Joint Resource Allocation and User Scheduling Scheme for Federated Learning

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***Abstract*—This paper investigates the impact of communication factors on the convergence performance of federated learning (FL) in wireless networks. Considering the limited communication resources in wireless networks, it is difficult to schedule all users to participate in a comprehensive training and the convergence performance of training model relies much on the user scheduling scheme. To minimize the maximum update delay of user training, we propose a joint resource allocation and user scheduling scheme in this paper. Particularly, the user communication delay and user training results are jointly considered to dynamically schedule users and allocate communication resources. Simulation results show that the convergence time can be reduced by 41.6% compared with the random scheduling allocation scheme.**

I. INTRODUCTION

Traditional centralized machine learning (ML) algorithms require a server in the data center to collect data set from all users. However, it will bring a lot of communication overhead when delivers the user's data set and which may infringe the user's privacy. In order to train the model without collecting the user's data set, a distributed machine learning method called federated learning (FL) is proposed [1]. FL enables distributed users to collaborate with each other for training and protect user privacy by only sharing model parameters. In addition, by transmitting the slight-weight model parameters instead of the user's data set, it can effectively reduce the communication overhead. However, due to limited communication resources, we may only be able to select a portion of users to participate in the distributed training when deploying FL in a wireless network [2]. Besides, the instability of the channel in the wireless network degrades communication quality. Thus, the communication delay caused by this for model parameters transmission cannot be ignored and the high communication delay will greatly reduce the convergence performance of FL. Especially for some time-sensitive application scenarios, such as autonomous driving and VR which generally holds restrictive constraint of the time for updating model [3]–[5]. Therefore, it is significant to consider optimizing resource allocation and user scheduling in the training process under the premise of ensuring the accuracy of the model to improve the convergence performance of FL [6].

Recently, some related works have studied the deployment of FL in wireless networks. To better adapt dynamic bandwidth and unreliable networks when performing FL. A joint learning architecture for cloud-edge-clients called Cecilia is proposed with an new algorithm called adaptive compressed federated learning (ACFL). ACFL adopts an information sharing method different from traditional FL, which can adaptively compress the shared information according to network conditions [7]. Besides, a problem of joint power and resource allocation of ultra-reliable low-latency communication (URLLC) is investigated in [8]. A FL protocol called FedCS is proposed in [9], which collects the required information in the pre-resource request step and assists the subsequent participant selection process. In addition, Hybrid-FL protocol has been further extended from FedCS, which alleviates the problem that the data sets of each participant are not i.i.d. by constructing an approximately i.i.d. data set [10]. By using reinforcement learning, an asynchronous FL scheme based on hybrid blockchain is proposed in [11] and the deep reinforcement learning is adopted to select participating nodes. In [12], the deep Q-learning is adopted to optimize the resource allocation for the model training process which is better adapt to the complex and changeable environment. A FEDL algorithm is proposed in [13] which can handle heterogeneous data among users and the issues of resource allocation from the perspective of optimization is also discussed. To optimize the convergence rate of the training process, a user scheduling and resource allocation scheme is proposed in [14]. However, only resource allocation is optimized, and the user scheduling mechanism doesn't consider the actual spatial location of the user. Similarly, the user scheduling and resource allocation are considered in [15] and the loss function of FL is optimized. However, this scheme sacrifices the speed of convergence to obtain higher model accuracy.

In this paper, a novel user scheduling and resource allocation scheme is proposed and an optimization problem is formulated to minimize the maximum update delay. We investigate the user's contribution to the model convergence through the norm of gradient calculated by the user, and the corresponding penalty term is included in our objective function. Particularly,

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the user's communication rate and the user's contribution are simultaneously considered. Specifically, we convert the primal optimization problem into a mixed integer linear programming problem. During the training process, the branch and bound algorithm is used to achieve a dynamic user scheduling and resource allocation. The scheme is flexible and can be applied to a variety of wireless communication systems with limited communication resources, such as IoT networks and wireless cellular networks. Finally, the simulations are conduct to evaluate the convergence performance of FL and the results show that our proposed user scheduling and resource allocation scheme can significantly improve the model convergence speed while guaranteeing the accuracy of the model.

