Exploiting UAV for Air-Ground Integrated Federated Learning: A Joint UAV Location and Resource Optimization Approach

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***Abstract*—Recently, many exciting usage scenarios and ground-breaking technologies for sixth generation (6G) networks have drawn more and more attention. The revolution of 6G mainly lies in ubiquitous intelligence, which promotes the development of edge intelligence (EI) by running artificial intelligence (AI) algorithms at the network edge. By embedding training capabilities across the network nodes, federated learning (FL) can achieve high security and alleviate network traffic congestion, which provides a promising way to realize the ubiquitous EI. While traditional FL usually relies static terrestrial base stations (BSs) for the global model aggregation, unmanned aerial vehicles (UAVs) could effectively supplement the terrestrial BSs because of their high maneuverability, thereby building the air-ground integrated FL (AGIFL). Nevertheless, how to effectively deploy the UAV and allocate resources to boost the learning performance and achieve high energy efficiency in the AGIFL remains largely unexplored. In this paper, we study how to jointly optimize the UAV location and resource allocation to minimize the incurred cost in terms of two objectives: i) the minimization of terrestrial users' energy consumption; ii) the minimization of tradeoff between energy consumption and training latency. The formulated non-convex problems are efficiently solved by alternating optimization techniques based on successive convex approximation (SCA) approaches after appropriate problem decomposition. Extensive simulation results show that our proposed algorithms can reduce more cost than three benchmarks while guaranteeing the learning accuracy. Furthermore, we construct a real-world AGIFL system, implement the proposed algorithms in the system, and carry out field experiments to verify the superiority of our algorithms.**

***Index Terms*—UAV location, resource allocation, air-ground integrated federated learning**

I. INTRODUCTION

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WITH the commercialization and global deployment of fifth generation (5G) networks from 2020, both academy and industry have come up with visions and ground-breaking technologies for sixth generation (6G). To develop the ambitious use cases of 6G in the future, artificial intelligence (AI) is deemed to be one of the revolutionary approaches to design and optimize 6G networks. It is expected that 6G will support ubiquitous AI services, promoting the development of intelligence from the center to the edge of networks [1], [2]. Given the requirements of burgeoning 6G, edge intelligence (EI) is expected to become a focus of 6G [1]. EI offers a promising paradigm for delivering intelligence by collecting, processing, and analyzing the huge amount of data traffic generated at the edge of the network [3], [4].

Creating a reliable and efficient EI system is critical to infusing intelligence for 6G. To be specific, credibility in terms of privacy and efficiency in data exchange is one of the key requirements for 6G smart services, which needs to meet general data protection regulations (GDPR) that prohibit users from directly transmitting or collecting raw data [5]. Recently, federated learning (FL), emerges as a promising distributed ML paradigm that can enable multiple users to collaboratively train machine learning (ML) models without sharing raw data [1]. In FL, each user trains a local model based on its own data and sends the recent model parameter to a parameter server node for global model aggregation [6], [7]. FL can achieve high security and reduce network traffic congestion and energy consumption, by embedding training capabilities across the network nodes [5]. Therefore, from that point of view, FL at the edge is a potential paradigm to realize the much-needed ubiquitous EI.

Traditional edge FL usually relies on terrestrial communication infrastructure. However, in some areas far from hot spots (*e.g.,* rural and mountains) or under some emergencies (*e.g.,* large gatherings and military exercises), the restricted terrestrial communication infrastructures may have a huge influence on communication of edge FL. Fortunately, unmanned aerial vehicle (UAV) equipped with edge computing server may be a prevailing trend due to its flexibility, mobility, and agility in the air-ground integrated network (AGIN) [8]. UAVs could replace traditional base stations (BSs) as parameter servers to provide communication and computing services for terrestrial users, thereby building the air-ground integrated federated learning (AGIFL) [2], [9]. Employing the UAV as edge server in the AGIFL has two prominent advantages. On one hand, when terrestrial users or network status change, the UAV can quickly adjust at low cost for flexible deployment. On the other hand, the effective line-of-sight (LoS) channel avoids signal attenuation and penetration loss caused by encountering obstacles [10].

However, in order to realize the aforementioned potential benefits of the AGIFL with the help of the UAV, we are faced with the following challenges. *i) Where to place the UAV to boost the learning performance of the AGIFL?* Improving FL performance through the deployment of the UAV is a top priority in the AGIFL. In traditional UAV-assisted networks, the deployment of UAV is usually only concerned with communication coverage. Nevertheless, model upload and download are the two most important links of FL, so that the impact of air-ground wireless channel should be strictly considered, because of the maneuverability of the UAV. *ii) How to satisfy the differentiated needs of FL applications?* Facing the diverse requirements, such as energy-saving, training acceleration or both, traditional FL which normally considers training to be completed in a predefined latency budget may not be suitable. It is necessary and non-trivial to study how to optimize the AGIN to efficiently satisfy the diverse requirements of different FL applications.

To address the aforementioned challenges, we focus on how to jointly optimize the UAV location and network resources to simultaneously meet the diverse requirements and minimize the incurred cost in the AGIFL. Specifically, we formulate two optimization problems: one is the minimization of all terrestrial users' energy consumption in the FL under predefined learning accuracy and latency constraints, the other is the minimization of the weighted sum of energy consumption and learning latency under the same constraints, which are both non-convex and difficult to solve. Leveraging convex and successive convex approximation techniques, we propose efficient convergence-guaranteed algorithms to them after appropriate problem decomposition. Furthermore, besides extensive simulations, we carry out field experiments to verify the effectiveness of the proposed algorithms.

II. Related Works

The related works fall into three main categories: FL in wireless network, UAV-assisted FL, and UAV placement.

1) FL in wireless network: There exist many researches on how to reduce energy consumption or latency and improve convergence performance of FL in wireless network.

Reduce energy consumption or latency: Tran *et al.* [11] constructed FL as an optimization problem that captures the tradeoff between the FL latency and UE energy consumption in the terrestrial network. Furthermore, Luo *et al.* [12] introduced a novel Hierarchical Federated Edge Learning (HFEL) framework. They formulated a joint computation and communication resource allocation and edge association problem for terrestrial users under HFEL framework to achieve global cost minimization. Rakpong *et al.* [13] proposed a hierarchy of quantum key distribution-secured FL (QKD-FL) systems in which QKD resources and routing are jointly optimized for FL applications to minimize the deployment cost of QKD nodes under various uncertainties, including security requirements. Besides, Xu *et al.* [14] used the coordinated multiple base station access mechanism to achieve wireless FL acceleration with the fully decoupled uplink and downlink Wireless Access Network (FD-RAN) architecture. In order to reduce the total energy consumption and ensure the learning performance, an energy-saving strategy for bandwidth allocation and scheduling was proposed based on the state of ground channel and users' computing power [15].

Improve convergence performance: Restricted by spectrum bandwidth, participation of all mobile devices in iterative aggregation presents challenges in practical FL applications. Hence, existing work [16]–[18] studied different scheduling strategies to improve the convergence performance of FL in terrestrial wireless network. Yang *et al.* [16] derived the convergence rate of FL in terrestrial wireless environment, and considerd the effect of scheduling scheme and intercell interference. Moreover, Nishio *et al.* [17] proposed a new FL protocol called FedCS, which alleviates the problem of training inefficiency caused by limited computing and communication resources, effectively executes FL, actively manages terrestrial client resource conditions, and speeds up the performance improvement of ML model. Similarly, a control algorithm was proposed in the work [18] to determine the optimal tradeoff between local update and global parameter aggregation and minimize the loss for a resource budget.

To summarize, the aforementioned works [11]–[18] consider the performance of FL happens in the terrestrial networks only. Actually, the UAV is an efficient alternative to base station in wireless network. This paper devotes to reducing energy consumption and improving convergence to boost the performance of FL with the help of the UAV. To be specific, we jointly optimize the UAV location and resource allocation to realize the reduction of energy and latency. In addition, compared with other works [12], [15] that constrain training by setting deadline, we introduce latency into the objective function to achieve both fast and energy-saving AGIFL.

