(v_i,\ v_j)}(p_i - p_j)$, $\forall v_i,\ v_j \in \nu$ and $i \neq j$;
  Maximize the weight matching on G, and the optimal matching is defined $\mathcal{M}_o$.
  $\varrho = R + 1$;
  $\varpi_1 \leftarrow -p_\varrho - \sum_{e \in \mathcal{M}_o} w_e$;
  $\varpi_2 \leftarrow -1 + \sum_{k=1}^{R} p_k$;
  $\varpi_3 \leftarrow min_{1 \leq k \leq R} p_k$;
  $\varpi \leftarrow min(\varpi_1, \varpi_2, \varpi_3)$;
  $u \leftarrow u_\varpi$;
  if $\varpi \geq 0$ **then**
    return maximum σ and $B_\sigma = B_\varpi$;
  else
    $B \leftarrow B_\varpi$;

The basis B is a square matrix that derives from U and contains $R+1$ columns. In Algorithm 1, f_B is the elements of f corresponding to basis B. To optimize throughput σ, we require a column derived from U, which enable u_k have negative reduced cost $f_k - p^\top u_k \leq 0$ to trigger the basis. When $\varpi \geq 0$, there are no more column can increase σ, and we achieve an optimal throughput.

With achievement of optimal throughput σ and basis B_σ in step (1), we optimize the schedule $\mathcal{S}$ to maximize the throughput of cell wall between S_1 and S_2. With convenience of solving to constraints (5b), we add a difference z to remove the inequality of constraint $\mathcal{A}^R t^{\mathcal{S}} \geq \sigma 1$ with $\mathcal{A}^R t^{\mathcal{S}} - 1z = \sigma 1$. When the cell wall achieves max-min throughput σ, the z is supposed to all zeros. With alignment of constraints of (7), step (2) is converted into the formation of (7). The basis matrix U is not changed, we make a revision to the following matrix: $f^\top = [-c^\top|0|0^\top]$, $x^\top = [(t^{\mathcal{S}})^\top|z|s^\top]$, and $g = [\sigma 1^\top|1]$. The pseudocode is shown as Algorithm 2.

Algorithm 2: MTFS optimization

Initial $B = B_\sigma$; $\mathcal{S} = \mathcal{S}_0$;
while *True* **do**
  Calculate $p^\top = f_B^\top B^{-1}$;
  Weight setting for links $(v_i,\ v_j)$ of G:
  $w_{(v_i,\ v_j)} = c_{(v_i,\ v_j)}(p_i - p_j)$, $\forall v_i,\ v_j \in \nu$ and $i \neq j$;
  Maximize $\mathcal{M}_o$;
  $\varpi_1 \leftarrow -p_\varrho - \sum_{e \in \mathcal{M}_o} w_e$;
  $\varpi_2 \leftarrow -1 + \sum_{k=1}^{R} p_k$;
  $\varpi_3 \leftarrow min_{1 \leq k \leq R} p_k$;
  $\varpi \leftarrow min(\varpi_1, \varpi_2, \varpi_3)$;
  $u \leftarrow u_\varpi$;
  if $\varpi \geq 0$ **then**
    return optimal $\hat{\mathcal{S}}_\varpi \leftarrow \mathcal{S}(B_\varpi)$;
  else
    $B \leftarrow B_\varpi$;

Based on the achieved MTFS, we can achieve the optimal throughput between swarm S_1 and swarm S_2 with collision tolerance which can decrease the validity of the connection. Due to only one beam connection enabled, one vertex can not have multiple connections with other vertexes in the same $t^{\mathcal{S}}$ simultaneously. We add one additional constraint for (5) to reduce the collisions on the same vertexes. The optimal throughput from swarm S_1 to swarm S_2 can be given:

$$\max_{\mathcal{V}} \sum_{k=1}^{\mathcal{N}} \sum_{j=1}^{n \times R} t_k \cdot s_k \cdot c_j \tag{8a}$$

$$subject\ to \sum_{k=1}^{\mathcal{N}} t_k \leq 1, t_k \geq 0 \tag{8b}$$

$$\mathcal{E}_i \cap \mathcal{E}_j = \emptyset, \forall i, j \in R \tag{8c}$$

We assume that there are n vertexes from swarm S_1 and m vertexes from swarm S_2. There are two situations recognized when the cell wall is finished. If $n \leq m$, the solution is just to discover the link set is of greatest throughput. t_e can be equal and distributed in the unit time. In the unit time, all links can be enabled without collisions which means we can achieve the optimal throughput once MTFS is finished. The optimal throughput from swarm S_1 to swarm S_2 through cell wall can be:

$$\max_{\mathcal{E}} \sum_{j=1}^{n} c_j \tag{9a}$$

$$subject\ to\ (8c) \tag{9b}$$

The solution of throughput from swarm S_1 to swarm S_2 for $n \leq m$ is a constraint to the performance of MTFS optimizations.

