A Crowd-enabled Task Execution Approach in UAV Networks Towards Fog Computing

Shashi Raj Pandey, Kitae Kim, Madyan Alsenwi, Yan Kyaw Tun, Choong Seon Hong

Department of Computer Science and Engineering
Kyung Hee University,446-707
Republic of Korea
Email:{shashiraj, glideslope, malsenwi, ykyawtun7, cshong}@khu.ac.kr

Abstract—In this paper, the problem of constrained computational resources in the UAV networks to serve users in a limited coverage area for diverse applications is studied. In particular, a flexible crowd-enabled task execution solution with multiple participating UAVs over a broadband wireless local area network (WLAN) is proposed in order to achieve mobility advantages, high throughput, and low latency. Then, an incentive mechanism is developed so as to encourage UAVs to trade their unused computing resources for the cooperative task execution, while benefiting, jointly, both the task owner and the participating UAVs. We analyze the interaction for determining the offered price against the availability of the participants and the computational resource units for the task execution using a two-stage Stackelberg game. Furthermore, we derive the unique Stackelberg equilibria of the game with a simplified solution approach. Finally, we provide some insightful results to evaluate the efficacy of the proposed solution.

Index Terms—Crowdsourcing, fog computing, UAVs, task execution, incentive mechanism, Stackelberg game.

I. INTRODUCTION

Due to their mobility and ability to cost-effectively be deployed in various geographical locations, unmanned aerial vehicles (UAVs) can be used to provide effective communications and network services to areas with limited network coverage and computing capabilities [1]. In particular, the use of UAVs to share task execution is an attractive solution for emerging applications such as the Internet of Things (IoT) and augmented/virtual reality [2] applications. In such applications, one can adopt a UAV-aided edge computing framework in which UAVs do not only act as a gateway for data delivery, but they also provide computing services to the associated users such as crowdsensing (e.g., spatial sensing), image/video processing, and light-weight edge learning applications. However, the UAVs are energy-constrained without fixed charging point, and have limited computational capabilities [3]. Thus, it is challenging to harness such *on-demand* services in the UAV networks. In this regard, the resource scarcity at the source UAV can be tackled by further offloading its computing tasks to the edge node or cloud/cloudlets [4], [5]. Moreover, it is beneficial for the overloaded source UAV to achieve performance gain by leveraging the distributed, idle computing
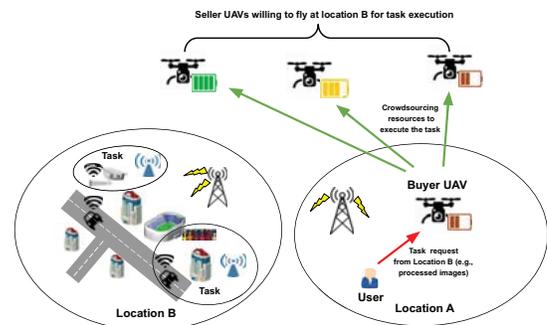
Fig. 1: Illustration of the proposed framework.

resources of multiple neighboring UAVs. Consequently, it is cheaper than using an expensive backhaul [6], and unlike a fixed computing facility [7] that cannot meet specific goal oriented services such as image/video crowdsensing, it provides better spatial opportunities and prolonged battery life.

A. Related Works and Contributions

Prior works mostly considers UAV as a *relay* or as a flying base station that serves for better connectivity and maximal network throughput [1], [8]. In [6], the authors investigated a UAV-based mobile cloud computing infrastructure which provides computing opportunities to the mobile users, consequently, enabling fog computing. This work [6], like the existing literature [9], [10] generally assumes the offloading decision at a single UAV computing node from the user's perspective. However, the performance of energy-constrained UAV is compromised when it has to perform some heavy tasks, specifically requiring mobility and guaranteed in-air time (e.g., for crowdsensing). Under such scenario, crowdsourcing the maneuvering UAVs can offer larger geographical coverage (spatial advantages) for applications such as image crowdsensing, data collection and processing, and related applications

with edge learning, which are not considered yet [3], [6], [9]–[11].