2) UAV-assisted FL: UAV-enabled wireless communication networks have been recognized as an important part of 5G and beyond networks to realize full converge and enhance network performance [19], [20]. Based on that, UAV-enabled FL has the potential to further improve the computation performance besides communication, which significantly increases the complexity of system design because the scheduling of UAV movement trajectories needs to be addressed meanwhile.

FL in UAV swarms: Jer Shyuan Ng *et al.* [21] used UAVs as wireless relays to facilitate communication between internet of things (IoT) components and FL servers, thereby improving the accuracy of FL. Furthermore, Xiao *et al.* [22] proposed a FL framework in UAV swarm which provides fast convergence and high communication efficiency for specific on-board tasks to some extent. Besides, Zeng *et al.* [23] proposed a combined power distribution and scheduling design to optimize the convergence rate of FL, considering the energy consumption during convergence and the delay requirements imposed by group control systems.

Reduce energy consumption or latency: Tran *et al.* [11]

constructed FL as an optimization problem that captures the tradeoff between the FL latency and UE energy consumption in the terrestrial network. Furthermore, Luo *et al.* [12] introduced a novel Hierarchical Federated Edge Learning (HFEL) framework. They formulated a joint computation and communication resource allocation and edge association problem for terrestrial users under HFEL framework to achieve global cost minimization. Rakpong *et al.* [13] proposed a hierarchy of quantum key distribution-secured FL (QKD-FL) systems in which QKD resources and routing are jointly optimized for FL applications to minimize the deployment cost of QKD nodes under various uncertainties, including security requirements. Besides, Xu *et al.* [14] used the coordinated multiple base station access mechanism to achieve wireless FL acceleration with the fully decoupled uplink and downlink Wireless Access Network (FD-RAN) architecture. In order to reduce the total energy consumption and ensure the learning performance, an energy-saving strategy for bandwidth allocation and scheduling was proposed based on the state of ground channel and users' computing power [15].

The aforementioned works [21]–[23] consider the performance of FL happens in the aerial networks only and they are focus on training acceleration. Unlike these existing reseraches, we study the tradeoff between energy consumption and FL latency in the AGIFL. Meanwhile, there are few researches focus on optimization simulation and practical verification of the AGIFL. In [24], the UAVs only serve as the aerial relay to collect local models of terrestrial equipments and transmit them to a centralized aggregator. In [25], UAVs and terrestrial remote radio heads jointly serve as heterogeneous Base Stations (BSs) of a Cloud Radio Access Network (HCRAN), while we are considering scenarios where BSs are not available. In [26], UAVs are used as edge nodes rather than servers, and the final aggregation takes place in the cloud. However, we use the UAV as the server to aggregate the local model. Compared with [2], [27], [28], we not only carry out optimization simulations in the AGIFL, but also firstly complete the small-scale real-world experimental for the AGIFL system to verify the simulation results.

3) UAV placement: There exist many researches on UAV placement, which can be divided into two categories based on the number of UAVs.

Placement of single UAV: Alzenad *et al.* [29] investigated a new 3D placement method for the UAV that maximizes the number of covered users with different QoS requirements when the UAV is deployed at high and low altitude. Then, Hayajneh *et al.* [30] used the UAV empowered small cellular networks (DSCNs) to deploy resilient communication networks for smart cities, studied the coexistence characteristics of covered DSCN networks. They significantly improved the coverage probability of terrestrial users in post-disaster situations by optimizing the altitude and number of UAV. Equally, Al-Hourani *et al.* [31] proposed an analytical method to optimize the height of low-altitude aerial platforms, a key enabler of the rapid deployment rescue network, to provide maximum ground radio coverage.

Placement of multiple UAVs: In order to realize real-time communication with more terrestrial users, multiple UAVs can also be deployed in coordinated formation. Mozaffari *et al.* [32] studied the optimal deployment of multiple UAVs equipped with directional antennas as aerial BSs. They proposed an efficient deployment method based on circular packaging theory, which can achieve maximum coverage while using minimum transmitting power for each UAV. Furthermore, Kalantari *et al.* [33] described a new UAV deployment plan to serve users according to their traffic needs with as few UAVs as possible. Besides, Sharma *et al.* [34] proposed an optimal layout and distribution method for cooperative UAVs in heterogeneous networks to optimize overall network latency. In addition, Mohammad *et al.* [35], proposed a new framework, efficiently deploy UAVs for data collecting from terrestrial IoT devices. They also studied the effective movement of UAVs to collect data in time-varying IoT networks.

The aforementioned works [29]–[31] focus on the 3D deployment of the UAV for UAV-assisted wireless networks, these studies are aimed at finding the best deployment location to maximize coverage. And the aforementioned works [32]–[35] provide on-demand and reliable wireless access to terrestrial users through multi-UAV in cooperative formation. Different from the above works, considering how to boost the FL performance by deploying the UAV is the focus in the AGIFL. In particular, compared to traditional UAV-assisted networks, the UAV is no longer the object of mission offloading in the AGIFL. Plenty of computational training happens on the client side, which requires deploying the UAV and allocating network resources to ensure the training and communication environment of users. Therefore, in this paper, we study the joint optimization of the UAV location and resources allocation.

A. Contributions and Organization

The main contributions are summarized as follows:

• *Novel cost-efficient FL framework utilizing the UAV:* To be the best of our knowledge, this is the first work to study how to jointly optimize the UAV location and resource allocation to minimize the incurred cost in the AGIFL. Specifically, we formulate two optimization problems with different cost objectives: one is the minimization of all terrestrial users' energy consumption in the FL under predefined learning accuracy and latency constraints, the other is the minimization of the weighted sum of energy consumption and learning latency under the same constraints. The formulated problems are nonconvex with complicated relationships among variables and thus difficult to solve.

• *Convergence-guaranteed suboptimal algorithms:* We propose the joint UAV location and resource allocation (JULRA) algorithms to solve the aforementioned problems after appropriate problem decomposition. To be specific, we exploit the special structure of objective functions and decompose them into two subproblems: the computation resource allocation subproblem, and joint UAV location and communication resource allocation subproblem. Leveraging convex and successive convex approximation techniques, we alternately optimize the above subproblems and obtain the suboptimal solution until converge. We also theoretically prove the convergence and the complexity of our algorithms.

- *Extensive simulations and practical field experiments:* We conduct both extensive simulations and small-scale real-world experiments to validate the effectiveness of the proposed algorithms. Simulation results show that, compared to three benchmarks, our algorithms can reduce the overall users' energy consumption by ∼53.8% on average while maintaining the learning accuracy. After introducing latency into objective function, the weighted sum of energy consumption and latency can be reduced by ∼54% on average. We are also the first to build a practical AGIFL system and implement the proposed algorithms for the AGIFL. Experimental results show that the proposed algorithms reduce the energy consumption by ∼38.6% on average compared to three benchmarks.

The rest of this paper is organized as follows: Section III provides the system model and problem formulation. In Section IV, the problem is solved by our proposed joint UAV location and resources allocation optimization algorithm. The case of considering tradeoff between energy consumption and latency is explored in Section V. Simulation results are presented in Section VI and field experiments are conducted in Section VII. We also discuss the optimization of learning parameters in Section VIII. Finally, Section IX concludes the paper.

III. Model and Problem Formulation

As shown in Fig. 1, we consider a UAV-assisted network consisting of one UAV equipped with an edge server hovering in the sky and several terrestrial users, where the set of the users is denoted by $\mathcal{U} = \{1, 2..., U\}$. A modern intelligent user can be thought of as a personal computer with an integrated processor with a certain amount of computing power for computing tasks, and plethora of sensors (e.g., cameras, microphones, and GPS) for collecting a wealth amount of data, which ensures the feasibility of FL to foster more intelligent applications [36]. Note that in practical, some terrestrial BS may be congested or unavailable due to large-scale sport/festival events or BS malfunction, and even fails to provide network coverage in remote areas, which necessitates the deployment of UAV to provide essential communication and computation services. Suppose that the coordinates of the u-th user and the UAV are represented as $[x_u, y_u]$ and $[X, Y, H]$, respectively. With the help of the UAV as the parameter sever, each terrestrial user $u \in \mathcal{U}$ aims to train a FL model based on a local dataset $\mathbf{D}_u$, whose size is represented as D_u. Naturally, the total data size of all users is denoted by $D = \sum_{u=1}^{U} D_u$. For $\mathbf{D}_u$, the data sample is a set of vector pairs of input and output, expressed as $\left\{\boldsymbol{x}_n^{'}, y_n^{'}\right\}_{n=1}^{D_u}$. The data can be generated through the usage of terrestrial users, for example, via interactions with mobile apps or images captured by a camera which constitutes the diversity of user data. With these users data, and location information, the current optimal location of the UAV as a edge server can be calculated. In the adopted FL, we use the publicly available MNIST dataset [37], which has which has 10 categories of handwritten digits, from "0" to "9". For the non-IID, each user has a certain number of samples, but 80% of the samples are from one dominant category and the remaining 20% belong to other categories.