II. System Model

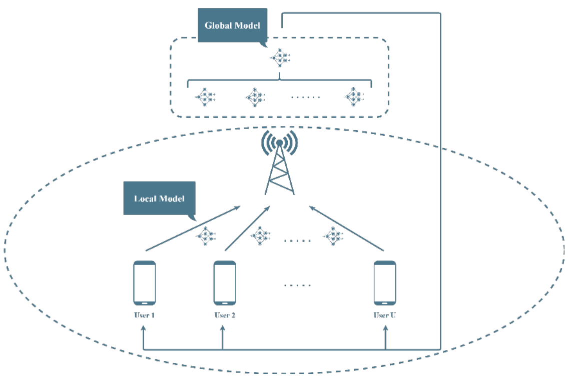

Fig. 1. Joint resource allocation and user scheduling scheme for FL.

Fig. 1 shows the scenario of FL in wireless network, which contains a base station (BS) and a users set $\mathcal{U}$ with U users. Particularly, all the users and the BS can cooperate with each other to perform FL to train a model. Each user holds a data set containing D_i training samples and each sample is consisted of a network input $\boldsymbol{x}_{id}$ and its corresponding label $\boldsymbol{y}_{id}$. The data sets held by each user are assumed to be independent of each other with following the identical distribution. Then the training process of FL can be regarded as solving the following optimization problem

$$\min_{\boldsymbol{w}_\mu^g} \frac{1}{D} \sum_{i=1}^{U} \sum_{d=1}^{D_i} l(\boldsymbol{w}_\mu^g, \boldsymbol{x}_{id}, \boldsymbol{y}_{id}), \tag{1}$$

where $D = \sum_{i=1}^{U} D_i$ denotes the total number of data samples held by all users, $\boldsymbol{w}_\mu^g$ represents the global model in the training process after server aggregation, and $l(\boldsymbol{w}_\mu^g, \boldsymbol{x}_{id}, \boldsymbol{y}_{id})$ represents the loss function used to measure the difference between the model output and the label during the training process.

A. Federated Learning Model

Defining the local model obtained by any user i in any round of iterative μ training as $\boldsymbol{w}_{i,\mu}^l$, the aggregated global model can be represented as

$$\boldsymbol{w}_\mu^g = \sum_{i=1}^{U} \boldsymbol{w}_{i,\mu}^l \frac{s_{i,\mu} D_i}{\sum_{j=1}^{U} s_{j,\mu} D_j}, \tag{2}$$

where $\frac{s_{i,\mu} D_i}{\sum_{j=1}^{U} s_{j,\mu} D_j}$ is the weight of local model aggregation, $\boldsymbol{w}_{i,\mu}^l$ is the local model and which depends on the specific training algorithm adopted by users, and $\boldsymbol{s}_\mu = [s_{1,\mu}; \cdots; s_{U,\mu}]$ denotes the user's scheduling vector, $s_{i,\mu} \in \{0, 1\}$. If $s_{i,\mu} = 1$, it means that the user i is scheduled in the μ^{th} iteration, and the user will send the trained model $\boldsymbol{w}_{i,\mu}^l$ to the BS, and $s_{i,\mu} = 0$ means that the user i is not scheduled.

When the gradient descent is used to update the global model $\boldsymbol{w}_\mu^g$, the update process of the local model can be written as

$$\boldsymbol{w}_{i,\mu}^l = \boldsymbol{w}_{\mu-1}^g - \frac{\lambda}{D_i} \sum_{d=1}^{D_i} \nabla l(\boldsymbol{w}_{\mu-1}^g, \boldsymbol{x}_{id}, \boldsymbol{y}_{id}), \tag{3}$$

where λ is the learning rate, and $\nabla l(\boldsymbol{w}_{\mu-1}^g, \boldsymbol{x}_{id}, \boldsymbol{y}_{id})$ is the gradient of the loss function $l(\boldsymbol{w}_{\mu-1}^g, \boldsymbol{x}_{id}, \boldsymbol{y}_{id})$ with respect to $\boldsymbol{w}_{\mu-1}^g$.

B. Uplink Model

In the uplink, OFDMA is adopted for multiple users to access. Assuming that the total available resource block (RB) at the BS is R, and at most each user can only be allocated by one RB. Therefore, the uplink rate of the user i in the μ^{th} iteration can be given as

$$v_i(\boldsymbol{a}_{i,\mu}) = \sum_{n=1}^{R} a_{in,\mu} B \log_2 \left(1 + \frac{P h_{i,\mu}}{I_{n,\mu} + B N_0} \right), \tag{4}$$

where P is the transmit power of user, $\boldsymbol{a}_{i,\mu} = [a_{i1,\mu}; \cdots, a_{iR,\mu}]$ is the resource allocation vector of the i^{th} user in the μ^{th} iteration, i.e., $a_{in,\mu} \in \{0, 1\}$, $h_{i,\mu}$ is the channel gain from the user to BS, B is the bandwidth of a RB, N_0 is the noise power spectral density, and $I_{n,\mu}$ is the interference between users with using the same RB in other cells.