Unlike the aforementioned works, this paper proposes an incentive mechanism for a flexible and novel cooperative task execution framework in the UAV networks that enables fog computing. This framework allows the tasks of the energy-constrained source UAV to be offloaded and executed to its neighboring UAVs, which subsequently eliminates the burden on overloaded source UAV to serve its users. When the information related to UAV's maneuvering time is unknown, it is challenging for the source UAV to decide the optimal trading point of computing resources from its neighboring UAV. Moreover, the neighboring UAVs required to participate in the framework are strategic. Therefore, a two-stage Stackelberg game is formulated that considers the maneuvering period of UAVs to characterize the interactions between the source and the participating UAVs for solving this problem. Next, we proved the existence of Stackelberg equilibrium and derived it to analyze the best response behaviors of the players involved in the game. For obtaining the equilibrium point, we proposed a simplified and less-complexity numerical solution. The main contributions are summarized as follows:

- We model a cooperative task execution framework in the UAV networks that enables fog computing. In particular, a novel paradigm for on-demand computation is revealed with the dynamic collaboration between the UAVs to address the stringent application requirements of the users, limited by their mobility in the next-generation network architecture.
- We design an incentive mechanism that spur collaboration amongst UAVs to share their available resources (computation, caching, and energy) for the joint task execution. We consider the availability (in-air time) of the UAVs as a key design aspect while characterizing the economic interactions.
- We show the interactions between the buyer and the sellers follow a leader-followers game structure, where each of the players aims at maximizing their own utilities. To this end, the hierarchical game structure is modeled as a two-stage Stackelberg game, where at the Stage I the buyer (the leader) offers the reward rate to the sellers (the followers) over which the sellers strategically provide computing services, following a non-cooperative game at the Stage II.
- We follow the best response dynamic algorithm to derive the Stackelberg equilibrium. For this, with the first-order conditions, we first show the existence and uniqueness of Nash equilibrium at the Stage II non-cooperative game among the seller UAVs. Then, we formulate the backward induction methodology to solve the Stage I utility maximization problem.
- To this end, we propose a low-complexity, interior-points solution to reach the Stackelberg equilibrium with the constraints of budget and latency for the task execution.

The remainder of this paper is organized as follows. The system model is presented in Section II. We introduce our problem formulation for the crowd-enabled task execution approach with the incentive mechanism design in Section IV. Numerical results and discussion are presented in Section V. Finally, we Section VI concludes the paper.

II. SYSTEM MODEL

Consider a network of K UAVs in a set $\mathcal{K}$ that are able to communicate with each other[1]. Each UAV $k \in \mathcal{K}$ has a light-weight server attached to it and is an agent capable of participating and offloading the description of computational tasks to its neighboring UAVs. At UAV k, a task is defined by the triplet $\varpi_k = (D_k, L_k, t_k^{\max})$ and its location description, e.g., to collect and process imagery information at a given location in smart city, as illustrated in Fig. 1. Here, D_k is the size of execution data measured in bits, L_k is the available CPU-cycles for computation, and $t_k^{\max}$ is the maximum tolerable latency required for effective task execution. Therefore, the corresponding local energy consumption (in Joules) for the task ϖ_k is

$$E_k^l(\varpi_k) = \frac{\alpha_k}{2} D_k L_k f_k^2, \tag{1}$$

where α_k and f_k are the effective capacitance of the computing chipset and local computing capacity at the UAV k. In our model, any given UAV k who has a low battery level will seek to offload the description of some of its tasks (when possible) to its nearby UAVs using a less expensive network such as WLAN/WiFi instead of requesting remote cloud/cloudlets using expensive backhaul, or executing by itself causing battery drainage. Hereinafter, we refer the source UAV as *buyer* UAV and the neighbouring UAVs as *sellers*. Specifically, by crowd-sourcing the neighbouring UAVs, the required computational task can be executed. Then, corresponding performance gain in energy resource for the buyer k due to resource purchasing from the seller k' is

$$\zeta_{k'} = \left| \frac{E_k^l - E_{k'}}{E_k^l} \right|, \forall k' \in \mathcal{K} \setminus k, \tag{2}$$

where $E_{k'}$ is the energy consumption at UAV k' for executing the task ϖ_k. Notably, each energy-constrained UAVs are strategic and sells calculated amount of computing resources to avoid possible power outage, i.e., over an offered incentive plan by the buyer for its task execution.

