Air-Ground Integrated Low-Energy Federated Learning for Secure 6G Communications

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Abstract: Federated learning (FL) is a distributed machine learning approach that could provide secure 6G communications to preserve user privacy. In 6G communications, unmanned aerial vehicles (UAVs) are widely used as FL parameter servers to collect and broadcast related parameters due to the advantages of easy deployment and high flexibility. However, the challenge of limited energy restricts the popularization of UAV-enabled FL applications. An air-ground integrated low-energy federated learning framework is proposed, which minimizes the overall energy consumption of application communication while maintaining the quality of the FL model. Specifically, a hierarchical FL framework is proposed, where base stations (BSs) aggregate model parameters updated from their surrounding users separately and send the aggregated model parameters to the server, thereby reducing the energy consumption of communication. In addition, we optimize the deployment of UAVs through a deep Q-network approach to minimize their energy consumption for transmission as well as movement, thus improving the energy efficiency of the air-ground integrated system. The evaluation results show that our proposed method can reduce the system energy consumption while maintaining the accuracy of the FL model.

Keywords: federated learning; 6G communications; privacy preserving; secure communication

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1 Introduction

Even though 5G specifications are still being developed, 6G of mobile communications has already attracted great attention from both academia and industry[1]. Compared with 5G communications, 6G[2] will achieve faster speed, higher energy efficiency, wider coverage, etc. However, the wireless channel used for 6G is usually open, which gives wireless users the freedom to communicate but brings insecurity factors at the same time[3]. For example, the communication content can be easily eavesdropped or tampered with[4]. At the same time, data servicers collect large amounts of user information[5], which leads to frequent private data leaks. These factors pose a threat to the data security of 6G users.

Federated learning (FL) is a distributed machine learning framework[6]. In FL, participants train the model with local datasets and upload the obtained model parameters instead of the user privacy data to the parameter server, which aggregates the parameters to obtain the updated global model. With the distributed nature of FL, users can benefit from the global model while keeping the data in their own hands[7–8]. Therefore, utilizing FL at the 6G edge can protect user data, thus making users more willing to participate and fully utilize the value of their local dataset for the training of the global model[9]. In recent years, there have been some studies on integrating FL into wireless communication to improve its privacy and security[10–12], but they still face many realistic problems, e.g., low deployment flexibility in terrestrial communication networks and huge communication costs.

Unmanned aerial vehicles (UAVs) have the advantages of high flexibility and mobility which can give FL more possibilities. Specifically, it can easily provide air-ground integrated

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line-of-sight communication and effectively improve the transmission range of terahertz signals in 6G networks. As a result, the air-ground integrated network (AGIN) has gradually become the trend for 6G development, aiming to provide users with ubiquitous connectivity and seamless global coverage. In this paper, we consider the organic combination of the air-ground integrated network and FL in the 6G network. We utilize UAVs as parameter servers for FL to collect data from dispersed users, providing wider coverage for users while protecting the private data of 6G users. However, in 6G communications, the framework will face the challenge of limited energy for mobile users as well as for UAVs[13–14]. Specifically, users are reluctant to spend too much energy on the FL process, and the UAV does not have a constant source of energy to support multiple rounds of the FL model transfer and aggregation process. As a result, it may lead to delays in updating the global model. Therefore, to achieve a sustainable FL solution, the issue of energy efficiency in the system has to be considered. Existing solutions that optimize the energy efficiency of air-ground integrated FL[15] generally focus on UAV scheduling optimization and resource allocation, in which mobile devices need to communicate directly with the server, which may increase energy consumption.

In this paper, we propose air-ground integrated low-energy federated learning (AGILFL). Specifically, we use terrestrial base stations (BSs) as message middleware for users and the UAV parameter server to aggregate model parameter updates from their surrounding users separately and send the aggregated model parameters to the server, thus reducing the energy consumption of communication. In addition, deep Q-network (DQN) is adopted to optimize the deployment of UAVs, thus further reducing the overall energy consumption. To implement this procedure, we face the challenge that in some dynamic scenarios, the users' locations are not fixed[16], which would lead to a load on the BS when too many users move within a range of a certain BS. In such a case, users are required to send model parameters directly to the UAV server. To ensure that the 6G communication is always highly reliable, we consider predicting the BS load situation in advance and performing an emergency scheduling for the UAV. Our main contributions are summarized as follows:

1) We propose AGILFL, a framework that integrates AGIN and FL, which is devised to provide low-energy FL for secure 6G communications.

2) We use hierarchical aggregation to reduce the communication consumption efficiency of AGILFL by using BSs as middleware between users and the UAV parameter server significantly. The BS collects and aggregates the updated parameters of users within its coverage area, and sends the aggregated parameters to the UAV server for a second aggregation. With this approach, we can reduce the aggregation workload of the UAV server and the redundant communication between the UAV and users.

3) To ensure the reliability of 6G communication, we consider predicting the BS load situation in advance and urgently dispatching the UAV to cope with extreme situations, e.g., scenarios with a high density of smart devices such as weekend supermarket promotions and concerts, etc.

4) Extensive evaluation experiments are conducted on the MINIST dataset to demonstrate the effectiveness of our proposed method. Experiments have shown that our method can improve the system's overall energy efficiency while maintaining the model's accuracy, which is better than the comparison algorithm.