If $n > m$, there always exists the situation that some links can not exist in the same slot with the same vertexes. In each slot, the active links need to be separated into multiple pieces which allow the maximum links active in each slot. Here, we install the active link time as t^g for $\lceil \frac{t_k}{t^g} \rceil - 1$ links and the rest links are assigned with mod(t_k, t^g) (mod is the modulo operation). We perform edge coloring on this situation to schedule the active link time and reduce the collisions. The G_n can be edge-colored with γ colors from swarm S_1. Each color is corresponded to one set of active links in slot t_k which has a length of t^g in G_n. In each slot, each link is assigned with γt^g for activation and minimize the collisions. Here,

$$\begin{aligned} \gamma t^g &= (\lceil \frac{t_k}{t^g} \rceil - 1) t^g + mod(t_k, t^g) \\ &< (\lceil \frac{t_k}{t^g} \rceil - 1) t^g + t^g \\ &\leq \lceil t_k \rceil \leq 1 \end{aligned} \tag{10}$$

(10) shows that the whole scheduling can be assigned into the slot t_k completely, γt^g does not need the extra scaling. In the slot t_k, the whole length of scheduling can be shrunk into γt^g. Based on the scheduled length, the optimal throughput for swarm S_1 can be given:

$$\max_{\mathcal{E}} \sum_{k=1}^{N} (\sum_{j=1}^{\gamma-1} \sum_{i \in \tilde{G}_n} t^g \cdot c_i + \sum_{i \in \hat{G}_n} mod(t_k, t^g) \cdot c_i) \tag{11a}$$

$$subject\ to\ (5) \tag{11b}$$

Here, $\tilde{G}_n = G_n\{\lceil \frac{t_k}{t^g} \rceil - 1\}$ and $\hat{G}_n = G_n\{mod(t_k, t^g)\}$. Based on the optimization of throughput, the less color we use for edge-coloring, we can achieve more throughput from swarm S_1. With the fixed upper bound for the color selections, the searching space can shrink a lot to reduce the time consumption of optimization. Due to the complexity of computation for the minimum edge coloring, we adopt a simplified multigraph edge-coloring algorithm proposed in [37] to achieve the upper bound of colors selection $3\lceil \triangle(G)/2 \rceil$ for G. Here, $\triangle(G)$ is the maximum node degree of G. Based on the algorithm proposed in [37], we obtain the degree of G:

$$\begin{aligned} \triangle(G) = \sum_{k=1}^{\mathcal{N}} \lceil \frac{t_k}{t^g} \rceil &< \sum_{k=1}^{\mathcal{N}} (\frac{t_k}{t^g} + 1) \\ &\leq \frac{t^g(m+n-1)+1}{t^g} \end{aligned} \tag{12}$$

With $\triangle(G)$, we can have γ for the edge coloring of G:

$$\gamma = 3 \cdot \lceil \frac{t^g(m+n-1)+1}{2 \cdot t^g} \rceil \tag{13}$$

With the minimum of edge-coloring for G, we continue to optimize the colors γ of G to minimize the swift interval caused by physical layers. The pseudocode algorithm is shown as Algorithm 3.

Algorithm 3: Edge-coloring scheduling

```
Compare n and m;
if m < n then
    Rendering G_n(V, E);
    Assign link time t^g to ⌈t_k/t^g⌉ − 1 links;
    Assign the time of mod(t_k, t^g) to the left links;
    Calculate △(G);
    Calculate γ;
    while γt^g ≤ 1 and t^g ≤ t_k do
        Reduce γ;
        Color G;
```

The throughput for swarm S_1 is fair for the bi-directions. With the optimal coloring for G, the rendering of MTFS is optimized and assigned the corresponding sequences for connection. With the collision mitigation, the throughput can be escalated significantly. Simultaneously, swarm S_2 is a symmetry to swarm S_1, the optimization for swarm S_2 is similar to swarm S_1.

The above shows the optimal throughput is based on the single beam for each UAS in the cell wall at each slot. The prominent characteristic of 5G NR can allow different beams to work on the same physical devices simultaneously. The compact array antennas can allow the multiple beams to generate connections in the variable frequencies and spatial distributions.