Our goal is to enable a novel fog computing paradigm in the UAV-assisted wireless network. The goal is achieved by adopting the proposed crowdsourcing framework that allows offloading of task descriptions to the neighboring UAVs so as to improve the performance gain of an energy-constrained buyer UAV. In practice, the buyer UAV has no prior information about the flight duration of the seller UAVs. As a result, the uncertainty of active flight time makes it difficult for the buyer to quantify the reliability of traded resources and timely

[1]We consider the UAVs exchange information about their available resources via broadband wireless local area network (WLAN) infrastructure. Moreover, the message exchange cost is usually less considering small size of the transmitted information.
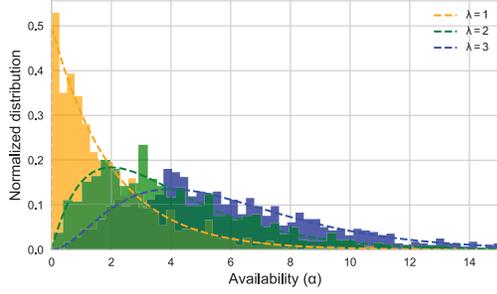
247

Fig. 2: Availability samples from a gamma distribution for three UAVs with different values of λ.

task execution. Thus, the buyer cannot optimally design the incentive mechanism to enable participation.

III. PROBLEM FORMULATION

To address the aforementioned problem, we propose a novel task execution framework for UAV networks and derive the optimal reward-resource pairs for attaining a specific performance gain with resource trading. We incorporate the maneuvering period of UAVs when defining its utility function, which in fact is a critical aspect to consider.

A. Utility Design

We consider a local parameter $a_{k'}$ defined as the availability of UAV $k' \in \mathcal{K}$ indicating its *in-air time period*[2]. We model this parameter with a *gamma hazard function* [12] using a *2-parameter gamma distribution*, $G(\theta, \lambda)$ that can effectively capture the charge decay during the flight time, as samples drawn shown in Fig. 2. As a result, for $\theta < 1$ and $\lambda > 0$, the hazard function is convex and decreasing. Therefore, it is reasonable that the reward received by the participating UAV will be proportional to its availability $a_{k'}$, and the traded resource $f_{k'}$. Then, for an uniform offered reward rate[3] r (e.g., \$/execution units) by the buyer UAV k, the utility of the participating UAV k' is the difference between the obtained reward based on its contribution in participation and the cost for executing the task, defined as

$$U_{k'}^s(f_{k'}) := f_{k'}^{\max}\left[\frac{f_{k'}a_{k'}}{\sum_{k \in \mathcal{K}} f_k a_k}\right] r - \gamma_{k'} f_{k'}, \tag{3}$$

where $f_{k'}^{\max}$ is the maximum available computing resource and $\gamma_{k'}$ is a unit cost factor. Any rational seller will participate in the cooperative task execution framework for a reward rate guaranteed by the individual rationality (IR) criterion, i.e., $r \geq \frac{\gamma_{k'}}{f_{k'}^{\max}a_{k'}} \sum_{k \in \mathcal{K}\setminus k'} f_k a_k$. Therefore, for a given reward rate r,

[2]The UAV in-air time (maneuvering period) can be characterized by its available battery level, which is random over the time.

[3]Here, we considered uniform pricing which is meaningful in terms of fairness, and unlike differentiated pricing, has less information exchange and lower complexity.

each rational seller k will aim at maximizing its utility with the objective function

$$\begin{aligned} \max_{f_{k'}} \quad & U_{k'}^s(f_{k'}) \\ \text{s.t.} \quad & r \geq \frac{\gamma_{k'}}{f_{k'}^{\max}a_{k'}} \sum_{k \in \mathcal{K}\setminus k'} f_k a_k, \end{aligned} \tag{4}$$

where the constraint satisfies the IR condition and guarantees a non-negative utility for the participating UAVs. Note that the definition of utility function (4) is an extension to a widely accepted platform-centric design in mobile crowd-sourcing/crowdsensing, such as in [13], [14], [11]. Moreover, our design scenario and formulation characterize the availability of computational resource, the energy constraints, the cost of expensive backhaul link, and time constraints for task executions.