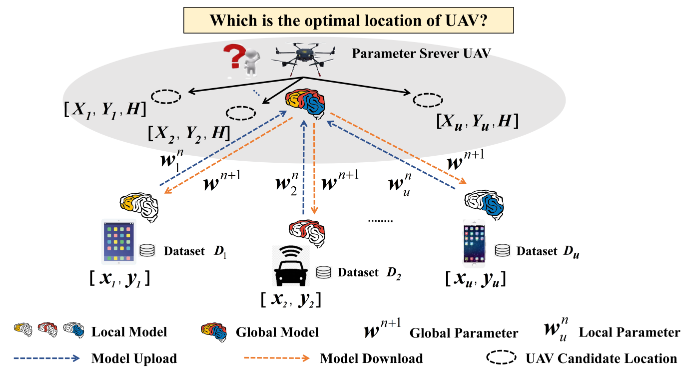


Fig. 1: An illustration of AGIFL with the help of a UAV.

For example, a "0"-dominated user has 480 data samples with the label "0", while the remaining 120 data samples have labels evenly distributed among "1" to "9" [38]. Furthermore, the same category also has different forms of expression because the same numbers are written differently by different people. In addition, the imbalance of data leads to the difference in the number of user samples, which is also the reason why we optimize the allocation of user computing resource. In fact, the optimal location is indeed different for different applications. We aim to design an algorithm that can calculate the optimal location of the UAV and the resource allocation of the users based on the current state of the terrestrial users, not limited to a certain application. According to different applications, the proposed algorithm can change the input to get the optimal UAV location. To be specific, different applications will have corresponding learning models, and different models have different upload model parameters. In this case we need to change the data size of upload parameters.

A. Federated Learning Model for UAV-assisted Networks

In this section, we adapt the FL model [39] to the wireless networks in detail. First, we call the model obtained by the terrestrial users' calculation of their sample data as the local model, and the model obtained by the UAV aggregation as the global model. Referring to existing studies [11], we use a vector $\boldsymbol{w}$ to represent the relevant parameters of the global model, and the loss function can be defined as $f\left(\boldsymbol{w}, \boldsymbol{x}_{ui}, y_{ui}\right)$. It's worth noting that the loss function is derived from one sample data of u-th user. Therefore, the total loss function can be represented by: $F_u\left(\boldsymbol{w}, x_{u1}, y_{u1}, \cdots, x_{uD_u}, y_{uD_u}\right) = \frac{1}{D_u}\sum_{i=1}^{D_u} f\left(\boldsymbol{w}, \boldsymbol{x}_{ui}, y_{ui}\right)$. In FL, the sample data is used to train the underlying model in order to aggregate a global FL model for all terrestrial users which shares none of the datasets. The learning model is the minimizer of the following global loss function minimization problem:

$$\min_{\boldsymbol{w}} F(\boldsymbol{w}) \triangleq \sum_{u=1}^{U} \frac{D_u}{D} F_u(\boldsymbol{w}) = \frac{1}{D}\sum_{u=1}^{U}\sum_{i=1}^{D_u} f\left(\boldsymbol{w}, \boldsymbol{x}_{ui}, y_{ui}\right). \quad (1)$$

In each iteration, all the terrestrial users need to download the initial global model from the UAV, and then upload the local model parameters to the UAV after calculating the sample dataset at local. The UAV aggregates these models to obtain a new global model and broadcasts it to the terrestrial users. At

TABLE I: A list of frequently used symbols.

Symbol	Description	Symbol	Description
U	Number of terrestrial users	a	Size of model parameters uploaded
$\mathcal{U}$	Set of terrestrial users	B	Bandwidth
$\boldsymbol{D}_u$	Local data set of u-th user	p_u	Transmission power of the u-th user
D_u	Size of local data set in the u-th user	α	Effective capacitance coefficient
D	Total data size	α_0	Channel gain
c_u	Number of CPU cycles of the u-th user	θ	Local accuracy
H	Fixed height of the UAV	ϵ_0	Global accuracy
$\boldsymbol{w}$	Global model vector	σ^2	Background noise power
r_u	Uplink transfer rate of the u-th user	K	The weight of energy and latency
$\nabla F(\boldsymbol{w})$	Global gradient	$\nabla F_u(\boldsymbol{w})$	Local gradient of u-th user

u-th iteration, the UAV broadcasts the global model $w^{(n)}$ and the global gradient $\nabla F\left(\boldsymbol{w}^{(n-1)}\right)$, and the u-th user acquires local gradient $\nabla F_u\left(\boldsymbol{w}^{(n)}\right)$ by calculating its local dataset with received $w^{(n)}$ and then send it to the UAV. The user evaluates the following minimization problem on the local side:

$$\min_{d_u} \quad g_u\left(\boldsymbol{w}^{(n)}, \boldsymbol{d}_u\right) \triangleq -\left(\nabla F_u\left(\boldsymbol{w}^{(n)}\right)-\mu \nabla F\left(\boldsymbol{w}^{(n)}\right)\right)^T \boldsymbol{d}_u + F_u\left(\boldsymbol{w}^{(n)}+\boldsymbol{d}_u\right), \tag{2}$$

where μ is a parameter that can be adjusted, $\boldsymbol{d}_u$ records the difference between the local and global models. This problem is numerical difficult to solve the minimization of local loss function $g_u\left(\boldsymbol{w}^{(n)}, \boldsymbol{d}_u\right)$, but we can find its feasible solution with certain accuracy. According to [11], the optimal feasible solution needs to meet the following two conditions:

$$g_u\left(\boldsymbol{w}^{(n)}, \boldsymbol{d}_u^{(n)}\right)-g_u\left(\boldsymbol{w}^{(n)}, \boldsymbol{d}_u^{(n)*}\right) \leq \theta g_u\left(\boldsymbol{w}^{(n)}, \mathbf{0}\right) - \theta g_u\left(\boldsymbol{w}^{(n)}, \boldsymbol{d}_u^{(n)*}\right), \tag{3}$$

$$F\left(\boldsymbol{w}^{(n)}\right)-F\left(\boldsymbol{w}^*\right) \leq \epsilon_0\left[F\left(\boldsymbol{w}^{(0)}\right)-F\left(\boldsymbol{w}^*\right)\right], \tag{4}$$

where $\boldsymbol{d}_u^{(n)*}$ is the optimal solution of problem (2), condition (3) means the difference between the parameter of the optimal solution and the parameter of the n-th local model over the difference between the parameter of the optimal solution and the parameter of the original local model cannot beyond the local accuracy θ. Meanwhile $\boldsymbol{w}^*$ is the optimal solution of problem (1) and condition (4) denotes the difference between the parameter of the optimal solution and the parameter of the n-th global model over the difference between the parameter of the optimal solution and the parameter of the original global model can not beyond the global accuracy ϵ_0. According to existing works [40], [41], the relationship between global iteration rounds and accuracy should satisfy the following constraints: $L(\theta) \geq \frac{\frac{2l^2}{\gamma^2 \xi} \ln \frac{1}{\epsilon_0}}{1-\theta}$, where l, γ, and ξ are constant values. In this paper, the global accuracy ϵ_0 is considered as a fixed value, we can normalize $\frac{2L^2}{\gamma^2 \xi} \ln \frac{1}{\epsilon_0}$ to 1, so that $L(\theta)=\frac{1}{1-\theta}$ [11].