In this situation, we need to loose the constraint of (8b) to $\mathcal{P}$. The optimization with collision avoidance of (8) can be modified to:

$$\max_{k \in \mathcal{V}} \sum_{k=1}^{\mathcal{N}} \sum_{j=1}^{\mathcal{E}} t_k \cdot s_k \cdot c_j \tag{14a}$$

$$subject\ to\ \sum_{k=1}^{\mathcal{N}} t_k \leq \mathcal{P}, t_k \geq 0 \tag{14b}$$

$$\mathcal{E}_i \cap \mathcal{E}_j = \emptyset, \forall i, j \in R \tag{14c}$$

Corresponding to the modification of the active beams for each UAS at t^g, the assigned activation can be modified to:

$$\begin{aligned} \gamma t^g &= (\lceil \frac{t_k}{t^g} \rceil - 1) t^g + mod(t_k, t^g) \\ &\leq \mathcal{P} \end{aligned} \tag{15}$$

Regarding the minimum of interference between different frequencies, the γ is considered the same calculation from (13), and the constraint of $t^g \leq t_k$ keeps unchanged. Thereafter, we can have the optimal throughput for the heterogeneous UAS swarm networking for the cell wall communication with multiple beams enabled.

VI. Evaluation

Different from the hierarchical architectures of UAS swarm networking, cell wall communication do not need specific UAS

TABLE I
CELL WALL CONFIGURATION

Transmission Power, p	20 dBm
Distances between centers of S_1 and $S2$, d	100 m
Direct gain, g	30 dB
Carrier frequency, f	28 GHz
Noise power, N_0/B	-174 dBm/Hz
Bandwidth	1 GHz
Minimum SINR threshold	-5 dB

to play the role of gateway to provide delivery services. Each selected UAS in the cell wall can afford delivery services for its peers. The cell wall communication can build more connections compared with conventional communication approaches. With the optimization of the cell wall, the throughput between the heterogeneous swarm networking can be improved. In this section, we will present our evaluation of the cell wall construction and optimization on throughput between heterogeneous UAS swarm networking. The evaluation is conducted on Matlab 2019b and the specific configuration of hardware is the following. CPU: E5-1607 v4 @ 3.10GHz $\times$ 4; Memory: 15.6 GiB; OS: Ubuntu 18.04 LTS.

During each mission, UAS swarm networking is full of dynamics on mobility which is challenging to predict and maintain. The mobility difference can cause the connection duration to vary significantly which has a serious effect on the performance of throughput between the heterogeneous UAS swarm networking. With the limited connection duration for heterogeneous UAS swarm networking, the connection duration is divided into finite frames to schedule. With our proposed optimization, we can maximize the minimum throughput for UAS in the cell wall to achieve global optimization.

The fundamental configuration of the evaluation is depicted as TABLE I. In the cell wall, UAS is equipped with mobile beamforming devices to generate mmWave connections over the carriers on 28 GHz with a bandwidth of 1 GHz. Due to the power constraints of UAS, the transmission power of mmWave, p, is set to $20dBm$ and the direct gain, g, for the cell wall connections is set to $30dB$. Further, the noise power, N_0/B is set to -174 dBm/Hz, and the minimum SINR threshold for receiving is set to -5 dB. To approximate the distribution of UAS swarms in practice, we configure the cell wall distances between heterogeneous UAS swarms range from 15 m to 100 m with the distribution of Poisson ($\lambda = 20$ [38]). In practice, the oval formation of swarms can achieve the maximization of the stability and the efficiency of the deployment which is ubiquitous in natural swarm formations. More details about the deployment of UAS swarms are presented in the following.

We deploy two UAS swarms in a $50m \times 200m \times 50m$ space shown as Fig. 3. The centers of S_1 and S_2 are marked in light blue filled circles and yellow filled circles respectively. With the modeling in section III and configuration for the cell wall, the cell wall is constructed between S_1 and S_2 simultaneously. With a feasible connection threshold, the connections between S_1 and S_2 for each UAS are multiple with different UAS in S_1 and S_2. As Fig. 3 depicted, the link constructed for cell wall communication is marked in blue. The following evaluation is based on the construction of the cell wall shown in Fig. 3.