For the buyer k, the corresponding costs involved to instantiate cooperative task execution following purchase of computational resources with the offered reward rate r are

- the buying cost per computation resource defined as $r \sum_{k' \in \mathcal{K}\setminus k} f_{k'} a_{k'}$, and
- the overall latency cost metric while executing task at the participating UAV's edge server, i.e., $\delta_k \sum_{k' \in \mathcal{K}\setminus k} C_k(f_{k'})$, where $C_k(f_{k'})$ is the cost of task execution at UAV k', and δ_k is the unit cost on the induced response delay when submitting execution solution to the buyer UAV.

Consider time interval T corresponds for the number of tasks processed at the UAV k deploying the computing resource f_k. Then, the cost metric evaluates the cost on residual tasks performed at the buyer's end, or to a remote cloud/cloudlets via an expensive backhaul link as

$$\begin{aligned} C_k(f_{k'}) \quad &= \left(\frac{D_k L_k}{f_k} - \frac{D_k L_k}{f_k + f_{k'}}\right) \\ &= T\frac{f_{k'}}{f_k + f_{k'}}. \end{aligned} \tag{5}$$

For a given budget of δ_k, we can have a constraint on the offered reward rate as given by

$$r \leq \beta_k \delta_k, \tag{6}$$

where $\beta_k > 0$ is a scaling factor that can be adjusted as per the buyer's requirements for the task execution. Then, the overall performance gain using the cooperative framework for the buyer is $\sum_{k' \in \mathcal{K}\setminus k} \zeta_{k'} f_{k'}$. Therefore, the overall utility of the buyer that quantifies its satisfaction measure over the offered reward rate for participation can be modeled as

$$\begin{aligned} U_k^b(r, \{f_{k'}^*\}, \forall k') := \nu \sum_{k' \in \mathcal{K}\setminus k} \zeta_{k'} f_{k'} - \Bigg(& r \sum_{k' \in \mathcal{K}\setminus k} f_{k'} a_{k'} \\ + \delta_k T \sum_{k' \in \mathcal{K}\setminus k} \frac{f_{k'}}{f_k + f_{k'}} \Bigg), \end{aligned} \tag{7}$$

where $\nu > 0$ is a unit cost factor. We introduce the total resource requirements for task execution as L and deduce the RHS in (7), which in actual indicates the cost on proportion of

248

residual resources required for the task execution, with $\delta_k(L - \sum_{k' \in \mathcal{K} \setminus k} f_{k'})$.

The buyer k aims at solving the following utility maximization problem:

$$\max_r \quad U_k^b(r, \{f_{k'}\}) \tag{8}$$
$$\text{s.t.} \quad r \leq \beta_k \delta_k.$$

B. A Two-Stage Stackelberg Game Formulation

The interaction between the buyer UAV and the seller UAVs can be modeled as a two-stage Stackelberg game, as illustrated in Fig. 3. The neighboring UAVs are energy-constrained and strategic, and therefore can only be stimulated to participate in the task execution framework with an appropriate incentive compensation. The buyer UAV bears the cost of participation in terms of traded computing resources to improve its performance gain, whereas, the seller UAVs are awarded rewards, who aims at maximizing their profits upon joining the framework. Here, the buyer acts as a leader offering reward (Stage I) and the neighboring UAVs act as the followers trading their computing resources for the offered reward (Stage II). Thus, such interaction between the buyer and the sellers form a leader-followers game, namely Stackelberg game, where both entities are looking to maximize their benefits, having the buyer a first-move advantage to influence the sellers [15], [16]. The competition amongst sellers forms a non-cooperative game structure, where a unilateral deviation of an individual UAV's strategy won't affect the other seller's utility. Hence, in Stage II, each seller will aim to maximize its utility following the best response strategy; thus, resulting in a Nash equilibrium (see Lemma 1).