On the other hand, computation and uplink communication time consist each global iteration. Since the downlink bandwidth is larger than the uplink bandwidth, and the UAV power is much higher than the user transmission power, compared with the uplink time, the downlink time can be ignored [11]. The computation time depends on the number of local iterations $\frac{2l^2}{\gamma^2 \xi} \ln \frac{1}{\theta}$. Meanwhile the total latency in one global iteration can be given by:

$$T_{glob}\left(\theta, T_{com}, T_{cmp}\right)=T_{com}+v \log (1/\theta) T_{cmp}, \tag{5}$$

where T_{cmp} is the time required for all the users to calculate the local model in an iteration and T_{com} is the time required for all the users to upload model parameters in an iteration. $v \log(1/\theta)$ denotes to the number of local computation rounds required. v is a positive constant which depends on the local data size. According to the above formula, θ is associated with local and global training rounds [40], [41], and can be used as a hyperparameter to adjust training performance. The parameter tuning is not performed on the server, but on the distributed nodes before local training begins.

B. Energy Consumption Model

We take the overall users' energy consumption as the goal, which includes two parts: computation consumption and communication consumption.

1) Computation Energy Consumption: We use $\boldsymbol{c}_u$ to denote the number of CPU cycles to solve one sample of data for u-th user. This is a predetermined value which is known as a priori [42], so we can measure it offline. Since all samples have different sizes, the number of CPU cycles required for u-th user to run a round of local computation is $c_u D_u$. Meanwhile the time for a round of computation of the u-th user can be expressed as $t_u^{cmp}=\frac{c_u D_u}{f_u}$, where f_u means the used CPU frequency. Naturally, the total computation energy consumption can be given by [43]:

$$E_u^{cmp}(f_u)=\alpha_u c_u D_u f_u^2, \tag{6}$$

where α_u refers to the effective capacitance coefficient of u-th user computation chipset [11].

2) Communication Energy Consumption: Users' communication energy consumption can be affected by the distance between UAV and terrestrial users. According to [11], we plan to upload the local model parameters generated by users after calculation in the way of time-domain multiple access (TDMA). The uplink data rate is defined as follows:

$$r_u=B \log_2\left(1+\frac{\alpha_0 p_u}{\sigma^2\left(H^2+R_u^2\right)}\right), \tag{7}$$

where B is the bandwidth, p_u is the transmission power of u-th user, α_0 denotes the channel gain at a certain distance, H is the hovering altitude of the UAV, and $R_u =$

$\sqrt{(X-x_u)^2+(Y-y_u)^2}$. We assume that the data size of the model parameters to be uploaded in each round is a, and thus the time of transmission delay is $t_u^{com}=a/r_u$. We can obtain the total communication energy consumption required for FL in a round:

$$E_u^{com}(X,Y)=\sum_{u=1}^{U} p_u \frac{a}{B\log_2\left(1+\frac{\alpha_0 p_u}{\sigma^2(H^2+R_u^2)}\right)}. \tag{8}$$

Therefore, we can denote the total energy by E_{glob}, which can be represented as:

$$E_{glob}\left(f_u,\theta,X,Y\right)=\sum_{u=1}^{U}(E_u^{com}+v\log(1/\theta)E_u^{cmp}). \tag{9}$$

C. Problem Formulation

We aim to minimize the users' energy consumption, by jointly optimizing the UAV location $[X,Y,H]$, resource allocation $\{f_u,T_{cmp},T_{com}\}$, while taking predefined learning accuracy θ, and training latency τ into account. It is logical that we can express the objective function as problem $\mathbf{P1}$:

$$\begin{aligned}
\mathbf{P1}:\ & \min_{f_u,X,Y,T_{com},T_{cmp}} L(\theta)E_{glob}(f_u,\theta,X,Y)\\
s.t.\ \ & L(\theta)T_{glob}\left(\theta,T_{com},T_{cmp}\right)\le\tau, && (10)\\
& t_u^{com}\le T_{com}/U,\forall u\in\mathcal{U}, && (11)\\
& \max_u \frac{c_uD_u}{f_u}=T_{cmp}, && (12)\\
& f_u^{\min}\le f_u\le f_u^{\max},\forall u\in\mathcal{U}. && (13)
\end{aligned}$$

In this minimization optimization problem, constraint (10) means global training should be completed within a given deadline τ. In constraint (11), it requires each user to complete the communication in the same time. Constraint (12) assures that T_{cmp} should not be shorter than the maximum time for the terrestrial user to compute locally. Constraint (13) guarantees the calculation frequency to be kept within a certain range. In this paper, the mission period is divided into T time slots with a certain length, where the set of the slots is denoted by $\mathcal{T}:=\{1,2,...,T\}$. In fact, the time slot length should be sufficiently small so that the users' limited movement distance can be regarded as relative stillness and the channel gain is approximately sampled within each time slot. To be specific, At the t-th slot, the terrestrial user locates through GPS, and transmits the location information to the UAV through the data transmission module and the UAV can get the optimal location by solving $\mathbf{P1}$. Then at $t+1$ slot, the location of the user has changed. The terrestrial users transmit the new location information to the UAV. We only need to repeat the steps and solve $\mathbf{P1}$ again to get the optimal location of the UAV. Therefore, for $\mathbf{P1}$, we can only consider the total energy consumption in a single time slot, instead of summing over the whole time. The index t can be omitted.

IV. Solution

It is crucial to deploy the UAV as a parameter server because of the heterogeneous of users such as raw data and computing power. Unfortunately, this optimization problem is difficult due to the large search space of UAV location combinations and their coupling with computational and communication

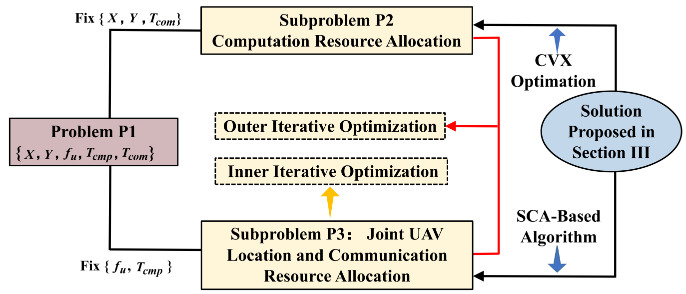


Fig. 2: A diagram of our proposed solutions.

resource allocation in the objective function. This means that it is impractical to obtain the global optimal solution in real time for a large number of inputs [36]. Therefore, efficient approximation algorithms with low complexity are ideal, which drives the design of the JULRA algorithm below.

A. Joint UAV Location and Resource Allocation Optimization

It is easy to see that the problem $\mathbf{P1}$ is non-convex with respect to R_u in the objective function. Eq. (9) shows that the total user energy consumption is composed of communication and computation. The communication energy consumption is affected by the UAV location and communication time, while the calculation energy consumption is only related to the computation frequency and time. Therefore, we first decompose $\mathbf{P1}$ into two subproblems $\mathbf{P2}$ and $\mathbf{P3}$, which are efficiently solved by existing convex techniques and SCA approaches, respectively, and then propose an efficient iterative algorithm based on the solutions of the subproblems. We can see the diagram of our proposed solutions clearly in Fig. 2.

For a target local accuracy θ, the global iteration round $L(\theta)$ is omitted because it has no effects on the solutions of these subproblems. We can decompose the objective function according to the dependence between the variables. Firstly, we consider fixing the hovering location of the UAV to find the optimal solutions of computation resources.

1) Computation Resource Allocation Optimization: In $\mathbf{P2}$, we fix the variables X, Y, and T_{com}, so that the communication energy consumption E_u^{com} becomes a constant value.

$$\begin{aligned}
\mathbf{P2}:\ & \min_{f_u,T_{cmp}} \sum_{u=1}^{U}\alpha_u c_u D_u f_u^2\\
s.t.\ \ & L(\theta)T_{glob}\left(\theta,T_{com},T_{cmp}\right)\le\tau, && (14)\\
& \frac{c_uD_u}{f_u}\le T_{cmp},\forall u\in\mathcal{U}, && (15)\\
& f_u^{\min}\le f_u\le f_u^{\max},\forall u\in\mathcal{U}. && (16)
\end{aligned}$$

Lemma 1. $\mathbf{P2}$ *is a convex problem.*

Proof. The second derivative of the objective function, Eq. (14) and Eq. (16) are all no less than zero. And the second derivative of the LHS of Eq. (15) is derived as: $\nabla^2(\frac{c_uD_u}{f_u})=\frac{2c_uD_u}{f_u^3}$, which is always no less than zero. Thus, problem $\mathbf{P2}$ is a simple convex problem. □

For the convex problem $\mathbf{P2}$, we can use the traditional convex optimization to get the optimal solution f_u^* and T_{cmp}^* [44].