C. Maximum Update Delay Definition

Since local model $\boldsymbol{w}_{i,\mu}^l$ and global model $\boldsymbol{w}_\mu^g$ have the same number of parameters, the local model $\boldsymbol{w}_{i,\mu}^l$ and global model $\boldsymbol{w}_\mu^g$ have the same size. By denoting the number of bits that the user needs to transmit when sending $\boldsymbol{w}_{i,\mu}^l$ to the BS as the size of the local model Z, the uplink communication delay of user i is

$$t_i(\boldsymbol{a}_{i,\mu}) = \frac{Z}{v_i(\boldsymbol{a}_{i,\mu})}, \tag{5}$$

In the μ^{th} iteration, the time required for the user and the BS to obtain an updated model is

$$\tau_\mu(\boldsymbol{s}_\mu, \boldsymbol{A}_\mu) = \max_{i \in \mathcal{U}} \left\{ s_{i,\mu} (t_i(\boldsymbol{a}_{i,\mu}) + T_{comp}^i) \right\}, \tag{6}$$

where $\boldsymbol{A}_\mu = [\boldsymbol{a}_{1,\mu}, \cdots, \boldsymbol{a}_{U,\mu}]$, T_{comp}^i is the time spent on user training. Particularly, $s_{i,\mu} = 0$ means that the user i will not send the local model trained by himself to the BS in the μ^{th} iteration. Therefore, the user i will not cause any delay in this iteration. When $s_{i,\mu} = 1$, the user i will send the local model trained by himself to the BS, which will cause delay $t_i(\boldsymbol{a}_{i,\mu}) + T_{comp}^i$. Therefore, the above formula represents the maximum delay among all scheduled users.

III. Problem Formulation

To minimize the maximum update delay, we jointly optimize the user scheduling and resource allocation, which can be formulated as

$$\min_{\boldsymbol{s}_\mu,\boldsymbol{A}_\mu} \ \tau_\mu(\boldsymbol{s}_\mu,\boldsymbol{A}_\mu)=\min_{\boldsymbol{s}_\mu,\boldsymbol{A}_\mu}\max_{i\in\mathcal{U}}\left(s_{i,\mu}t_i(\boldsymbol{a}_{i,\mu})\right) \tag{7}$$

$$\text{s.t.}\quad a_{in,\mu}\in\{0,1\},\quad \forall i\in\mathcal{U}, n=1,\cdots,R, \tag{7a}$$

$$s_{i,\mu}\in\{0,1\},\quad \forall i\in\mathcal{U}, \tag{7b}$$

$$\sum_{i\in\mathcal{U}} a_{in,\mu}\le 1,\quad \forall n=1,\cdots,R, \tag{7c}$$

$$\sum_{n=1}^{R} a_{in,\mu}=s_{i,\mu},\quad \forall i\in\mathcal{U}, \tag{7d}$$

$$\sum_{i=1}^{U} s_{i,\mu}=\zeta, \tag{7e}$$

where (7a) and (7b) are 0-1 constraints of the optimization variables; (7c) ensures that a RB can only be consumed by one user at most; (7d) ensures only one RB can be allocated to the scheduled user; (7e) specifies ζ users will be scheduled in each iteration. Since we do not consider the heterogeneity of the computing power of each user, we remove the term of the calculation time in the objective function.

To solve the problem in (7), we introduce a new variable $m=\max_{i\in\mathcal{U}}\left(s_{i,\mu}t_i(\boldsymbol{a}_{i,\mu})\right)$ and reformulate (7) as

$$\min_{\boldsymbol{s}_\mu,\boldsymbol{A}_\mu} \ m \tag{8}$$

$$\text{s.t.}\quad (7\text{a}),(7\text{b}),(7\text{c}),(7\text{d}),(7\text{e}), \tag{8a}$$

$$m\ge s_{i,\mu}t_i(\boldsymbol{a}_{i,\mu}),\quad \forall i\in\mathcal{U}, \tag{8b}$$

Since the constraint (8b) is nonlinear, we first convert it to a linear constraint. In the μ^{th} iteration, the uplink delay for user i to communicate using RB n is $t_{in,\mu}=\frac{Z}{B\log_2\left(1+\frac{Ph_{i,\mu}}{I_{n,\mu}+BN_0}\right)}$, so the uplink delay of user i can be represented as $t_i(\boldsymbol{a}_{i,\mu})=\sum_{n=1}^{R}a_{in,\mu}t_{in,\mu}$. Thus constraint (8b) can be written as $m\ge s_{i,\mu}\sum_{n=1}^{R}a_{in,\mu}t_{in,\mu}$.