The problems (4) and (8) together form the Stackelberg game, and the objective is to find the Stackelberg equilibrium which ensures the utility of the buyer UAV is maximized given that the seller UAVs trade their computing resources following their best responses. Next, we define the Stackelberg equilibrium in our problem:

Definition 1. For any values of r and $f_{k'}$, the strategies $(r^*, \{f_{k'}^*\})$ reaches to the Stackelberg equilibrium if the following conditions are satisfied:

$$U_k^b(r^*, \{f_{k'}^*\}) \geq U_k^b(r, \{f_{k'}^*\}),$$
$$U_{k'}^s(f_{k'}^*, f_{-k'}^*, r^*) \geq U_{k'}^s(f_{k'}, f_{-k'}^*, r^*), \forall k' \in \mathcal{K} \setminus k. \tag{9}$$

In the following Lemma 1, we derive the best response of the participating UAVs to reach the *Nash equilibrium* for the offered reward.

Lemma 1. *For a given reward rate $r > \frac{\gamma_{k'}}{f_{k'}^{max} a_{k'}} \sum_{k \in \mathcal{K} \setminus k'} f_k a_k$, we have the existence of a Nash equilibrium with $f_{k'}^*$ for the seller UAV k' in the non-cooperative game as*

$$f_{k'}^* = \sqrt{r \cdot \frac{f_{k'}^{max}}{\gamma_{k'} a_{k'}} \sum_{k \in \mathcal{K} \setminus k'} f_k a_k} - \frac{\sum_{k \in \mathcal{K} \setminus k'} f_k a_k}{a_{k'}}. \tag{10}$$

Proof. Since $\frac{\partial^2 U_{k'}^s(f_{k'})}{\partial f_{k'}^2} = \frac{r f_{k'}^{max} a_{k'}^2 \sum_{k \in \mathcal{K} \setminus k'} f_{k'} a_{k'} \cdot (-2)}{(\sum_{k \in \mathcal{K}} f_k a_k)^3} < 0$, utilities of the participating UAVs is strictly concave in

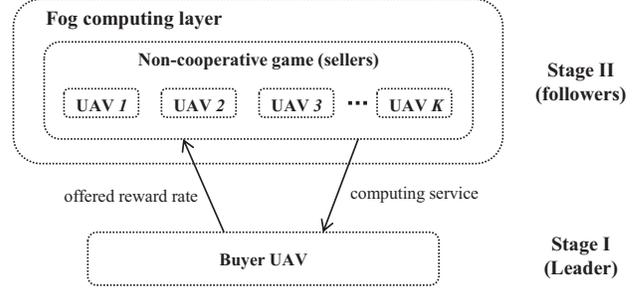
Fig. 3: Two-stage Stackelberg game model of interactions between the buyer and sellers in the proposed framework.

$f_{k'}, \forall k'$. We now aim at finding the solution by using the first-order condition, i.e.,

$$\frac{\partial U_{k'}^s(f_{k'})}{\partial f_{k'}} = 0, \tag{11}$$

$$\Rightarrow f_{k'}^{max} a_{k'} \left[\frac{\sum_{k \in \mathcal{K}} f_k a_k - f_{k'} a_{k'}}{(\sum_{k \in \mathcal{K}} f_k a_k)^2} \right] \cdot r - \gamma_{k'} = 0. \tag{12}$$

Rearranging (12), we get

$$r \cdot f_{k'}^{max} a_{k'} \sum_{k \in \mathcal{K} \setminus k'} f_k a_k = \gamma_{k'} \left(\sum_{k \in \mathcal{K}} f_k a_k \right)^2. \tag{13}$$

By further expanding the right-hand side of (13) as $\left(\sum_{k \in \mathcal{K} \setminus k'} f_k a_k + f_{k'} a_{k'} \right)^2$, and

$$r \cdot f_{k'}^{max} a_{k'} \sum_{k \in \mathcal{K} \setminus k'} f_k a_k = \gamma_{k'} \left[\left(\sum_{k \in \mathcal{K} \setminus k'} f_k a_k \right)^2 \right.$$
$$+ 2 \cdot (f_{k'} a_{k'}) \sum_{k \in \mathcal{K} \setminus k'} f_k a_k$$
$$+ \left. f_{k'}^2 a_{k'}^2 \right]. \tag{14}$$

Dividing the equation by $a_{k'}^2$ on both sides, we get

$$r \cdot f_{k'}^{max} a_{k'} \sum_{k \in \mathcal{K} \setminus k'} f_k a_k = \gamma_{k'} \left[\left(\frac{\sum_{k \in \mathcal{K} \setminus k'} f_k a_k}{a_{k'}} \right)^2 \right.$$
$$+ \frac{2 f_{k'}}{a_{k'}} \sum_{k \in \mathcal{K} \setminus k'} f_k a_k \tag{15}$$
$$+ \left. f_{k'}^2 \right].$$