2) Joint UAV Location and Communication Resource Allocation Optimization: Using the solutions f_u^* and T_{cmp}^*

obtained from $\mathbf{P2}$, E_u^{cmp} becomes a constant value, which we can omit in $\mathbf{P3}$:

$$\begin{aligned}\mathbf{P3}:\ &\min_{X,Y,T_{com}} \sum_{u=1}^{U} p_u \frac{a}{B\log_2\left(1+\frac{\alpha_0 p_u}{\sigma^2\left(H^2+(X-x_u)^2+(Y-y_u)^2\right)}\right)}\\ &s.t.\quad (11),\\ &\qquad L(\theta)[T_{com}+v\log(1/\theta)T^*_{cmp}]\le\tau.\end{aligned}\tag{17}$$

$\mathbf{P3}$ is continuous non-convex with respect to $\frac{a}{B\log_2\left(1+\frac{\alpha_0 p_u}{\sigma^2\left(H^2+(X-x_u)^2+(Y-y_u)^2\right)}\right)}$ and so as Eq. (11). To reduce the complexity, we introduce a continuous slack variable η_u, where $\eta_u \ge \frac{1}{B\log_2\left(1+\frac{\alpha_0 p_u}{\sigma^2\left(H^2+(X-x_u)^2+(Y-y_u)^2\right)}\right)}$, for $\forall u\in\mathcal{U}$. Then introduce relax variables into problem $\mathbf{P3}$, it becomes to:

$$\min_{X,Y,\eta_u,T_{com}} \sum_{u=1}^{U} p_u a\eta_u$$

$$s.t.\quad L(\theta)[T_{com}+v\log(1/\theta)T^*_{cmp}]\le\tau, \forall u\in\mathcal{U}, \tag{18}$$

$$a\eta_u \le T_{com}/U, \forall u\in\mathcal{U}, \tag{19}$$

$$B\log_2\left(1+\frac{\alpha_0 p_u}{\sigma^2\left(H^2+R_u^2\right)}\right)\ge\frac{1}{\eta_u}, \forall u\in\mathcal{U}. \tag{20}$$

After the above transformation, the object function and the LHS of Eq. (19) are now convex in η_u, the LHS and RHS of Eq. (20) are convex in R_u^2 and η_u. According to [45], [46], we employ the SCA to obtain the locally optimal solution of the above problem. For any given local point X^r, Y^r, the LHS of Eq. (20) can be approximated as follows:

$$B\log_2\left(1+\frac{\alpha_0 p_u}{\sigma^2\left(H^2+R_u^2\right)}\right)\ge\boldsymbol{\lambda}(R_u^2-R_u^{r2})+\boldsymbol{\kappa}, \tag{21}$$

$$\boldsymbol{\lambda}=-\frac{B\alpha_0 p_u\log_2 e}{\sigma^2\left(R_u^{r2}+H^2\right)\left(R_u^{r2}+H^2+\alpha_0 p_u/\sigma^2\right)}, \tag{22}$$

$$R_u^{r2}=(X^r-x_u)^2+(Y^r-y_u)^2, \tag{23}$$

$$\boldsymbol{\kappa}=B\log_2\left(1+\frac{\alpha_0 p_u}{\sigma^2\left(H^2+R_u^{r2}\right)}\right). \tag{24}$$

Then the r-th subproblem can be given by:

$$\begin{aligned}\mathbf{P3^r}:\ &\min_{X,Y,T_{com},\eta_u} \sum_{u=1}^{U} p_u a\eta_u\\ &s.t.\quad (18)(19),\\ &\qquad \boldsymbol{\lambda}(R_u^2-R_u^{r2})+\boldsymbol{\kappa}\ge\frac{1}{\eta_u}, \forall u\in\mathcal{U}.\end{aligned}\tag{25}$$

After a series of transformations, the original problem becomes a convex quadratic constrained quadratic program (QCQP) [47], which can be solved using standard convex solver given in Alg. 1.

B. Overall Iterative Algorithm and Analysis

As is shown in Alg. 2, the key idea of overall algorithm is to alternate iteration optimizes two subproblems by using CVX and SCA proposed in section III-A.

Theorem 1. *Alg. 2 converges to a suboptimal solution.*

Proof.

$$\begin{aligned}E_{glob}^{i-1}&=E_{glob}\left(\boldsymbol{f_u}^{i-1},\boldsymbol{X}^{i-1},\boldsymbol{Y}^{i-1}\right)\\ &\ge E_{glob}\left(\boldsymbol{f_u}^{i},\boldsymbol{X}^{i-1},\boldsymbol{Y}^{i-1}\right)\\ &\ge E_{glob}\left(\boldsymbol{f_u}^{i},\boldsymbol{X}^{i},\boldsymbol{Y}^{i}\right)=E_{glob}^{i}\end{aligned}\tag{26}$$

The first inequality holds because of the optimality of $\boldsymbol{f_u^i}$ by solving $\mathbf{P2}$, and the second inequality holds because of the suboptimality of $(\boldsymbol{X}^i,\boldsymbol{Y}^i)$ by solving $\mathbf{P3}$.

Algorithm 1 Joint UAV Location and Communication Resource Allocation Optimization Algorithm for $\mathbf{P3}$.

Input: Initial feasible UAV position $P(0)\triangleq\left\{(X^0,Y^0)\right\}$, iteration index $r=0$, maximum iterations $r^{max}=100$, step size sequence $\left\{\sigma^j\right\}\in(0,1]$.
Output: UAV location P and communication resources T_{com}.
while $r\le r^{max}$ **do**
  Compute $\hat{P}(P(r))$, the local optimal solution of $\mathbf{P3^r}$;
  Set $P(r+1)\leftarrow P(r)+\sigma^j(\hat{P}(P(r))-P(r))$;
  if $P(r+1)$ is a stationary solution of **P3 then**
    break;
  else
    Set $r\leftarrow r+1$;
  end if
end while
return $P(r)$ and T_{com}^r.

Algorithm 2 Joint UAV Location and Resource Allocation Optimization Algorithm for $\mathbf{P1}$.

Input: Initial feasible UAV location $P(0)\triangleq\left\{(X^0,Y^0)\right\}$, T_{com}^0, maximum iterations $i^{max}=100$, step size sequence $\left\{\sigma^i\right\}\in(0,1]$.
Output: UAV location P, computation resources f_u, T_{cmp} and communication resources T_{com}.
Set $i=0$;
repeat
  Solve problem $P2$ for given X^0, Y^0, T_{com}^0 by CVX, and denote the global optimal solution as f_u^i, T_{cmp}^i;
  Solve problem $P3$ for given f_u^i, T_{cmp}^i by Alg. 1, and denote the local optimal solution as X^i, Y^i, T_{com}^i;
  Set $i\leftarrow i+1$;
until the convergence condition is reached.
return $P(i)$, T_{com}^i, f_u^i, and T_{cmp}^i.

Since the objective value of problem $\mathbf{P3}$, which introduces relaxation variable $p_u a\eta_u$, decreases with the number of iterations (represented in eq.26) and has a finite lower bound (represented in eq.20), the convergence of Alg. 1 to the suboptimal solution is guaranteed [48].