The remainder of this paper is organized as follows. Section 2 presents the current research work combining FL and wireless networks, with consideration of their energy consumption. Section 3 provides an overview of FL and presents the system model and problem formulation of this paper. DQN and our allocation strategy for the UAV are introduced in Section 4. Section 5 verifies the effectiveness of AGILFL through experiments. Finally, we summarize the contributions and experiments of this paper and present future work in Section 6.

2 Related Work

FL enables a large number of users to train a machine learning (ML) model together in a distributed manner, as a result, it provides a secure and effective training model for ubiquitous 6G intelligence. Recently, studies have explored how FL can be integrated into wireless networks while considering their energy consumption. TRAN et al.[17] proposed a wireless FL model that implemented a trade-off between FL learning time and user energy consumption. HAMER et al.[18] proposed another FL approach to reduce the costs of server-to-client and client-to-server communications by building an ensemble of pretrained base predictors. However, the above studies are limited to terrestrial networks.

ZENG et al.[19] first investigated the possibility of implementing FL on UAVs. They proposed an optimization issue by considering the problem of limited energy of UAVs and designing algorithms to optimize the convergence performance of FL, thus reducing the energy consumption of UAVs in the system. SHIRI et al.[20] proposed an algorithm that combined channel allocation as well as equipment scheduling optimization to reduce the communication among swarms of a large number of UAVs. PHAM et al.[21] proposed a sustainable federal learning framework that used UAVs to provide wireless power to energy-limited FL participants' devices while improving the energy efficiency of UAVs. However, none of the above methods consider integrating UAVs into terrestrial communication networks.

To make full use of UAVs, QU et al.[22] first proposed a conceptual framework of air-ground integrated federated learning (AGIFL) to give FL greater flexibility, thus enhancing the much-needed artificial intelligence in 6G communication networks. JING et al.[23] verified for the first time the feasibility of FL deployment between UAVs and the terrestrial network through a practical platform based on AGIFL. However, none of them solves the problem of the huge energy consumption of the system.

In summary, few extant studies has considered how to reduce the energy consumption of AGIFL. In addition, the above approaches require terminal nodes to communicate directly with the parameter server, which may increase transmission costs. Therefore, in this paper, we propose AGILFL, in which BSs are used as message middleware between users and the UAV parameter server in the FL system. We also use the DQN algorithm to optimize the location of the UAV and minimize the total energy consumption for its movement and transmission, so that AGIFL can effectively reduce the energy consumption of the system.

3 Preliminaries

3.1 Federated Learning

FL is a distributed ML approach that trains shared models in the context of protecting individual privacy. In FL, many participants train the global model in cooperation through a parameter server by aggregating model parameter updates[24]. Participants download the latest global model from the parameter server in each communication round, train the model on their own devices using local datasets, and then upload the updated parameters of the trained model to the server. The server then aggregates (e.g., using FedAvg[6]) the collected updates to get a new global model. In the process, users can benefit from the global model while keeping the data in their own hands.

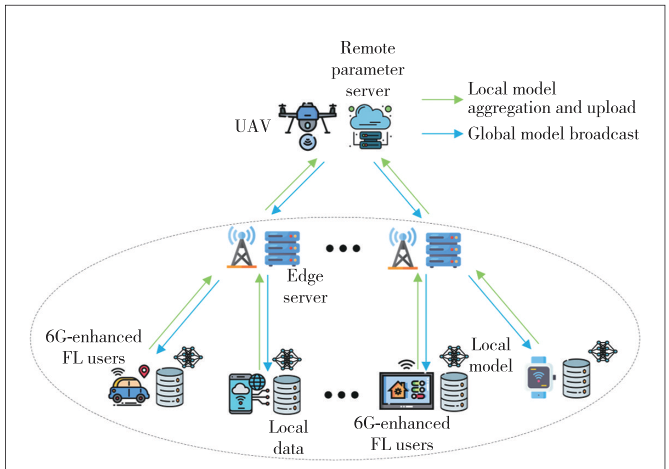
Let $[n] = \{1, \cdots, n\}$ represents the set of participants, the private dataset for each participant i is D_i for $i \in [n]$, and $D = D_1 \cup D_2 \cup \cdots \cup D_n$ is the complete training dataset. In the t-round of communication rounds, the participant i first downloads the latest global model w_t from the parameter server and then conducts local training. Then, the cumulative computational gradient $w_{t+1}^{(i)} - w_t$ is sent to the parameter server for the global model update, e.g., using FedAvg as in Eq. (1).

$$w_{t+1} = w_t + \frac{1}{n} \sum\nolimits_{i \in [n]} \left(w_{t+1}^{(i)} - w_t \right). \tag{1}$$

Note that the above process will be repeated until the global model reaches convergence.

3.2 System Model

In this paper, we consider an air-ground integrated 6G communication FL system that can protect the private security of 6G users, as shown in Fig. 1. It consists of a UAV server, m users (e. g., mobile users, Internet of things devices, and the UAV carrying data), and n BSs. These devices are randomly distributed in the air-ground domain. We define the set of users as $U = \{u_1, u_2, \cdots, u_m\}$, the UAV server as V, the n BSs as $B = \{b_1, \cdots, b_n\}$, and the model size of FL training is Ω.