Since $s_{i,\mu}\in\{0,1\}$, we discuss it in two situations. 1) If $s_{i,\mu}=0$, we can get $\sum_{n=1}^{R}a_{in,\mu}=0$ according to the constraint (7d). Since $a_{in,\mu}\in\{0,1\}$, we can derive that $a_{in,\mu}=0$, $n=1,\cdots,R$. So $\sum_{n=1}^{R}a_{in,\mu}t_{in,\mu}=0=s_{i,\mu}\sum_{n=1}^{R}a_{in,\mu}t_{in,\mu}$. Thus we can get $m\ge s_{i,\mu}\sum_{n=1}^{R}a_{in,\mu}t_{in,\mu}\iff m\ge\sum_{n=1}^{R}a_{in,\mu}t_{in,\mu}$. 2) If $s_{i,\mu}=1$, we can get $\sum_{n=1}^{R}a_{in,\mu}t_{in,\mu}=s_{i,\mu}\sum_{n=1}^{R}a_{in,\mu}t_{in,\mu}$. So we can derive that $m\ge s_{i,\mu}\sum_{n=1}^{R}a_{in,\mu}t_{in,\mu}\iff m\ge\sum_{n=1}^{R}a_{in,\mu}t_{in,\mu}$. Thus, the constraint (8b) can be reformulated as $m\ge\sum_{n=1}^{R}a_{in,\mu}t_{in,\mu}$, which is a linear constraint.

Considering that the factors that affect the convergence performance of FL also include the contribution of the user's training results to the global model, we further incorporate this factor into the consideration of the optimization problem. From the update process formula (3) of the local model, we can notice that the global model $\boldsymbol{w}_\mu^g$ will change $\frac{\lambda}{D_i}\sum_{d=1}^{D_i}\nabla l(\boldsymbol{w}_\mu^g,\boldsymbol{x}_{id},\boldsymbol{y}_{id})$ every time the user trains and the global model after each round of aggregation is

$$\begin{aligned}\boldsymbol{w}_{\mu+1}^g&=\sum_{i=1}^{U}\frac{D_i}{D}\left(\boldsymbol{w}_\mu^g-\frac{\lambda}{D_i}\sum_{d=1}^{D_i}\nabla l(\boldsymbol{w}_\mu^g,\boldsymbol{x}_{id},\boldsymbol{y}_{id})\right)\\&=\boldsymbol{w}_\mu^g-\frac{\lambda}{K}\sum_{i=1}^{U}\sum_{d=1}^{D_i}\nabla l(\boldsymbol{w}_\mu^g,\boldsymbol{x}_{id},\boldsymbol{y}_{id}),\end{aligned} \tag{9}$$

it can be seen from (9) that the contribution of the user's training results to the convergence of the global model increases as the gradient calculated by the user increases. Therefore we are more inclined to schedule users with larger gradients.

In order to consider the gradients calculated by users when scheduling, we define the gradient calculated by user i in the μ^{th} iteration as $grad_{i,\mu}=\frac{1}{D_i}\sum_{d=1}^{D_i}\nabla l(\boldsymbol{w}_\mu^g,\boldsymbol{x}_{id},\boldsymbol{y}_{id})$. By substituting the penalty item $\kappa\sum_{i\in\mathcal{U}}\|grad_{i,\mu}\|s_{i,\mu}$ into (8), (8) can be represented as

$$\min_{\boldsymbol{s}_\mu,\boldsymbol{A}_\mu} \ m-\kappa\sum_{i\in\mathcal{U}}\|grad_{i,\mu}\|s_{i,\mu} \tag{10}$$

$$\text{s.t.}\quad (7\text{a}),(7\text{b}),(7\text{c}),(7\text{d}),(7\text{e}), \tag{10a}$$

$$m\ge\sum_{n=1}^{R}a_{in,\mu}t_{in,\mu},\quad \forall i\in\mathcal{U}. \tag{10b}$$

We can find that (10) is a mixed integer linear programming problem and then a branch and bound method is used in each iteration to dynamically schedule users and allocate communication resources. The complete system workflow is detailed as shown in Algorithm 1.