Alg. 2 gives an alternate procedure for solving problem $\mathbf{P1}$, alternately optimizing one block from the users computation resource allocation variables in problem $\mathbf{P2}$ and the UAV location in problem $\mathbf{P3}$, with the other block fixed. This algorithm also called block coordinate descent method, which is often used to solve non-convex optimization problems and obtain suboptimal solutions [49]. Although the resulting overall algorithm (Alg.2) is generally suboptimal, we demonstrate the effectiveness of Alg. 2 in reducing user energy consumption by comparing with other benchmark schemes in Section VI [50]. □

Theorem 2. *The complexity of Alg. 2 is calculated as $\mathcal{O}(I(U^3(J+1)))$, where I is number of iterations of Alg. 2, J is number of iterations of Alg. 1, and U is the number of terrestrial users.*

Proof. The complexity of Alg. 2 can be calculated as follows. First of all, to obtain $\boldsymbol{f_u}^i$ with fixed $(\boldsymbol{X}^i,\boldsymbol{Y}^i)$, it is a convex optimization problem whose computation complexity is about

$\mathcal{O}(U^3)$ [51]. Then obtaining $(\boldsymbol{X}^i, \boldsymbol{Y}^i)$ with fixed $\boldsymbol{f_u}^i$ takes $\mathcal{O}(JU^3)$ time. Thus, the total computation complexity of Alg. 2 is $\mathcal{O}(I(U^3(J+1)))$. □

The proposed algorithm is polynomial in complexity and does not consume too much computational power for airborne embedded devices. Because airborne embedded devices are often small computers with powerful computing capabilities, for example, Jetson Xavier NX. The Jetson Xavier NX is equipped with NVIDIA Volta architecture with 384 NVIDIA CUDA cores and 48 Tensor cores, and 6-core NVIDIA Carmel ARM v8.2 64-bit CPU 6 MB L2 + 4 MB L3. Due to the limited coverage of a single UAV, the number of terrestrial users who can access the same UAV at the same time is also limited, which greatly reduces the complexity of the algorithm.

V. Extension to Tradeoff between Energy and Latency in AGIFL

When natural disasters or emergencies occur, existing terrestrial communication infrastructure or base station could be damaged. A fast, reliable and efficient emergency network is needed to effectively accomplish the task of public security. Because of the long transmission delays in wireless networks, FL has bottlenecks in communication and energy costs until satisfactory model accuracy can be achieved. It is crucial to complete training quickly and efficiently. Nevertheless the large number of computations and communications iterations over a short period of time require significant energy overhead, which can be a challenge for low-battery devices. Thus, in the extension paragraph, we consider the optimization problem of tradeoff between energy consumption and latency.

On the basis of problem $\mathbf{P1}$, we introduce FL latency into the objective function. To capture the optimal tradeoff between unit energy consumption and FL latency, we use weight K (joules/SEC) [36] in the target as an additional energy consumption per unit of training time. The tradeoff problem is described by the following formula:

$$\mathbf{P4} \min_{X,Y,f_u,T_{com},T_{cmp}} \quad L(\theta)\left(E_{glob} + KT_{glob}\right)$$

$$s.t. \quad L(\theta)T_{glob}\left(\theta, T_{com}, T_{cmp}\right) \le \tau, \tag{27}$$

$$t_u^{com} \le T_{com}/U, \forall u \in \mathcal{U}, \tag{28}$$

$$\frac{c_u D_u}{f_u} \le T_{cmp}, \forall u \in \mathcal{U}, \tag{29}$$

$$f_u^{\min} \le f_u \le f_u^{\max}, \forall u \in \mathcal{U}. \tag{30}$$

The problem can be decomposed into two subproblems as follows:

$$\text{SUB1:} \min_{f_u,T_{cmp}} \quad \sum_{u=1}^{U} E_u^{cmp} + KT_{cmp}$$
$$s.t. (27), (29), (30).$$

$$\text{SUB2:} \min_{X,Y,T_{com}} \quad \sum_{u=1}^{U} E_u^{com} + KT_{com}$$
$$s.t. (27), (28).$$

SUB1 is a CPU cycle control problem that computes latency and energy minimization, and SUB2 can be thought of as location optimization to determine the best UAV location to minimize UE's energy and communication latency.

1) *SUB1 solution*: The introduction of latency does not change the concavity of the problem. We also divide latency into two parts: computing latency and communication latency. Similarly, $\mathbf{P5}$ is still a problem that can be solved by convex optimization.

$$\mathbf{P5} \min_{f_u,T_{cmp}} \sum_{u=1}^{U} \alpha_u c_u D_u f_u^2 + KT_{cmp}$$
$$s.t. (27), (29), (30).$$

2) *SUB2 solution*: Using the solutions f_u^* and T_{cmp}^* obtained from $\mathbf{P5}$ by CVX [44], E_u^{cmp} becomes a constant value, which we can omit in $\mathbf{P6}$:

$$\mathbf{P6}: \min_{X,Y,T_{com}} \quad \sum_{u=1}^{U} p_u \frac{a}{B\log_2\left(1+\frac{\alpha_0 p_u}{\sigma^2\left(H^2+(X-x_u)^2+(Y-y_u)^2\right)}\right)} + KT_u^{com}$$
$$s.t. \quad (28),$$
$$L(\theta)[T_{com} + v\log(1/\theta)T_{cmp}^*] \le \tau. \tag{31}$$

$\mathbf{P6}$ is continuous non-convex with respect to $\frac{a}{B\log_2\left(1+\frac{\alpha_0 p_u}{\sigma^2\left(H^2+(X-x_u)^2+(Y-y_u)^2\right)}\right)}$ and so as Eq. (35). Similarly, we use the method introduced in section III to make convex approximations to non-convex functions. Then, for any given local point X^r, Y^r, the r-th subproblem can be given by:

$$\mathbf{P6^r}: \min_{X,Y,T_{com},\eta_u} \quad \sum_{u=1}^{U} p_u a\eta_u + KT_{com}$$
$$s.t. \quad (18), (19), (25).$$

The problem becomes a convex QCQP [47], which could be solved by the algorithm proposed in section III.

VI. Performance Evaluation

In this section, numerical results are provided to validate the proposed joint UAV location and resource allocation optimization algorithm as well as the fundamental energy-latency tradeoff in the AGIFL.

A. Simulation Settings

The adopted FL framework can be adapted to different models. A complex model requires a larger dataset to train the local model, and at the same time, more model parameters are uploaded, and their data size a is larger. These parameters are the inputs of our proposed algorithm. By changing these inputs, our algorithm can be realized under different applications. In the FL considered in this paper, we use the publicly available MNIST dataset [37], which is also commonly used for simulations and experiments [15]–[17], [28], [36], [52]. The actual size of MNIST is about 10MB, and using these samples for training, the local model can achieve high accuracy [37]. According to [2], we consider $U = 100$ terrestrial users to compute MNIST dataset (10MB), and they are randomly distributed in a square area in the range of $[0, 1000]$ m^2. The edge server UAV also hovers in this area, at a height of 100 m. Assume that the constant v that controls the local calculation turns is 4 and that the maximum time limit τ is 600 seconds. The relevant settings for ground users are as follows. The effective capacitance coefficient and the maximum CPU frequency of each terrestrial users are set as

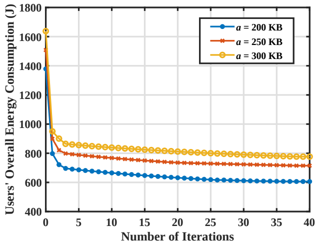


Fig. 3: Convergence & effectiveness of JULRA.

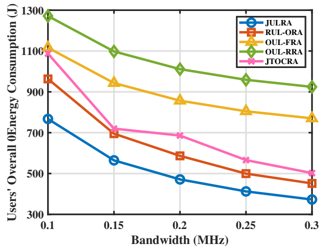


Fig. 4: Influence of bandwidth on E_{glob}.

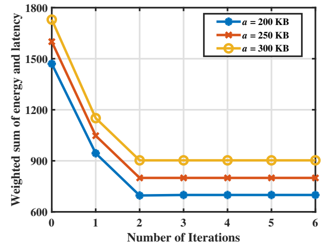


Fig. 7: Convergence of JULRA (K=0.1).

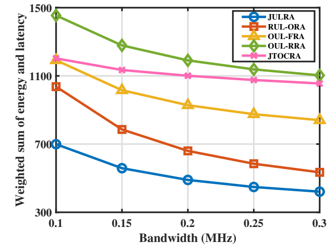


Fig. 8: Influence of bandwidth (K=0.1).

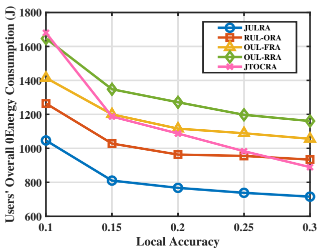


Fig. 5: Influence of local accuracy on E_{glob}.