▲Figure 1. Overview of AGILFL's framework

The user u_i is a participant who provides the model in the FL system. The user u_i receives the global model from the BS or the UAV, uses its own data for local training, and sends the trained model to the BS or the UAV. We define that if the user transmits the global model parameters to BS b_j, then $x_{ij} = 1$, $y_i = 0$; otherwise, the user passes the global model parameters to the UAV, and then $\sum_j x_{ij} = 0$, $y_i = 1$. The transmission rate[25] from user u_i to UAV V is expressed in Eq. (2).

$$R_i = b_i \log_2 \left(1 + \frac{g_i p_i}{b_k N_0} \right), \tag{2}$$

where b_i, g_i, p_i, and N_0 represent transmission bandwidth, channel gain, transmission power, and noise power density respectively. In order to ensure that Ω is transmitted within the upload time t_i, constraint $\Omega \leqslant R_i t_i$ needs to be satisfied. In this case, the energy transmitted to BS E_i^{u2b} and the energy transmitted to UAV E_i^{u2v} are expressed in Eq. (3).

$$E_i^{u2b} = E_i^{u2v} = t_i p_i. \tag{3}$$

In this paper, we use BS b_j as the message middleware between users and UAV V in the FL system. The BS set B is responsible for processing the global model parameters sent by surrounding users and then aggregating them. After aggregation, B will send the aggregation results of the global model parameters to UAV V. The transmission rate from BS b_j to UAV V is R_j. We assume that the transmission power of the BS is defined as p_j. Within the upload time t_j, the energy transferred between BS b_j and UAV is defined as E_j^{b2v}, which is the same as the calculation method of energy when the user transfers global model parameters.

When transferring global model parameters, we have the following restrictions. There is path loss during the transmission of global model parameters, that is, with the increase of transmission distance, the power gradually decreases. The corresponding relationship is expressed in Eq. (4).

$$P_r\left(P_s,l_s,l_r\right) = \varsigma \frac{P_s}{d^2\left(l_s,l_r\right)}, \tag{4}$$

where P_s and P_r represent the transmission power of the sender and the receiver respectively, l_s and l_r represent the location of the sender and the receiver respectively, $d(\cdot)$ is the distance function, and ς is the influence factor under different environments. We also limit the minimum received power of all devices to $p_{\min}$.

UAV V acts as the global model manager of the FL system. UAV V is responsible for automatically sending or receiving global model parameters from surrounding users or base stations, aggregating local training models, and updating global model parameters. We assume that UAV V has a fixed height H and moves only in the horizontal direction. Suppose the position of the UAV is $l = (x, y)$ and the position after moving is $l' = (x', y')$. According to Ref. [26], the energy of UAV V movement is expressed in Eq. (5).

$$E_s(l,l') = P_H \frac{d(l,l')}{v_h}, \tag{5}$$

where v_h is the velocity in the horizontal direction and P_H represents the power consumed by the energy of horizontal movement. P_H can be expressed in Eq. (6).

$$P_H = P_p + P_I, \tag{6}$$

where P_p is the energy consumption power to overcome its own skin friction from drag and its calculation formula is shown as follows.

$$P_P = \frac{1}{2}\rho C_D S v_h^3 + \frac{\pi}{4} M\rho c_b C_D w^3 \beta^4 \left(1 + 3\left(\frac{v_h}{w}\right)^2\right), \tag{7}$$

where C_D is the drag coefficient, c_b is the rotor chord, S is the front area of the UAV, w is the angular velocity, β is the rotor disk radius, and ρ denotes the fluid density of air. P_I is the energy consumed by the wing to redirect air to generate lift to compensate for the weight of the aircraft, and the specific formula is expressed as follows.

$$P_I = G\sqrt{\frac{\lambda - v_h^2}{2}}, \tag{8}$$

where $\lambda = \sqrt{v_h^4 + \left(\frac{G}{\pi\rho\beta^2}\right)^2}$ and G is the gravity of the UAV.

3.3 Problem Formulation

Our goal is to optimize the UAV position to minimize the energy consumed by the entire FL system while protecting the private security of 6G users. Because parameter aggregation and global model update are necessary tasks of the FL system, the energy of parameter aggregation and global model update is not considered when the energy is minimized. Aiming to optimize the energy of the AGILFL system, we will focus on the optimization problems as in Eq. (9).

$$\min \sum_{i=1}^{m}\left(\sum_j x_{ij}E_i^{u2b} + y_i E_i^{u2v}\right) + \sum_{j=1}^{n} E_j^{b2v} + E_s(l,l'), \tag{9}$$

$$\text{s.t.} \quad x_i \in \{0,1\}, y_i \in \{0,1\}, \tag{9a}$$

$$\sum_j x_{ij} + y_i = 1, \forall i, \tag{9b}$$

$$t_i R_i \geqslant \Omega, \forall i, \tag{9c}$$

$$t_j R_j \geqslant \Omega, \forall j, \tag{9d}$$

$$0 < l' < l_{\max}, \tag{9e}$$

$$P_r\left(p_i,l_i,l_j\right) \geqslant x_{ij}p_{\min}, \forall i,j, \tag{9f}$$

$$P_r\left(p_i,l_i,l'\right) \geqslant y_i p_{\min}, \forall i, \tag{9g}$$

$$P_r\left(p_j,l_j,l'\right) \geqslant p_{\min}, \forall j, \tag{9h}$$

where x_{ij} represents whether user u_i sends local model parameters to BS b_j, y_i indicates whether user u_i sends local model parameters to UAV V, E_j^{b2v} denotes the energy required for BS b_j to transmit to UAV V, l_i represents the location of user u_i, l_j means the location of BS b_j, l indicates the initial location of UAV V, l' shows the location of UAV V after it moves, and $l_{\max}$ represents the maximum movement range of UAV V.