Then,

$$r \cdot \frac{f_{k'}^{max}}{\gamma_{k'} a_{k'}} \sum_{k \in \mathcal{K} \setminus k'} f_k a_k = \left[\frac{\sum_{k \in \mathcal{K} \setminus k'} f_k a_k}{a_{k'}} + f_{k'} \right]^2. \tag{16}$$

By comparing the result in (16) with the IR constraint in (4), we observe that the optimal solution exists only if $r > \frac{\gamma_{k'}}{f_{k'}^{max} a_{k'}} \sum_{k \in \mathcal{K} \setminus k'} f_k a_k$, and is given as

$$f_{k'}^*(r) = \sqrt{r \cdot \frac{f_{k'}^{max}}{\gamma_{k'} a_{k'}} \sum_{k \in \mathcal{K} \setminus k'} f_k a_k} - \frac{\sum_{k \in \mathcal{K} \setminus k'} f_k a_k}{a_{k'}}. \tag{17}$$

Algorithm 1 Golden-search method to reach Stackelberg equilibrium point

1: Task owner initializes the golden ratio $\omega = \frac{1+\sqrt{5}}{2}$, $r_l = 0$, and $r_u = \beta_k \delta_k$.
2: **repeat**
3:     $d \leftarrow (\omega - 1)(r_u - r_l)$
4:     $r_1 \leftarrow r_l + d$
5:     $r_2 \leftarrow r_u - d$
6:     Solve (4) with r_1 and r_2 for $\{f_{k'}^*\}_{r=r_1}$ and $\{f_{k'}^*\}_{r=r_2}$ respectively.
7:     Evaluate $U^b(r_1, \{f_{k'}^*\}_{r=r_1})$ and $U^b(r_2, \{f_{k'}^*\}_{r=r_2})$
8:     **if** $U^b(r_1, \{f_{k'}^*\}_{r=r_1}) > U^b(r_2, \{f_{k'}^*\}_{r=r_2})$ **then**
9:         $r_l \leftarrow r_2$
10:     **else**
11:         $r_u \leftarrow r_1$
12:     **end if**
13: **until** $|r_1 - r_2| \leq \epsilon$
14: $r^* = \frac{r_1+r_2}{2}, \{f_{k'}^*\}_{r=r^*}$.

Hence, we obtain a unique solution given by the first-order condition. This completes the proof. □

At the buyer side, with the best response strategies $f_{k'}^*, \forall k'$ of the participating UAVs revealed, the buyer with aim to maximize its utility as

$$\max_r \quad U_k^b(r, \{f_{k'}^*\}) \\ \text{s.t.} \quad r \leq \beta\delta_k. \tag{18}$$

Using the solution $f_{k'}^*$, we obtain $\frac{\partial^2 U_k^b(r, f_{k'}^*)}{\partial r^2} < 0$ i.e., the utility is a strictly concave function in r. Thus, the maximization problem can be reformulated to a standard convex problem as

$$\min_r \quad -U_k^b(r, \{f_{k'}^*\}). \tag{19}$$

Next, to obtain the solution r^*, we adopt numerical methods [17] and propose a simplified, efficient, and low-complexity interior-points solution approach, namely Algorithm 1 to reach the Stackelberg equilibrium point. In Algorithm 1, we first define the search-space $[r_l, r_u]$ and obtain two interior points, respectively, r_1 and r_2 within the buyer's budget constraint using the golden ratio (line 3–5). Next, we evaluate the seller's best response strategy for the offered reward rates r_1 and r_2 (line 6). Given the best response strategies of the sellers, we evaluate the buyer's utility at these interior points, and compare their values to update the search-space (line 7–12). The iterative process (line 2–12) to find the optimal offered reward continues until the stopping criteria (line 13) is satisfied.