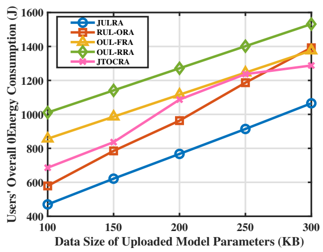


Fig. 6: Influence of data size on E_{glob}.

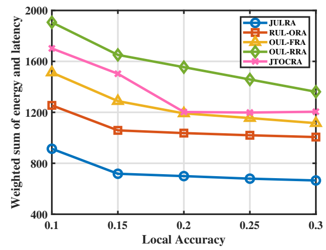


Fig. 9: Influence of local accuracy (K=0.1).

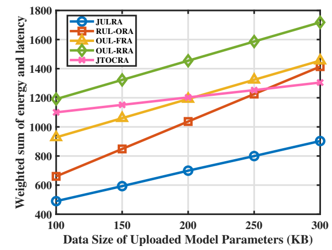


Fig. 10: Influence of data size (K=0.1).

$\alpha = 10^{-28}$ and $f^{max} = 0.5$ GHz [53]. CPU cycles needed is $C = 1000$ cycles/bit [53]. The model parameters uploaded is $a = 200$ KB and terrestrial users transmit power $p_u = [0.1, 1]$ W. Channel gain α_0, bandwidth B, and background noise power σ^2 are set to -50 dB, 0.1 MHz, and -90 dBm [54], respectively.

Since there is no available studies about the joint UAV location and network resource allocation in existing works, we involve the four benchmark algorithms for performance comparison (the proposed Alg. 2 is labeled as **JULRA**):

1) Random UAV Location with Optimized Resource Allocation **(RUL-ORA):** it randomly selects the position of the UAV and then optimizes both the computation and communication resource allocation similar to Alg. 2;

2) Optimized UAV Location with Fixed Resource Allocation **(OUL-FRA):** it uses a fixed computation resource allocation scheme (*i.e.*, $f_u = \frac{1}{2} f^{max}$) and optimizes the UAV location and communication resource allocation similar to Alg. 1;

3) Optimized UAV Location with Random Resource Allocation **(OUL-RRA):** it randomly chooses computation frequency from the feasible interval and optimizes the UAV location and communication resource allocation similar to Alg. 1;

4) Joint trajectory optimization and computing resource allocation **(JTOCRA):** similar to [55], this algorithm optimizes UAV trajectory and computing resource allocation to minimize delay by using SCA.

B. Results Analysis

1) *Convergence of JULRA*: It can be seen that JULRA algorithm can greatly reduce users' energy consumption and has good convergence in Fig. 3. Because compared with the initial scheme, the energy consumption is optimized by 56.02%, 52.65%, and 52.59% and our algorithm converges fast within a finite iterations.

2) *Impact of the Bandwidth*: In Fig. 4, when bandwidth increases, the users' energy consumption is reduced, since the large bandwidth can save the users' communication energy consumption. Because computation frequency is not optimized, when the bandwidth increased and the proportion of communication energy consumption decreased, the FL performance of OUL-FRA and OUL-RRA is worse than the other two algorithms. Compare to RUL-ORA, OUL-FRA, and OUL-RRA, the average gains of JULRA are 19.08%, 43.36%, and 51.67%, respectively.

3) *Impact of the Local Accuracy*: In Fig. 5, with the increase of θ, local computation turns reduces and overall communication energy consumption decreases. That is because θ refers to the FL convergence threshold and a smaller θ means the higher accuracy of the local model. Compare to RUL-ORA, OUL-FRA, and OUL-RRA, the average gains of JULRA are 20.97%, 30.84%, and 37.32%, respectively.

4) *Impact of the Data Size of Uploaded Model Parameters*: In Fig. 6, when data gets larger, the overall communication energy consumption increase due to face more pressure in communication. The curve of OUL-FRA and RUL-ORA intersect, because when the data becomes larger, the proportion of communication energy consumption gradually exceeds computation energy consumption, while RUL-ORA does not optimize the UAV location, resulting in poorer FL performance. Compare to RUL-ORA, OUL-FRA, and OUL-RRA, the average gains of JULRA are 21.3%, 32.48%, and 40.7%, respectively.

5) *When K = 0.1*: We explore the impact of tiny weight on the performance gain in cost reduction in Fig. 7-10. Under the weight K=0.1, JULRA algorithm accomplish a satisfying reduction on cost as 52.45%, 50.03%, and 47.81% in Fig. 7. Introducing latency into the objective function for optimization will accelerate algorithm convergence, which can be seen by comparing Fig. 3 and Fig. 7. Fig. 8 reflects the Influence

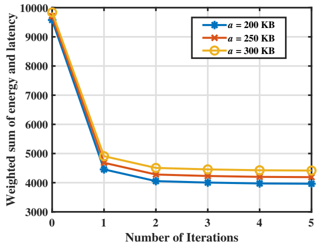


Fig. 11: Convergence of JULRA (K=10).

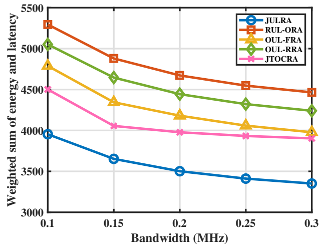


Fig. 12: Influence of bandwidth (K=10).

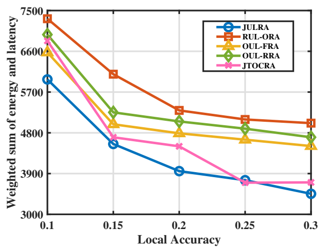


Fig. 13: Influence of local accuracy (K=10).

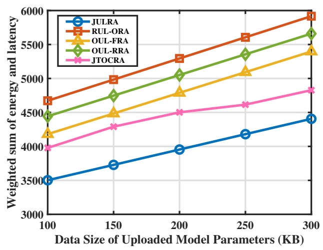


Fig. 14: Influence of data size (K=10).

of bandwidth, the FL performance of JULRA is better than the other algorithms due to the optimization of computation frequency and reach the gain of 25.09%, 16.25%, and 21.26%. Similar to Fig. 5, Fig. 9 describes the growing consumption of communication and computation due to the increase of local and global rounds. As described in Fig. 10, under the challenge of a mass of data, JULRA can still maintain significant performance compared with other algorithms and fulfills up to 25.31%, 17.37%, and 21.73% performance gain, respectively.

6) *When K = 10*: It is interesting to find that in Fig. 11, the performance gain of our JULRA scheme is better than that in Fig. 7, nearly eight percent. That is because in the objective function, the numerical value of learning delay is much larger than the value of energy cost, which implies that the delay weight plays a leading role in global cost reduction. Similarly, in contrast to three benchmarks, Fig. 12-14 shows the superior performance advantage of JULRA algorithm under different parameter settings including bandwidth, θ, and data size.

7) We have added the curve of the new comparison algorithm **(JTOCRA)** in Fig. 4-6,8-10,12-14. As shown in the Fig. 4-6, we change the bandwidth, local accuracy and the data size of uploaded model. The results show that compared with **JTOCRA**, our algorithm can reach the gain of 27.04%, 23.73%, and 25.98%. As shown in the Fig. 8-10, compared with the comparison algorithm, **JULRA** can improve by 53.26%, 42.54%, and 43.5%, respectively. Similarly, in the Fig. 12-14, our algorithm can reach the gain of 12.55%, 11.07%, and 8.78%. Compared with **JTOCRA**, our algorithm not only optimizes the allocation of computing resources, but also takes the allocation of communication resources into account, as a result, the performance has been greatly improved. Furthermore, as shown in Fig.7, 11, **JTOCRA** does not adopt the alternate iterative optimization method, which leads to the unstable performance.

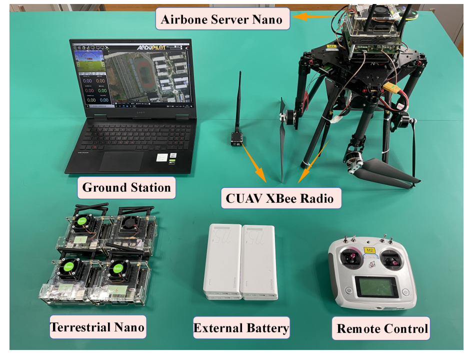


Fig. 15: Experimental equipments.