In the problem, Constraint (9a) limits the range of values of x_i and y_i; Constraint (9b) denotes that the user sends the global model parameters to either the BS or the UAV; Constraints (9c) and (9d) limit the time and rate of transmission parameters to ensure that the model size of FL training Ω is transmitted within upload time t_i or t_j; Constraint (9e) limits the range of movement of the UAV; Constraints (9f), (9g) and (9h) indicate that the power of the signal received by all the devices must be higher than the minimum power.

4 Allocation Strategy of UAV

In this section, we detail the strategy for UAV deployment. The algorithm we propose in this paper consists of two separate processes: model training and model application. We first train the model by the DQN algorithm to obtain the output Q-network model. Then we continuously update the environmental state of UAV V and put it into the Q-network to make the optimal action decision for the current state.

4.1 Deep Q-Network

The DQN algorithm is a reinforcement learning method combining deep learning and Q-learning, which has both the powerful feature-aware capability of deep learning and the trial-and-error learning advantage of reinforcement learning. In the DQN algorithm, $Q(s, a)$ represents the value assessment of action a taken by the agent under state s, and the agent selects the action with the highest Q value to perform to obtain a higher reward. In the Q-learning method, the Q-table is used to store the corresponding Q values of the actions in each state. However, the disadvantage of Q-learning is that it takes up a lot of memory space in a more complex state space and the calculation process is also complicated. Compared with traditional Q-learning, DQN can compute the Q-table of the current state in a huge state space as in Eq. (10).

$$Q_\theta(s, a) = Q(s, a), \tag{10}$$

where $Q_\theta(s, a)$ is a neural network with parameter θ, which is called Q-network, and its output result is an estimate of Q.

DQN proposes two improvements to overcome the problems of unstable learning targets and excessive correlation of consecutive samples: 1) experience replay; 2) target Q-network. In this context, the goal of the training process is to minimize the value of the loss function, and the loss function is the mean-square error between the target Q value and the Q value, which is expressed as in Eq. (11).

$$D(\theta_i) = E_{s,a,r,s'}[(Y_i - Q(s, a|\theta_i))^2], \tag{11}$$

where θ_i is the parameter of Q-network; Y_i is the target Q value. The formula is expressed as in Eq. (12).

$$Y_i = \gamma \max_{a'} Q(s', a'|\theta_i') + r, \tag{12}$$

where θ_i' is the parameter of the target Q-network. By fixing the Q value, the stability of the Q value can be guaranteed for a period of training time.

Algorithm 1. DQN model training for the UAV parameter server

Input: Distribution of BSs and users, state space and action space of UAV, learning rate α, and discount rate γ.

Output: Q-network $Q(s, a)$

1. Initialize action space A, state space S, learning rate α, discount rate γ, and replay buffer M.
2. Initialize Q-network parameters θ and target Q-network parameters θ'
3. **for** I in max_epoch **do**
4. Let the users move.
5. Calculate the energy consumption for the new system.
6. Initialize s as the previous state of the UAV parameter server;
7. Decide which action to be taken, using the greedy algorithm
8. Take action a, calculate reward r_t, and calculate the next state s' of the UAV parameter server;
9. Store interaction information (s, a, r_t, s') in experience pool M
10. Random batch sampling of batch samples $(s_i, a_i, r_{sum,i}, s_i')$ from M
11. $Q_i = \begin{cases} r_{\mathrm{sum},i}, & \text{if } s' \text{ is terminal} \\ r_{\mathrm{sum},i} + \gamma \max Q_{\theta'}(s', a') \end{cases}$
12. $\sum_{i=1}^{\mathrm{batch}} (Q_i - Q_\theta(s, a))$ as the loss function
13. Update state s of the UAV parameter server;
14. Update the Q-network $\theta' \leftarrow \theta$;
15. **end for**
16. output Q-network $Q(s, a)$

4.2 Allocation Strategy

We use the DQN algorithm to determine the 3D position of UAV V, thereby minimizing its communication and movement costs. The DQN algorithm predicts the value of the agent's behavior through a deep neural network, thus allowing the agent to obtain a higher return in subsequent decisions. Specifically, in our method, UAV V needs to decide on the appropriate working position based on the large number of distributed BSs around, which is a more complex task scenario. Due to many environmental elements in complex scenes in reinforcement learning, not only will it increase the training cycle and slow down the convergence of the model, but also bring the problem of sparse rewards, which causes the model to work improperly. Aiming to solve the potential sparse reward problem, we propose an energy field model to abstract various parameters in the environment and simplify the UAV state representation, thus speeding up the model convergence and avoiding the sparse reward problem. The energy field is modeled as in Eq. (13).

$$E = \sum_{i=1}^{n} \frac{\varepsilon L_i D_i U_{ri}}{d_i}, \tag{13}$$

where ε is the weight parameter used to control the order of magnitude of energy; d_i is the Euclidean distance between V and b_i; L_i is the load situation of b_i; D_i is the number of data that b_i needs to transmit to V; $U_{\mathrm{r}i}$ is the number of users connected to b_i. The formula calculates the energy situation of the UAV's location, and the total energy is the sum of the sub-energy of all BSs. The higher value of E means more users and base station loads near the point and more need for UAV V to serve. This energy field model can guide UAV V to fly to a more suitable working area and also generate the corresponding decision for the high load situation in the area.