IV. NUMERICAL RESULTS

We setup a small network topology as shown in Fig. 4, with four UAVs and random tasks spread across a physical space with dimension 150 meters × 150 meters. To stimulate the interaction scenario, we use availability metric a_k as the samples drawn following a gamma distribution, as in Fig. 2. At each UAV, L_k is uniformly distributed in 10–30 cycles/bits,
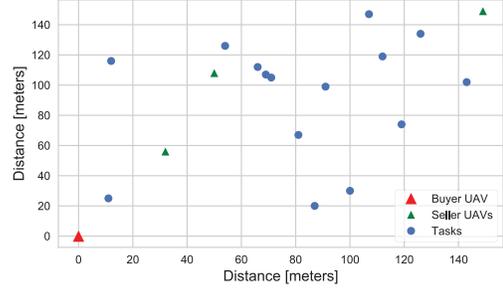
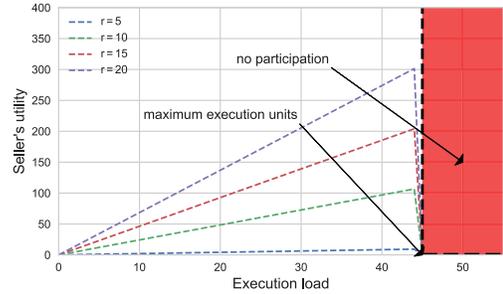

Fig. 4: Illustration of network topology.

Fig. 5: Variation of seller's utility over the offered reward rate r.

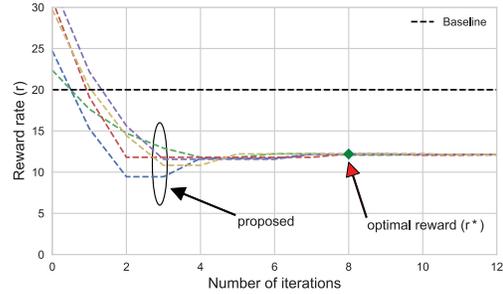

Fig. 6: Convergence of Algorithm 1.

α_k is 2×10^{-28}, and data size D_k for task completion is uniformly distributed in 5–15 MB, $\forall k \in \mathcal{K}$. The range of offered execution load is [0, 45] GHz, where 0 means no participation and 45 is $f_k^{\max}, \forall k$. The available budget at the buyer UAV is set to be 40 monetary units, and the latency requirements is captured using the time interval measurements T, which is fixed during simulations.

In Fig. 5, we show the variation of seller's utility over the offered reward rate r (\$/execution units) for increasing value of offered execution load. It is intuitive that we observe the increase in utility of seller's utility for higher offered reward rate. Furthermore, beyond the maximum available execution units, the utility of the seller is zero (the red shadowed area), hence, no participation in the cooperative task execution process.

In Fig. 6, we show the convergence analysis of Algorithm1 and performance evaluation of our proposed approach against
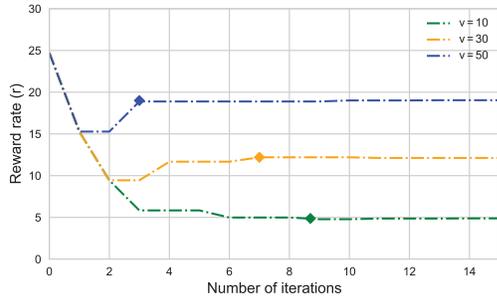
Fig. 7: Impact of buyer cost factor on the offer reward rate.

the naive equal sharing mechanism (Baseline). We show that the proposed numerical method obtains quick convergence (around 8 iterations) to the optimal solution for random reward initialization between 10–80 monetary units, given the budget limitation of 40, precision level $\epsilon = 10^{-9}$, and the scaling factor $\beta_k = 2$. Furthermore, we also observe the performance gain of nearly 40% compared with the Baseline approach. Similarly, in Fig. 7, we show the impact of buyer cost factor ν on the offered reward rate. We observe that increasing buyer cost factor results in higher offered reward rate to the sellers. This increase in the reward rate is the compensation for the sellers who have to trade more resources in order to maximize the utility of the buyer in the proposed game theoretic interaction. Furthermore, we also observe quick convergence due to smaller search space.