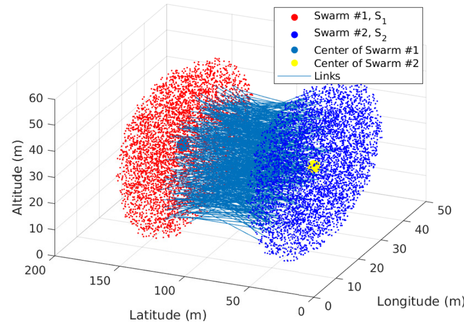

Fig. 3. Cell wall construction between two UAS swarms

Fig. 4 shows the relationship of the installed beams and the throughput from swarm S_1 and swarm S_2. As the beams increase, the throughput for swarm S_1, swarm S_2, and feasible throughput shows a positive increasing relationship respectively. Due to the incidents occurring in the cell wall, the feasible throughput is lower than the throughput from swarm S_1 and swarm S_2. Meanwhile, the imbalance of both swarm S_1 and S_2 caused some links are invalid to the connections in the same time slot. The reduction of the incidents and invalid links can improve the throughput remarkably.

Enhanced with 5G NR, mobile devices can generate multiple beams for communication. The UAS selected on the cell wall with beamforming devices can generate multiple beams in different frequencies to construct the connection between S_1 and S_2. We explored the minimum throughput for the cell wall with multiple beams which is shown as Fig. 5. For convenience, we convert the transmission power into beam connection ranges. We can observe as the beam ranging increases, the links between cell wall extends. With the negligible distance in signal dispersing, each link in the cell wall does not have a significant difference in practice. Fig. 5 shows ten subtle figures with multiple beams performance. Based on the rendering of minimum throughput from swarm S_1 and swarm S_2, we observe the throughput from for the cell wall with different beams and the result shows that Algorithm 1 can increase the throughput remarkably. Due to the incidents occurring in the cell wall connections, the minimum throughput does not increase sharply as the beam range increases which is weaker than the max-min throughput.

With multiple slots generated for each schedule $\mathcal{S}$, the interference between multiple beams is reduced and throughput for multiple beams is increased. To clarify the enhancement derived from Algorithm 2, we normalize the increasing of MTFS with Algorithm 2 in Fig. 6. As Fig. 6 depicts, MTFS is improved as the beam ranging inclines and keeps steady at 0.49 as the beam ranging is over 70 m. Generally, Algorithm 2 can improve the MTFS over 40% for the cell wall generated between the cell wall which is constructed between S_1 and S_2. Algorithm 2 can reduce the interference and incidents between beams, but can not eliminate the incidents between multiple beams in the same channels.

Fig. 7 shows Algorithm 3 scheduling for swarm S_1 and

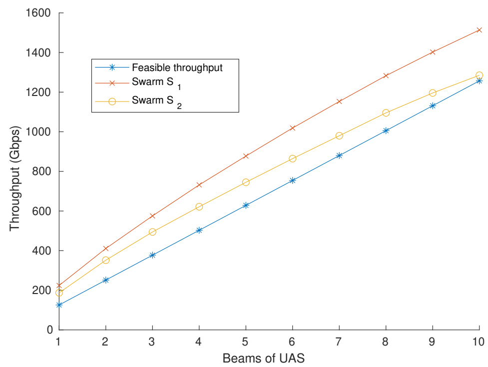

Fig. 4. Minimum throughput between cell wall

swarm S_2. The throughput from swarm S_1 and swarm S_2 shows that the less scaling of the time slot, the more throughput we obtain with a decreasing of t^g from $1s$ to $0.01s$. When the t^g is less than $0.01s$, the throughput will not rise any more. We observed that the whole valid links between swarm S_1 and swarm S_2 are scheduled when the t^g is less than $0.01s$. The feasible throughput between swarm S_1 and swarm S_2, marked in blue, in Fig. 7 shows the same trend with swarm S_1 and swarm S_2.

Fig.8 presents the normalized throughput improvement from swarm S_1 with the multiple beams. Based on Fig. 7 result, we just select the setting of t^g as $1s$, $0.1s$ and $0.01s$. With the mitigation of beams incidents occurring, the throughput increases with the expansion of beams. The sufficient time slot allows swarm S_2 to contain stable throughput when t^g are set to $0.1s$ and $0.01s$ respectively. The obvious improvement for $t_g = 1s$ shows that there are more incidents compared with the scenarios in $0.1s$ and $0.01s$.

Fig.9 shows the normalized throughput from swarm S_2. Generally, the optimization shows the same trend as swarm S_1. As the beams increases, the improved throughput extends for t^g of $1s$, and the throughput improvement keeps stable over 0.9 when t^g are $0.1s$ and $0.01s$ respectively. Simultaneously, the result shows that the multiple beams enabling can achieve more enhancement with edge coloring solving.