The state space of UAV V is composed of spatial coordinates, current energy consumption power, user coverage, and BS coverage. For the action space of UAV V, we have defined six possible actions: forward, backward, left, right, up, and down. The six actions are denoted as $a_1, a_2, \cdots, a_6$ respectively. If the energy consumption of the transmission of UAV V is higher than the previous energy consumption, UAV V needs to change its location. In this case, the agent must make behavioral decisions based on the state of the environment in which it is located. UAV V takes action a_j based on decisions and transfers to a new state s', while receiving a reward or punishment according to the reward rule to optimize the behavioral decision of the intelligence.

The purpose of this section is to determine suitable UAV locations to reduce the energy loss of the mission and also to perform emergency scheduling for possible regional loads (such as large sporting events, supermarket events, concerts, etc.). Combined with the energy field model proposed above, this paper proposes the reward function as in Eq. (14).

$$r_t = \Delta E + \omega \frac{D_{\text{sum}}}{E^{u2b} + E^{u2v} + E_s(l,l')}, \tag{14}$$

where ΔE is the change in energy at the location of the UAV. When the energy increases, which means that UAV V flies to a more suitable space position, it will be rewarded and the opposite will be punished; ω is the weight parameter that controls the order of magnitude of the reward; D_{sum} is the total amount of data transferred by the system.

Algorithm 2. DQN algorithm for 3D placement of the UAV parameter server

Input: Distribution of BSs and users, Q-network $Q(s, a)$
Output: Optimum position of the UAV parameter server
1. E_{th} is the calculated energy consumption for communication among UAV, users and BSs and UAV movement.
2. **while** the system is running **do**
3. Let the users move.
4. Calculate the energy consumption for the new system.
5. **if** (the energy consumption > E_{th}) **then**
6. **for** step in max_step **do**
7. Initialize s as the previous state of the UAV parameter server;
8. input s into $Q(s, a)$ to get the best decision a_t
9. Take action a_t, calculate the next state s of the UAV parameter server;
10. Update state s of the UAV parameter server;
11. **end for**
12. **else**
13. There is no need to move the UAV parameter server
14. **end if**
15: **end while**

The algorithm we propose in this paper consists of two separate processes: model training and model application. The training is performed in a simulated environment, the specific details are shown in Algorithm 1, where the target Q-network and Q-network are first initialized to predict the Q value of the previous step of the behavior and the current Q value, respectively. In each training epoch, the environmental status of UAV V is first updated, such as pedestrian movement, BS model aggregation, BS load, user model training, system energy consumption, etc. Then current state s of the UAV is determined according to the external state, and is input into the Q-network to get the Q values of all actions. Action a is selected for execution based on the greedy method, UAV state s is changed to s' after the execution of the action, and then reward information r_t is obtained. Then quaternion (s, a, r_t, s') is stored in replay buffer M and batch samples are taken from M to train the Q-network. After that, the Q-network is updated with the target Q-network and finally, the Q-network model is output. Although the process of training UAV V requires some energy, the energy consumption of the proposed DQN method is much smaller and even negligible compared with the traditional greedy scheme[27].

Algorithm 2 shows the process of applying our DQN model, which continuously updates the environment state during the system operation and then calculates the required energy consumption of the system. If the energy consumption is greater than the threshold value, it means that UAV V is required to move, and in this process, UAV V constantly updates its state and inputs the state into the Q-network. UAV V makes action decisions based on the Q-network output and then updates the environment state until the step reaches the max.

5 Experiment and Evaluation

In this section, we evaluate the performance of our proposed algorithm. Firstly, we introduce the default settings, datasets, benchmarks, and metrics in detail. Secondly, we evaluate the utility of AGILFL on the overall energy. Finally, we evaluate the utility of AGILFL on average resource utilization and model accuracy.

5.1 Default Settings

We consider that the FL system is composed of users, BSs, and the UAV. In order to reduce the space for parameter search, we set up 100 users, 5 BSs, and 1 UAV. Each trainable device trains locally using the lenet-5 model. The maximum number of iterations of the global model is set to 200, which is optimized by the mini batch stochastic gradient descent (SGD) optimizer, and the minimum mini batch is 50. During model training, the learning rate is set to 0.03, and the loss function uses cross entropy. The maximum epoch to train the UAV mobile model is set to 200, and the maximum epoch to train the FL model is set to 40.