V. CONCLUSION

In this paper, a flexible crowd-enabled task execution solution in UAV networks towards fog computing is proposed. In particular, the problem of constrained computational resource in the UAV networks to serve users in a limited coverage area for diverse applications is tackled by leveraging incentive mechanism for unused computing resource trading. In doing so, the game theoretic interactions between a resource constrained UAV (the buyer) and the sellers UAVs is exploited, which offers mobility advantages, high throughput, and low latency. Hence, jointly benefiting both the task owner and the participating UAVs. To that end, a unique Stackelberg equilibria of the game with a simplified solution approach is derived. Additionally, insightful observations are derived to demonstrate the efficacy of the proposed solution approach via numerical simulations. For future work, we will implement differentiated pricing scheme, and consider trajectory plan and self-organizing resource management in the UAV networks to enable fog-like environment.

REFERENCES

[1] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, and M. Debbah, "A tutorial on uavs for wireless networks: Applications, challenges, and open problems," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2334–2360, Mar. 2019.

[2] M. Chen, W. Saad, and C. Yin, "Virtual reality over wireless networks: Quality-of-service model and learning-based resource management," *IEEE Transactions on Communications*, vol. 66, no. 11, pp. 5621–5635, Jun. 2018.

[3] Y. K. Tun, Y. M. Park, N. H. Tran, W. Saad, S. R. Pandey, and C. S. Hong, "Energy-efficient resource management in uav-assisted mobile edge computing," *IEEE Communications Letters (Early Access)*, Sep. 2020.

[4] M. Satyanarayanan, P. Bahl, R. Caceres, and N. Davies, "The case for vm-based cloudlets in mobile computing," *IEEE Pervasive Computing*, vol. 8, no. 4, pp. 14–23, Oct. 2009.

[5] M. Alsenwi, Y. K. Tun, S. R. Pandey, N. N. Ei, and C. S. Hong, "Uav-assisted multi-access edge computing system: An energy-efficient resource management framework," in *International Conference on Information Networking (ICOIN)*, Barcelona, Spain, Jan. 2020.

[6] S. Jeong, O. Simeone, and J. Kang, "Mobile edge computing via a uav-mounted cloudlet: Optimization of bit allocation and path planning," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 3, pp. 2049–2063, May 2017.

[7] A. Greenberg, J. Hamilton, D. A. Maltz, and P. Patel, "The cost of a cloud: research problems in data center networks," *ACM SIGCOMM Computer Communication Review (CCR)*, Seattle, WA, USA, Aug. 2008.

[8] 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, Sep. 2016.

[9] F. Zhou, Y. Wu, H. Sun, and Z. Chu, "Uav-enabled mobile edge computing: Offloading optimization and trajectory design," in *IEEE International Conference on Communications (ICC)*, Kansas City, MO, USA, May 2018.

[10] L. Wang and M. Hua, "Optimal bit allocation for uav-enabled mobile communication," in *IEEE International Conference on Computer and Communications (ICCC)*, Chengdu, China, Dec. 2017.

[11] D. Yang, G. Xue, X. Fang, and J. Tang, "Crowdsourcing to smartphones: Incentive mechanism design for mobile phone sensing," in *International conference on Mobile computing and networking (MOBICOM)*, New York, NY, USA, Aug. 2012.

[12] D. R. Cox, *Analysis of survival data*. Chapman and Hall/CRC, Jun. 2018.

[13] D. Fudenberg and J. Tirole, "Game theory," *Cambridge, Massachusetts*, vol. 393, no. 12, p. 80, Aug. 1991.

[14] S. R. Pandey, N. H. Tran, M. Bennis, Y. K. Tun, Z. Han, and C. S. Hong, "Incentivize to build: A crowdsourcing framework for federated learning," in *IEEE Global Communications Conference (GLOBECOM)*, Waikoloa, HI, USA, Dec. 2019.

[15] S. R. Pandey, N. H. Tran, M. Bennis, Y. K. Tun, A. Manzoor, and C. S. Hong, "A crowdsourcing framework for on-device federated learning," *IEEE Transactions on Wireless Communications*, vol. 19, no. 5, pp. 3241–3256, Feb. 2020.

[16] J. Zhang and Q. Zhang, "Stackelberg game for utility-based cooperative cognitiveradio networks," in *International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, New Orleans, LA, May 2009.

[17] R. Hamming, *Numerical methods for scientists and engineers*. Courier Corporation, Apr. 2012.