VII. Conclusion

In this paper, we propose an optimal cell wall paradigm to improve the throughput between heterogeneous UAS swarm networking. With ADS-B, we construct a cell wall the heterogeneous UAS swarm networking. Thereafter, we map the optimization of throughput into a polyhedron scheduling problem and solved it with MTFS. With the edge-coloring solution, our algorithm can achieve over 40% improvement of MTFS globally. In terms of MTFS solving, our algorithm shows promising potential to improve the throughput and mitigate the incidents and interference for the heterogeneous UAS swarm networking. In the future, we will explore the time consumption and computation complexity reduction of MTFS solving heterogeneous UAS swarm networking on a large scale. Concurrently, we will focus on the multiple cell wall collaboration and corporation on a large scale.

VIII. Acknowledgement

This research was partially supported by the National Science Foundation under Grant No. 1956193.

References

[1] H. Song, R. Srinivasan, T. Sookoor, and S. Jeschke, *Smart cities: foundations, principles, and applications*. John Wiley & Sons, 2017.

[2] J. Lee and D. Kim, "A study on innovation in university education: Focusing on 5g mobile communication," in *2020 IEEE 17th Annual Consumer Communications Networking Conference (CCNC)*, 2020, pp. 1–4.

[3] T. Yang, J. Zhao, T. Hong, W. Chen, and X. Fu, "Automatic Identification Technology of Rotor UAVs Based on 5G Network Architecture," in *2018 IEEE International Conference on Networking, Architecture and Storage (NAS)*, Oct 2018, pp. 1–9.

[4] Z. Na, Y. Wang, M. Xiong, X. Liu, and J. Xia, "Modeling and Throughput Analysis of an ADO-OFDM Based Relay-Assisted VLC System for 5G Networks," *IEEE Access*, vol. 6, pp. 17 586–17 594, 2018.

[5] X. Ge, J. Yang, H. Gharavi, and Y. Sun, "Energy Efficiency Challenges of 5G Small Cell Networks," *IEEE Communications Magazine*, vol. 55, no. 5, pp. 184–191, May 2017.

[6] Y. Sun, H. Song, A. J. Jara, and R. Bie, "Internet of things and big data analytics for smart and connected communities," *IEEE Access*, vol. 4, pp. 766–773, 2016.

[7] Y. Liu, X. Weng, J. Wan, X. Yue, H. Song, and A. V. Vasilakos, "Exploring data validity in transportation systems for smart cities," *IEEE Communications Magazine*, vol. 55, no. 5, pp. 26–33, 2017.

[8] P. Dinh, T. M. Nguyen, S. Sharafeddine, and C. Assi, "Joint location and beamforming design for cooperative uavs with limited storage capacity," *IEEE Transactions on Communications*, vol. 67, no. 11, pp. 8112–8123, 2019.

[9] W. Yuan, C. Liu, F. Liu, S. Li, and D. W. K. Ng, "Learning-based predictive beamforming for uav communications with jittering," *IEEE Wireless Communications Letters*, pp. 1–1, 2020.

[10] Y. Xu, L. Xiao, D. Yang, Q. Wu, and L. Cuthbert, "Throughput maximization in multi-uav enabled communication systems with difference consideration," *IEEE Access*, vol. 6, pp. 55 291–55 301, 2018.

[11] L. Xie, J. Xu, and R. Zhang, "Throughput maximization for uav-enabled wireless powered communication networks," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 1690–1703, 2019.

[12] W. Shi, H. Zhou, J. Li, W. Xu, N. Zhang, and X. Shen, "Drone assisted vehicular networks: Architecture, challenges and opportunities," *IEEE Network*, vol. 32, no. 3, pp. 130–137, 2018.

[13] Y. Zeng, R. Zhang, and T. J. Lim, "Throughput maximization for uav-enabled mobile relaying systems," *IEEE Transactions on Communications*, vol. 64, no. 12, pp. 4983–4996, 2016.

[14] L. Xie, J. Xu, and R. Zhang, "Throughput maximization for uav-enabled wireless powered communication networks - invited paper," in *2018 IEEE 87th Vehicular Technology Conference (VTC Spring)*, 2018, pp. 1–7.

[15] M. Hua, L. Yang, C. Pan, and A. Nallanathan, "Throughput maximization for full-duplex uav aided small cell wireless systems," *IEEE Wireless Communications Letters*, vol. 9, no. 4, pp. 475–479, 2020.

[16] N. Zhang, S. Zhang, P. Yang, O. Alhussein, W. Zhuang, and X. S. Shen, "Software defined space-air-ground integrated vehicular networks: Challenges and solutions," *IEEE Communications Magazine*, vol. 55, no. 7, pp. 101–109, 2017.

[17] L. Xie, J. Xu, and Y. Zeng, "Common throughput maximization for uav-enabled interference channel with wireless powered communications," *IEEE Transactions on Communications*, vol. 68, no. 5, pp. 3197–3212, 2020.