5.2 Dataset

We use a well-known image classification data set named MINIST, which is composed of 70 000 grayscale pictures of 28 × 28 pixels and each picture corresponds to a number from 0 to 9. In the MINIST dataset, 55 000 pictures are used as the training set, 5 000 pictures as the verification set, and 10 000 pictures as the test set. In our experiment, we evenly place 55 000 pictures among 50 users, and each device contains 1 000 pictures. The parameter UAV places 10 000 pictures as a test set for model training.

5.3 Benchmarks

Firstly, in order to evaluate the advantage of the AGILFL system, we choose the FL system without BSs and the multi-hop transmission (MHT) with BSs as the benchmark. They all have the same number of users. Secondly, in assessing the advantage of AGILFL UAV training, we use DQN training and random movement as benchmarks. Finally, to prove that AGILFL can achieve precision without degradation, we use FL and ML as benchmarks. AGILFL, ML and FL use the same number of data for training, and AGILFL and FL have the same number of users.

5.4 Metrics

We adopt the total energy consumption as an evaluation metric, that is, the energy consumed by the whole system in energy transmission and UAV movement during each training of FL. In assessing the UAV training performance of AGILFL, we use the reward function during training as a metric. Finally, we also use accuracy as a metric to evaluate the impact on the FL model accuracy.

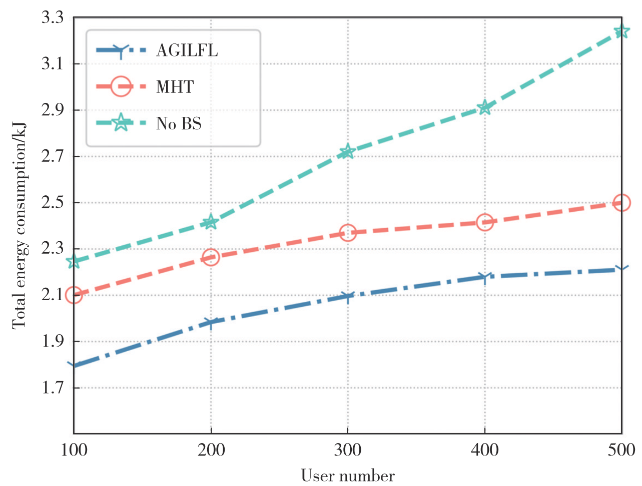
5.5 Results Analysis

We uniformly generate five BSs in the 200×200×200 air-ground integrated area. To evaluate the impact of user growth on total energy consumption, we randomly generate 100 to 500 users in the region and calculate the total energy consumption. Fig. 2 shows the energy comparison of AGILFL and other benchmarks in the AGIFL system. AGILFL can reduce the total energy consumption by using the BSs as caching devices and by controlling the UAV to find the best position. This experiment shows that AGILFL reduces the overall energy by 11.9% and 18.4% respectively, compared with the other two algorithms.

Our UAV, which is trained to complete the DQN intensive learning network, is placed in the AGIFL system. The UAV starts from a random point and moves in the FL system according to the movement strategy. Fig. 3 shows the trajectory of the UAV in AGILFL. Each step of the UAV's movement maximizes the reward function. Every step the UAV moves, it moves toward the BS and is close to the central BS. We can also see that UAVs will not be far away from users or base stations to avoid wasting energy.

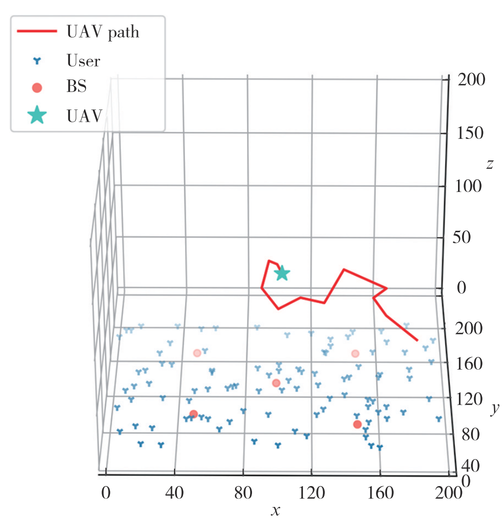
In default settings, we evaluate the performance of the UAV movement strategy. Fig. 4 shows the performance of our optimization algorithm. In the AGIFL system, we use AGILFL, DQN algorithm and random movement respectively to compare their performance in the reward function. AGIFL adopts DQN with an empirical replay algorithm. AGILFL can learn the optimal parameters faster than the DQN algorithm, and experience replay can make the training more stable. Compared with the other two algorithms, AGILFL improves the reward function by 59.5% and 13.5%, respectively.

In default settings, we evaluate the accuracy change of the training model using users' data in different scenarios. Fig. 5 shows the accuracy performance of AGILFL, FL, and ML. AGILFL can reduce total energy consumption without causing