Algorithm 1 FL framework proposed

1: Initialization: global model $\boldsymbol{w}_\mu^g$.
2: BS broadcasts the initialized $\boldsymbol{w}_\mu^g$ to all users.
3: **repeat**
4: The users calculate the norm of gradient $\|grad_{i,\mu}\|$ based on the global model received;
5: The users send the norm $\|grad_{i,\mu}\|$ to the BS;
6: The BS determines $\boldsymbol{s}_\mu,\boldsymbol{A}_\mu$ by solving the problem (10);
7: The BS schedules users and allocates RBs based on $\boldsymbol{s}_\mu,\boldsymbol{A}_\mu$;
8: The scheduled users conduct training and send the training results $\boldsymbol{w}_{i,\mu}^l$ to the BS;
9: BS aggregates the received training results from scheduled users to update the global model $\boldsymbol{w}_\mu^g$, and sends the updated $\boldsymbol{w}_\mu^g$ to all users;
10: **until** The model converges or reaches the maximum number of iterations.

IV. Simulation Result

In this section, we consider a wireless communication cell with the radius of $r=100$ m, where a BS is located in the center of the cell and 20 users are randomly and evenly distributed in this cell and the moving direction is randomly selected. The path loss factor of channel gain from mobile user to BS is 2. The transmit power of each user is set to 30 dBm and the bandwidth of a RB in the uplink is 50 MHz. The size of the model transmitted between the user and the BS is 3 Mbits. The total number of RBs that can be allocated by the BS is 10. The entire FL system is implemented by the Tensorflow and sockets. Particularly, the BS cooperates with users to train a classification model for handwritten digit recognition on the MNIST data set. The model contains a Flatten layer with an input dimension of (28, 28); a fully connected layer containing 128 neurons, which is activated by the Relu function; a layer with a scale of 0.2 Dropout layer; and a fully connected output layer containing 10 neurons, which is activated by the Softmax function. The data set held by each user contains 3000 samples and the BS schedules 10 users to participate in a round of Global Model update. In addition, the benchmark is to randomly determine the user scheduling and resource allocation.

A. Comparison of Scheduled Locations

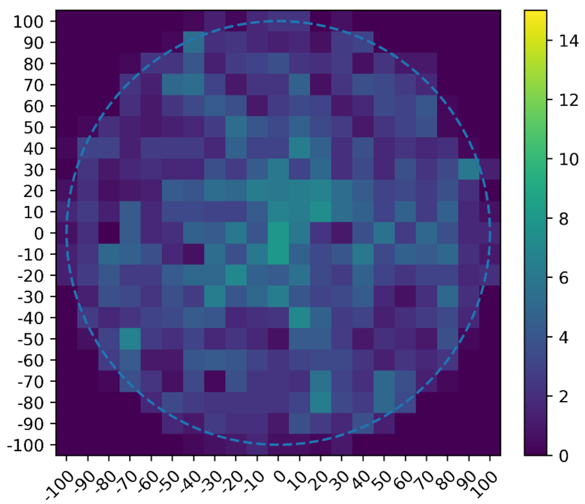

Fig. 2. Heat map of the user's scheduled location in the random scheme.

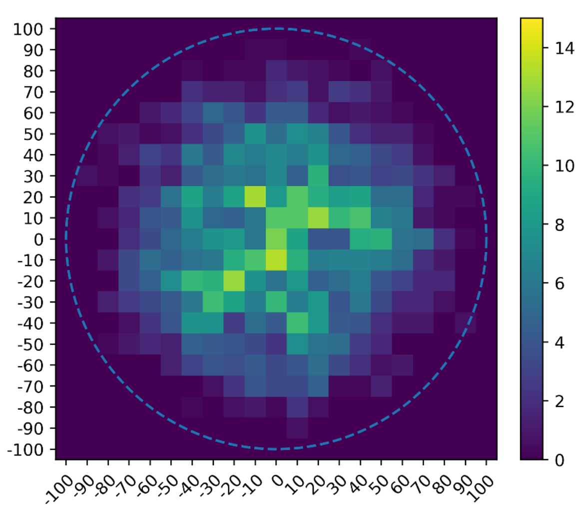

Fig. 3. Heat map of the user's scheduled location in our scheme.