[18] J. Li, G. Lei, G. Manogaran, G. Mastorakis, and C. X. Mavromoustakis, "D2d communication mode selection and resource optimization algorithm with optimal throughput in 5g network," *IEEE Access*, vol. 7, pp. 25 263–25 273, 2019.

[19] L. Sboui, H. Ghazzai, Z. Rezki, and M. Alouini, "On the throughput of cognitive radio mimo systems assisted with uav relays," in *2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC)*, 2017, pp. 939–944.

[20] J. Wang, Y. Liu, S. Niu, and H. Song, "5g-enabled optimal bi-throughput for uas swarm networking," in *2020 International Conference on Space-Air-Ground Computing (SAGC)*, 2020, pp. 43–48.

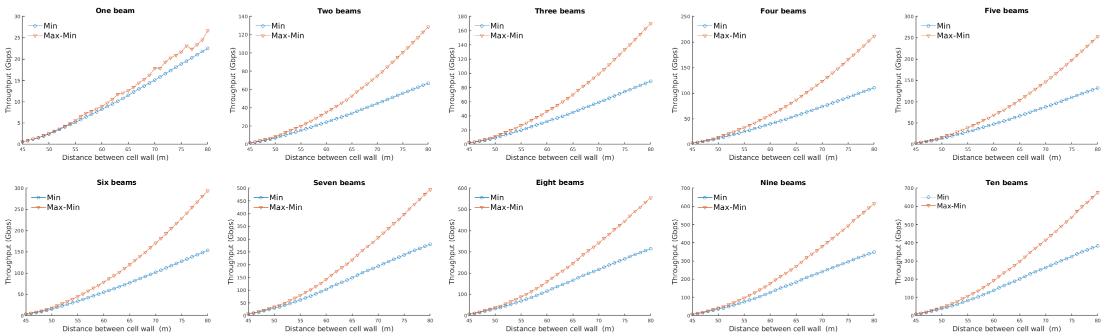

Fig. 5. Throughput over the variable beams

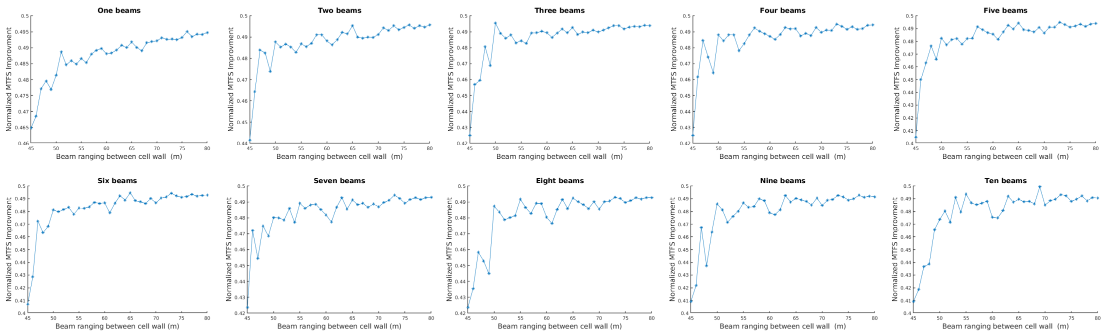

Fig. 6. Normalized MTFS improvement over the variable beams

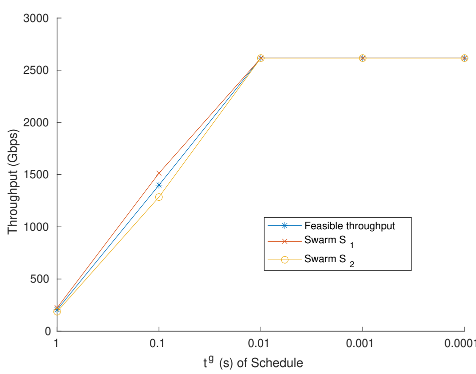

Fig. 7. Scheduled Throughput Swarm S_1 and Swarm S_2

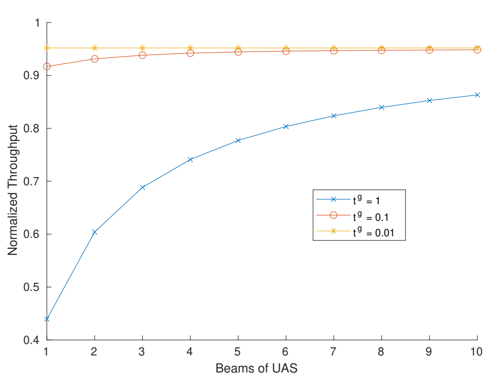

Fig. 8. Normalized Throughput from Swarm S_1

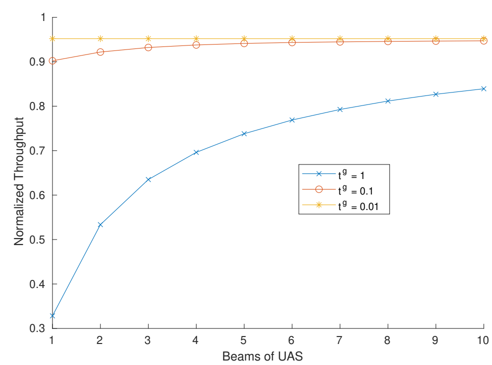

Fig. 9. Normalized Throughput from Swarm S_2

[21] A. M. Koushik, F. Hu, and S. Kumar, "Deep Q -learning-based node positioning for throughput-optimal communications in dynamic uav swarm network," *IEEE Transactions on Cognitive Communications and Networking*, vol. 5, no. 3, pp. 554–566, 2019.

[22] M. Hua, C. Li, Y. Huang, and L. Yang, "Throughput maximization for uav-enabled wireless power transfer in relaying system," in *2017 9th International Conference on Wireless Communications and Signal Processing (WCSP)*, 2017, pp. 1–5.

[23] J. Fan, M. Cui, G. Zhang, and Y. Chen, "Throughput improvement for multi-hop uav relaying," *IEEE Access*, vol. 7, pp. 147 732–147 742, 2019.

[24] X. Liang, W. Xu, H. Gao, M. Pan, J. Lin, Q. Deng, and P. Zhang, "Throughput optimization for cognitive uav networks: A three-dimensional-location-aware approach," *IEEE Wireless Communications Letters*, vol. 9, no. 7, pp. 948–952, 2020.

[25] J. M. Batalla, M. Kantor, C. X. Mavromoustakis, G. Skourletopoulos, and G. Mastorakis, "A novel methodology for efficient throughput evaluation in virtualized routers," in *2015 IEEE International Conference on Communications (ICC)*, 2015, pp. 6899–6905.

[26] L. Chiaraviglio, L. Amorosi, F. Malandrino, C. F. Chiasserini, P. Dell'Olmo, and C. Casetti, "Optimal throughput management in

uav-based networks during disasters," in *IEEE INFOCOM 2019 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, 2019, pp. 307–312.