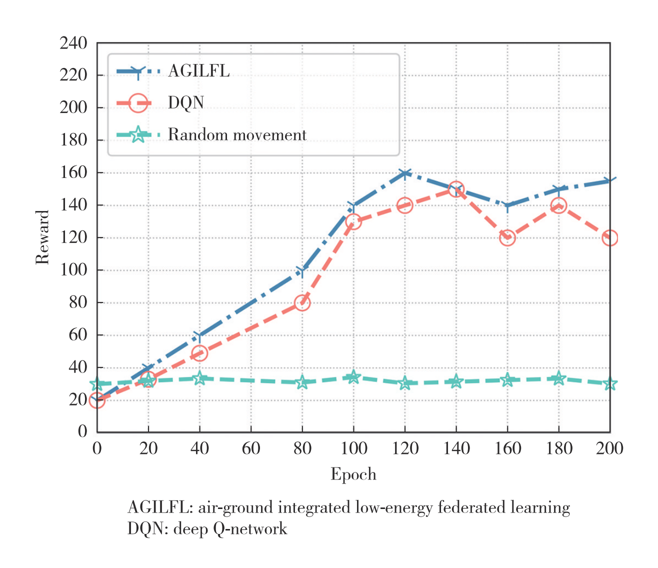
AGIFL: air-ground integrated federated learning MHT: multi-hop transmission
BS: base station

▲Figure 2. Performance of total energy consumption

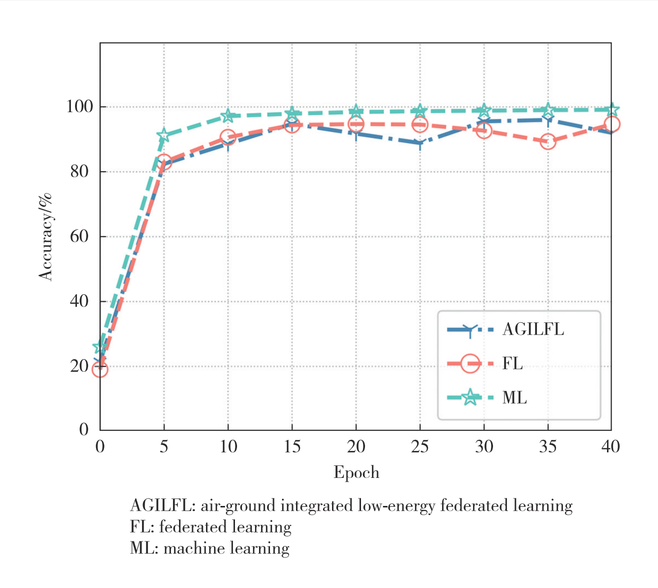


BS: base station UAV: unmanned aerial vehicle

▲Figure 3. Movement trajectory of UAV



▲Figure 4. Performance of reward



▲Figure 5. Performance of accuracy

serious accuracy degradation. Therefore, we propose AGILFL as a friendly, privacy-safe, and low-energy FL framework.

6 Conclusions and Future Work

In this paper, we investigate the problem of how to improve the energy efficiency of AGIFL and propose the AGILFL framework which can guarantee the private security of 6G users. Specifically, in AGILFL, we use a hierarchical aggregation method to improve the energy efficiency of communication by using BSs as middleware between users and the UAV parameter server. At the same time, to ensure that the 6G communication is always in a highly reliable state, we predict the overloaded BSs in advance and make emergency scheduling of the UAV. We use the DQN algorithm to optimize the position of the UAV to minimize the overall energy consumption for UAV movement as well as communication. Finally, through simulation experiments, our proposed method is proven to be real and effective. Compared with the baseline, AGILFL reduces the overall energy by 11.9% and 18.4%, respectively, and improves the reward function by 59.5% and 13.5%, respectively.

The way to reduce the energy consumption of local computing for 6G users in the AGILFL framework is not explored in this paper. In the mechanism we designed, we should also consider a replacement option when the UAV is almost out of power. Our future work will focus on addressing the above issues and exploring the possibility of applying our solutions on a large scale in real-world environments.

References

[1] DANG S P, AMIN O, SHIHADA B, et al. What should 6G Be? [J]. Nature electronics, 2020, 3(1): 20 – 29. DOI: 10.1038/s41928-019-0355-6
[2] GUI G, LIU M, TANG F X, et al. 6G: opening new horizons for integration of comfort, security, and intelligence [J]. IEEE wireless communications, 2020, 27(5): 126 – 132. DOI: 10.1109/MWC.001.1900516
[3] WANG C G, RAHMAN A. Quantum-enabled 6G wireless networks: opportunities and challenges [J]. IEEE wireless communications, 2022, 29(1): 58 – 69. DOI: 10.1109/MWC.006.00340
[4] WANG M H, ZHU T Q, ZHANG T, et al. Security and privacy in 6G networks: new areas and new challenges [J]. Digital communications and networks, 2020, 6(3): 281 – 291. DOI: 10.1016/j.dcan.2020.07.003
[5] NGUYEN V L, LIN P C, CHENG B C, et al. Security and privacy for 6G: a survey on prospective technologies and challenges [J]. IEEE communications surveys & tutorials, 2021, 23(4): 2384 – 2428. DOI: 10.1109/COMST.2021.3108618
[6] MCMAHAN B, MOORE E, RAMAGE D, et al. Communication-efficient learning of deep networks from decentralized data [EB/OL]. (2016-02-17)[2022-09-01]. https://arxiv.org/abs/1602.05629v2
[7] YANG Q, LIU Y, CHEN T J, et al. Federated machine learning [J]. ACM transactions on intelligent systems and technology, 2019, 10(2): 1 – 19. DOI: 10.1145/3298981
[8] LI T, SAHU A K, TALWALKAR A, et al. Federated learning: Challenges, methods, and future directions [J]. IEEE signal processing magazine, 2020, 37(3): 50 – 60. DOI: 10.1109/MSP.2020.2975749
[9] YANG Z H, CHEN M Z, WONG K K, et al. Federated learning for 6G: Applications, challenges, and opportunities [J]. Engineering, 2022, 8: 33 – 41. DOI: 10.1016/j.eng.2021.12.002
[10] LIU Y, PENG J L, KANG J W, et al. A secure federated learning framework for 5G networks [J]. IEEE wireless communications, 2020, 27(4): 24 – 31. DOI: 10.1109/MWC.01.1900525
[11] CHEN M Z, GÜNDÜZ D, HUANG K B, et al. Distributed learning in wireless networks: recent progress and future challenges [J]. IEEE journal on selected areas in communications, 2021, 39(12): 3579 – 3605. DOI: 10.1109/JSAC.2021.3118346
[12] YANG M, WANG X M, QIAN H, et al. An improved federated learning algorithm for privacy preserving in cybertwin-driven 6G system [J]. IEEE transactions on industrial informatics, 2022, 18(10): 6733 – 6742. DOI: 10.1109/TII.2022.3149516
[13] YUAN Z W, TANG H, WANG P F, et al. Human-UAV collaborative task scheduling for 360° video generating in intelligent transportation [C]//The 8th