Fig. 2 and Fig. 3 show the heat map of the user's scheduled location in the random scheme and our scheme respectively. We can see that there is an obvious hot spot in the center of the cell in Fig. 3 and not in Fig. 2. This is because the difference of user channel condition impacts the scheduling result by our proposed scheme and the hot areas show the users with better channel condition are scheduled frequently. Moreover, our scheme is more inclined to schedule users with higher communication rate or the users closer to BS are preferred.

B. Comparison of Model Convergence

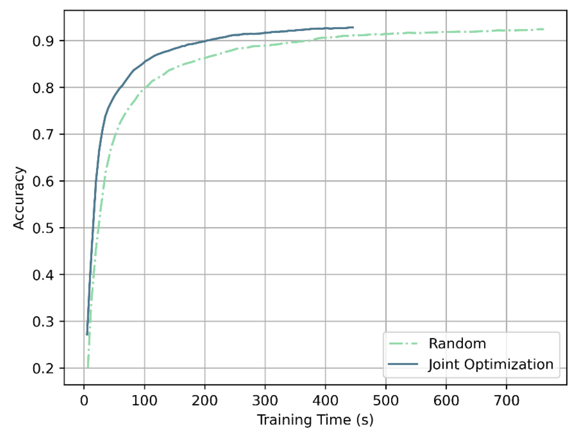

Fig. 4. Comparison of the convergence speed (accuracy).

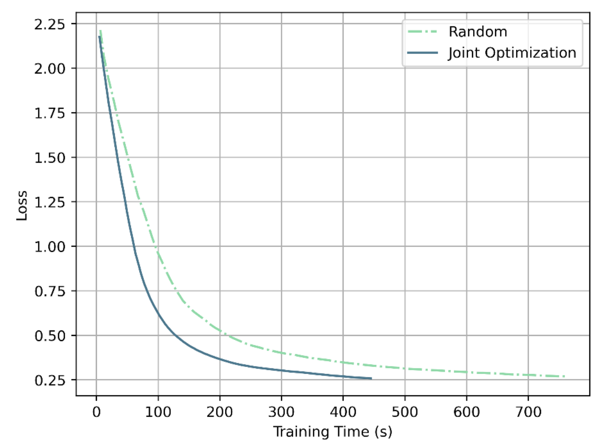

Fig. 5. Comparison of the convergence speed (loss).

We evaluate the convergence speed from the perspective of validation accuracy and loss in Fig. 4 and Fig. 5, respectively. It can be seen that the accuracy of the two schemes increases as the time and the loss of that decreases. After 400 seconds, the curves gradually stabilized which indicating that the FL algorithm is gradually converging. The convergence speed of our proposed scheme is significantly faster. This is mainly because two reasons, 1) we schedule users who have larger norm of gradient, which indicating larger step size in every iteration and therefore fewer iterations; 2) we schedule users closer to BS, which indicating lower communication delay and therefore lower iteration time. By jointly optimizing the user scheduling and resource allocation, the convergence time can be reduced by 41.6%.

C. Comparison of Uplink Delay

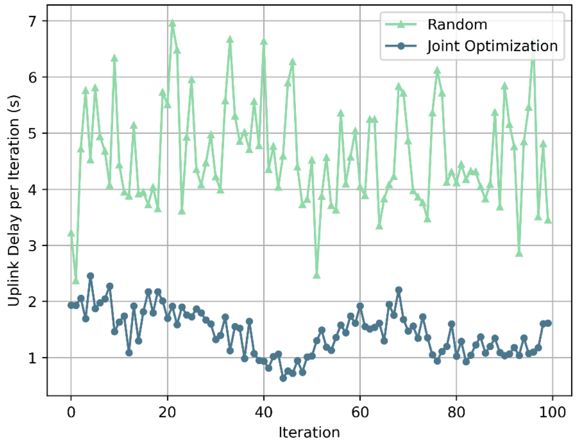

Fig. 6. Comparison of the maximum uplink delay.