[27] L. Chiaraviglio, F. D'Andreagiovanni, W. Liu, J. Gutierrez, N. Blefari-Melazzi, K. R. Choo, and M. Alouini, "Multi-area throughput and energy optimization of uav-aided cellular networks powered by solar panels and grid," *IEEE Transactions on Mobile Computing*, pp. 1–1, 2020.
[28] L. Chiaraviglio, F. D'andreagiovanni, R. Choo, F. Cuomo, and S. Colonnese, "Joint optimization of area throughput and grid-connected microgeneration in uav-based mobile networks," *IEEE Access*, vol. 7, pp. 69 545–69 558, 2019.
[29] J. Park, H. Lee, S. Eom, and I. Lee, "Uav-aided wireless powered communication networks: Trajectory optimization and resource allocation for minimum throughput maximization," *IEEE Access*, vol. 7, pp. 134 978–134 991, 2019.
[30] S. Ahmed, M. Z. Chowdhury, and Y. M. Jang, "Energy-efficient uav-to-user scheduling to maximize throughput in wireless networks," *IEEE Access*, vol. 8, pp. 21 215–21 225, 2020.
[31] G. Manogaran, C.-H. Hsu, B. S. Rawal, B. Muthu, C. X. Mavromoustakis, and G. Mastorakis, "Isof: Information scheduling and optimization framework for improving the performance of agriculture systems aided by industry 4.0," *IEEE Internet of Things Journal*, vol. 8, no. 5, pp. 3120–3129, 2021.
[32] M. Hua, L. Yang, C. Li, Q. Wu, and A. L. Swindlehurst, "Throughput maximization for uav-aided backscatter communication networks," *IEEE Transactions on Communications*, vol. 68, no. 2, pp. 1254–1270, 2020.
[33] H. Li and X. Zhao, "Throughput maximization with energy harvesting in uav-assisted cognitive mobile relay networks," *IEEE Transactions on Cognitive Communications and Networking*, pp. 1–1, 2020.
[34] B. Jiang, J. Yang, H. Xu, H. Song, and G. Zheng, "Multimedia data throughput maximization in internet-of-things system based on optimization of cache-enabled uav," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 3525–3532, 2019.
[35] K. Krishnamoorthy, M. Pachter, and P. Chandler, "Maximizing the throughput of a patrolling uav by dynamic programming," in *2011 IEEE International Conference on Control Applications (CCA)*, 2011, pp. 916–920.
[36] D. Yuan, H. Lin, J. Widmer, and M. Hollick, "Optimal joint routing and scheduling in millimeter-wave cellular networks," in *IEEE INFOCOM 2018 - IEEE Conference on Computer Communications*, 2018, pp. 1205–1213.
[37] H. J. Karloff and D. B. Shmoys, "Efficient parallel algorithms for edge coloring problems," *Journal of Algorithms*, vol. 8, no. 1, pp. 39 – 52, 1987. [Online]. Available: http://www.sciencedirect.com/science/article/pii/0196677487900265
[38] C. C. Cheah, S. P. Hou, and J. J. E. Slotine, "Region-based shape control for a swarm of robots," *Automatica*, vol. 45, no. 10, pp. 2406–2411, 2009. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0005109809003215