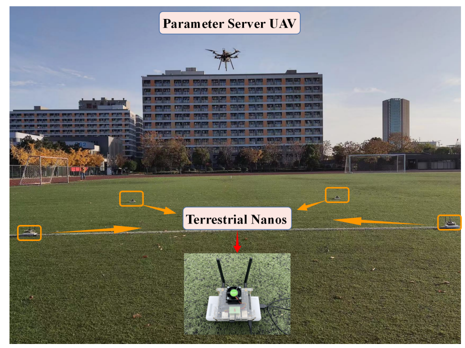


Fig. 16: Small-scale field experiments with one UAV and four terrestrial nodes on a football pitch.

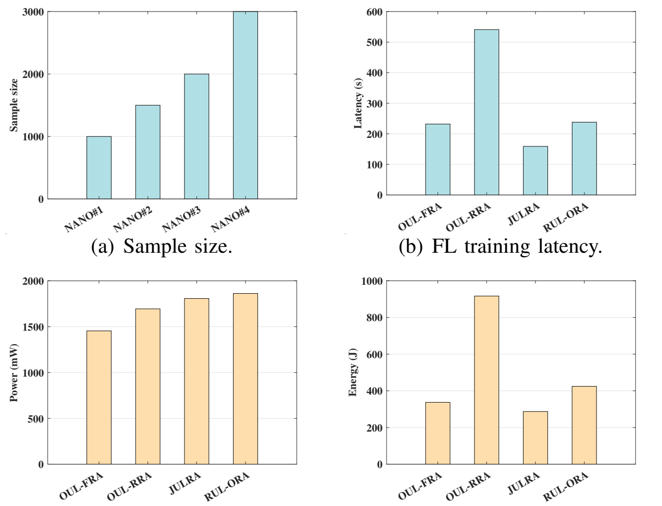
VII. Field Experiments

In this section we conduct field experiments by implementing an AGIFL system to further prove the superiority of our proposed algorithm JULRA. We use the FedAvg [56] for image classification application, and employ the proposed algorithm to optimize the UAV location and network resource allocation in this scenario. More than that, our algorithm is not only suitable for the recognition of handwritten digital images used in the actual experiment in this paper, which can be extended to a variety of other FL applications. Specifically, this algorithm can obtain the optimal position of the UAV and the optimal computing resource allocation of the user as long as the user's location, sample data volume, transmission rate and other parameters are input.

A. Settings

As is shown in Fig. 15, our testbed consists of one UAV mounted with a Jetson Nano, one UAV remote control, four terrestrial devices (Jetson Nano), one HP laptop, and one CUAV XBEE Radio. Terrestrial devices connect to the airborne nano's hot spot, and communicate with the UAV to implement the transfer of the model. The laptop of the terrestrial station is also connected to this LAN and reads actual FL training information from the airborne Nano via remote access software VNC. We can obtain the loss function and precision curve of FL remotely.

The algorithm proposed above is verified on the FL platform developed by ourselves. Specifically, we use Python tools to build a set of FL platform in Linux system, which is divided



(a) Sample size. (b) FL training latency. (c) Total power. (d) Total energy.

Fig. 17: Comparison of training effects of different schemes.

into two parts: client and server. The client can locally fetch the MNIST dataset from the Python library for local training. The specific process is as follows: firstly, the handwritten digital picture is converted into a matrix of 28*28 representing the gray value of pixels, which is used as the input value of the first-layer neural network. After the output result passes the activation function ReLU, it is input to the second-layer neural network, and the result passes the activation function softmax. Therefore, the local training model is composed of two layers of DNN network. We use mean squared error as loss the function to measure the output loss of training samples, and then optimize this loss function to find the minimum extreme value. In DNN, the optimal extremum of the loss function is solved step by step iteratively by mini batch gradient descent method. After the local training is completed, the local model is transmitted to the airborne Nano through the communication module for model aggregation. The airborne Nano finally broadcasts the global model to terrestrial devices.

Following [57]–[59], some hyperparameter settings are as follows: we set the learning rate to 1.0 and the decay rate of learning rate in each communication round is 0.999. We choose a training set of different numbers of images for the users and use the test and predict set of 10,000 pictures for evaluation. The size of training batch is 2, testing batch is 1024, and predicting batch is 1.

Experimental settings and baselines: As shown in Fig. 16, we consider a small-scale experimental scenario that one UAV hover in the sky to provide communication and computation services for four Jetson Nanos which are placed into a square as terrestrial training nodes to train the local MNIST data set. The number of local epochs and iterations before one round average are both 2. We adopt the stochastic gradient descent method to minimize the loss function value quickly, learning rate is set as 1 and decay rate of learning rate in each communication round is 0.999. Obviously, we also take the three comparison schemes in the simulation experiment as the benchmarks of the field experiment.

B. Results Analysis

As is shown in Fig. 17(a), the heterogeneity of users is reflected by different sample sizes of the four devices. In each round of local training, each device will train 1000, 1500, 2000, and 3000 data samples respectively. According to the calculation results of the proposed algorithm, we set the working frequency of each nano through nvpmodel.conf file to ensure the heterogeneity of computation power. Fig. 17(b) describes the time it takes for FL training to reach the accuracy threshold in each scheme and Fig. 17(c) shows the total average power of the nanos to complete training in each scenario. Actually, the total average power depends on the computational frequency assigned by the algorithm, thus we can measure it to reflect the CPU operating frequency. Although the power consumption of the proposed algorithm is not the minimum, it greatly reduces the training time. Thus, the total energy consumption of training is reduced, which is reflected in Fig. 17(d). Compared with the comparison algorithms, the energy consumption can be saved by 38.6% on average.

VIII. Discussion

Extension to optimization of learning parameters: In our problem, we increase or decrease the number of local computation rounds by changing the value of θ, since the size of θ determines the number of computed rounds. Nevertheless, θ could also be optimized for minimal energy consumption.

We observe that the solutions to SUB1 and SUB2 have no dependence on θ so that θ-related problem can be broken up into a third subproblem. Hence, the optimal f_u^*, X^*, Y^*, T_{com}^*, T_{cmp}^* can be used for resolution of SUB3, as will be shown in what follows.

$$\text{SUB3:} \quad \min_{\theta} \quad L(\theta)\left[E_{glob}\left(f_u^*, X^*, Y^*, \theta\right) + KT_{glob}\left(T_{cmp}^*, T_{com}^*, \theta\right)\right]$$
$$s.t. \qquad 0 \le \theta \le 1. \tag{32}$$

There exist a special solution θ^* that satisfies following equation:

$$\frac{1}{\log\left(e^{1/\theta^*}\theta^*\right)} = \Phi, \tag{33}$$

where

$$\Phi = \frac{\sum_{u=1}^{U} E_u^{cmp}\left(f_u^*\right) + KT_{cmp}^*}{\sum_{u=1}^{U}\left[E_u^{cmp}\left(f_u^*\right) + E_u^{com}\left(X^*, Y^*\right)\right] + K\left[T_{cmp}^* + T_{com}^*\right]}. \tag{34}$$

After obtaining the special solution of θ in the current situation (f_u^*, X^*, Y^*, T_{com}^*, T_{cmp}^*), we can substitute it into the calculation formula of local and global rounds to calculate the energy consumption. In this way, we can add the optimization of θ to the iterative optimization of the overall algorithm.

IX. Conclusion

We have studied how to jointly optimize the UAV location and network resource allocation in the AGIFL. The problem is formulated as an overall users' energy consumption minimization problem with the constraints of learning accuracy and training latency. Then we also have considered the tradeoff between energy consumption and latency as the optimization goal. Based on SCA and alternating optimization techniques, we have proposed a suboptimal algorithm that iteratively optimizes the UAV location and communication resource allocation, and the computation resource allocation. The convergence of the proposed algorithm is also theoretically proved. Finally, the proposed algorithm is deployed in a real air-ground integrated network and preliminarily verified by practical experiments. One promising future work would be thinking about UAVs collaboration in air-ground integrated network.

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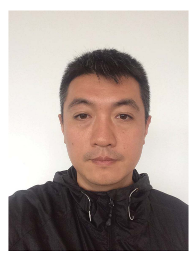

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