International Conference on Virtual Reality (ICVR). IEEE, 2022: 407 – 414. DOI: 10.1109/ICVR55215.2022.9847919

[14] WANG P F, YAN Z H, HAN G J, et al. A2E2: Aerial-assisted energy-efficient edge sensing in intelligent public transportation systems [J]. Journal of systems architecture, 2022, 129: 102617. DOI: 10.1016/j.sysarc.2022.102617

[15] JING Y Q, QU Y B, DONG C, et al. Joint UAV location and resource allocation for air-ground integrated federated learning [C]//IEEE Global Communications Conference. IEEE, 2021: 1 – 6. DOI: 10.1109/GLOBECOM46510.2021.9685150

[16] WANG P F, PAN Y Z, LIN C, et al. Graph optimized data offloading for crowd-AI hybrid urban tracking in intelligent transportation systems [J]. IEEE transactions on intelligent transportation systems, 2022: Early Access. DOI: 10.1109/TITS.2022.3141885

[17] TRAN N H, BAO W, ZOMAYA A, et al. Federated learning over wireless networks: optimization model design and analysis [C]//IEEE Conference on Computer Communications. IEEE, 2019: 1387 – 1395. DOI: 10.1109/INFOCOM.2019.8737464

[18] HAMER J, MOHRI M, SURESH A T, et al. FedBoost: communication-efficient algorithms for federated learning [C]//International Conference on Machine Learning. ICML, 2020: 3973 – 3983

[19] ZENG T C, SEMIARI O, MOZAFFARI M, et al. Federated learning in the sky: Joint power allocation and scheduling with UAV swarms [C]//IEEE International Conference on Communications. IEEE, 2020: 1 – 6. DOI: 10.1109/ICC40277.2020.9148776

[20] SHIRI H, PARK J, BENNIS M. Communication-efficient massive UAV online path control: Federated learning meets mean-field game theory [J]. IEEE transactions on communications, 2020, 68(11): 6840 – 6857. DOI: 10.1109/TCOMM.2020.3017281

[21] PHAM Q V, ZENG M, RUBY R, et al. UAV communications for sustainable federated learning [J]. IEEE transactions on vehicular technology, 2021, 70(4): 3944 – 3948. DOI: 10.1109/TVT.2021.3065084

[22] QU Y B, DONG C, ZHENG J C, et al. Empowering edge intelligence by air-ground integrated federated learning [J]. IEEE network, 2021, 35(5): 34 – 41. DOI: 10.1109/MNET.111.2100044

[23] JING Y Q, QU Y B, DONG C, et al. Joint UAV location and resource allocation for air-ground integrated federated learning [C]//IEEE Global Communications Conference. IEEE, 2021: 1 – 6. DOI: 10.1109/GLOBECOM46510.2021.9685150

[24] WANG P F, ZHAO Y A, OBAIDAT M S, et al. Blockchain-enhanced federated learning market with social Internet of Things [J]. IEEE journal on selected areas in communications, 2022, 40(12): 3405 – 3421. DOI: 10.1109/JSAC.2022.3213314

[25] PHAM Q V, LE M, HUYNH-THE T, et al. Energy-efficient federated learning over UAV-enabled wireless powered communications [J]. IEEE transactions on vehicular technology, 2022, 71(5): 4977 – 4990. DOI: 10.1109/TVT.2022.3150004

[26] LU J X, WAN S, CHEN X H, et al. Beyond empirical models: pattern formation driven placement of UAV base stations [J]. IEEE transactions on wireless communications, 2018, 17(6): 3641 – 3655. DOI: 10.1109/TWC.2018.2812167

[27] LIU L S, XIONG K, LU Y, et al. Age-constrained energy minimization in UAV-assisted wireless powered sensor networks: a DQN-based approach [C]//IEEE Conference on Computer Communications Workshops. IEEE, 2021: 1 – 2. DOI: 10.1109/INFOCOMWKSHPS51825.2021.9484487

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