Jian Wang is a Ph.D. candidate in the Department of Electrical Engineering and Computer Science, Embry-Riddle Aeronautical University (ERAU), Daytona Beach, Florida, and a graduate research assistant in the Security and Optimization for Networked Globe Laboratory (SONG Lab, www.SONGLab.us). He received his M.S. from South China Agricultural University in 2017 and B.S. from Nanyang Normal University in 2014. His major research interests include wireless networks, unmanned aircraft systems, and machine learning.

Jian Wang is a recipient of 3 Best Paper Awards from CPSCom-2019, CBDCom 2020, and WASA 2020.

Yongxin Liu received his B.S. and M.S. from SCAU in 2011 and 2014, respectively, and he received Ph.D. from the School of Civil Engineering and Transportation, South China University of Technology. He is a Ph.D. candidate in Electrical Engineering and Computer Science, Embry-Riddle Aeronautical University and a graduate research assistant in the Security and Optimization for Networked Globe Laboratory (SONG Lab, www.SONGLab.us). His major research interests include data mining, wireless networks, the Internet of Things, and unmanned aerial vehicles.

Shuteng Niu is a Ph.D. candidate in the Department of Electrical Engineering and Computer Science, Embry-Riddle Aeronautical University and a graduate research assistant in the Security and Optimization for Networked Globe Laboratory (SONG Lab, www.SONGLab.us). He received his M.S. from Embry-Riddle Aeronautical University in 2018 and B.S. from Civil Aviation University of China (CAUC) in 2015. His major research interests include machine learning, data mining, and signal processing.

Weipeng Jing received the Ph.D. degree from Harbin Institute of Technology. Currently, he is an Professor at College of Information and Computer Engineering of Northeast Forestry University. His research interests and expertise include modeling and scheduling for distributed computing systems, system reliability estimation, fault-tolerant computing and cloud computing. He is a member of the IEEE.

Houbing Song (M'12–SM'14) received the Ph.D. degree in electrical engineering from the University of Virginia, Charlottesville, VA, in August 2012, and the M.S. degree in civil engineering from the University of Texas, El Paso, TX, in December 2006.

In August 2017, he joined the Department of Electrical Engineering and Computer Science, Embry-Riddle Aeronautical University, Daytona Beach, FL, where he is currently an Assistant Professor and the Director of the Security and Optimization for Networked Globe Laboratory (SONG Lab, www.SONGLab.us). In 2007 he was an Engineering Research Associate with the Texas A&M Transportation Institute. He has served as an Associate Editor for IEEE Transactions on Intelligent Transportation Systems (2021-present), IEEE Internet of Things Journal (2020-present) and IEEE Journal on Miniaturization for Air and Space Systems (J-MASS) (2020-present). He is the editor of eight books, including Smart Cities: Foundations, Principles and Applications, Hoboken, NJ: Wiley, 2017. He is the author of more than 100 articles. His research interests include cyber-physical systems/internet of things, cybersecurity and privacy, AI/machine learning/big data analytics, unmanned aircraft systems, and connected vehicle. His research has been featured by popular news media outlets, including IEEE GlobalSpec's Engineering360, U.S. News & World Report, and Association for Unmanned Vehicle Systems International (AUVSI).

Dr. Song is a senior member of ACM and an ACM Distinguished Speaker. Dr. Song was a recipient of 5 Best Paper Awards from CPSCom-2019, ICII 2019, ICNS 2019, CBDCom 2020, and WASA 2020.