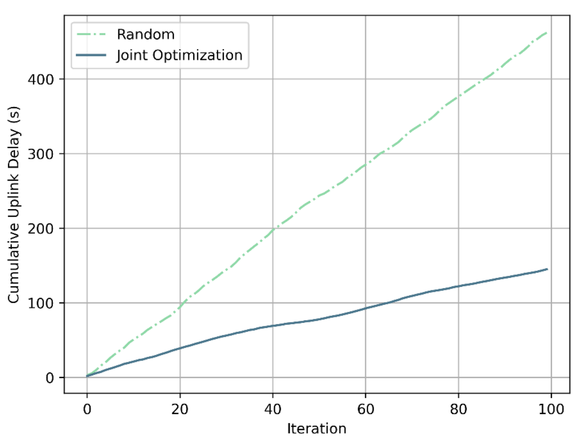

Fig. 7. Comparison of the cumulative uplink delay.

Fig. 6 and Fig. 7 show the comparison of maximum uplink communication delay among all users during the training process from different perspective. We can see that our scheme out performs random scheme with lower uplink delay and smaller jitter. This is because we schedule users closer to BS, which indicates higher SINR we can get and therefore higher communication rate. Besides, RBs with lower inference power are allocated to users farther from the BS to reduce the maximum uplink delay. In addition, by jointly optimizing the user scheduling and resource allocation, the uplink delay can be reduced by 68.6% compared with random scheme.

V. Conclusion

This paper considers a FL system deployed in a wireless network and the user scheduling and resource allocation are jointly optimized to improve the convergence speed. Particularly, a nonlinear problem for minimizing the maximum update delay is formulated and which is further converted into a mixed integer linear programming problem. Then, by the branch and bound algorithm, an optimal user scheduling and resource allocation scheme is achieved. The results show that our proposed scheme can significantly decrease the convergence time by 41.6% and the uplink communication time is decreased by 68.6%.

References

[1] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-Efficient Learning of Deep Networks from Decentralized Data," in *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics*, ser. Proceedings of Machine Learning Research, A. Singh and J. Zhu, Eds., vol. 54. Fort Lauderdale, FL, USA: PMLR, Apr. 2017, pp. 1273–1282.

[2] X. Shen, J. Gao, W. Wu, K. Lyu, M. Li, W. Zhuang, X. Li, and J. Rao, "Ai-assisted network-slicing based next-generation wireless networks," *IEEE Open Journal of Veh. Technol.*, vol. 1, pp. 45–66, Jan. 2020.

[3] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," *IEEE Commun. Surv. & Tut.*, vol. 19, no. 4, pp. 2322–2358, Aug. 2017.

[4] G. Ananthanarayanan, P. Bahl, P. Bodík, K. Chintalapudi, M. Philipose, L. Ravindranath, and S. Sinha, "Real-time video analytics: The killer app for edge computing," *Comput.*, vol. 50, no. 10, pp. 58–67, Oct. 2017.

[5] J. Zhao, X. Sun, Q. Li, and X. Ma, "Edge caching and computation management for real-time internet of vehicles: An online and distributed approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 4, pp. 2183–2197, 2021.

[6] N. Cheng, F. Lyu, W. Quan, C. Zhou, H. He, W. Shi, and X. Shen, "Space/aerial-assisted computing offloading for iot applications: A learning-based approach," *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 5, pp. 1117–1129, 2019.

[7] X. Zhang, X. Zhu, J. Wang, H. Yan, H. Chen, and W. Bao, "Federated learning with adaptive communication compression under dynamic bandwidth and unreliable networks," *Inform. Sci.*, vol. 540, pp. 242–262, May 2020.

[8] S. Samarakoon, M. Bennis, W. Saad, and M. Debbah, "Distributed federated learning for ultra-reliable low-latency vehicular communications," *IEEE Trans. on Commun.*, vol. 68, no. 2, pp. 1146–1159, Nov. 2020.

[9] T. Nishio and R. Yonetani, "Client selection for federated learning with heterogeneous resources in mobile edge," in *ICC 2019 - 2019 IEEE Int. Conf. on Commun. (ICC)*, Jul. 2019, pp. 1–7.

[10] N. Yoshida, T. Nishio, M. Morikura, K. Yamamoto, and R. Yonetani, "Hybrid-fl for wireless networks: Cooperative learning mechanism using non-iid data," in *ICC 2020 - 2020 IEEE Int. Conf. on Commun. (ICC)*, Jul. 2020, pp. 1–7.

[11] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Blockchain empowered asynchronous federated learning for secure data sharing in internet of vehicles," *IEEE Trans. on Veh. Technol.*, vol. 69, no. 4, pp. 4298–4311, Feb. 2020.

[12] T. T. Anh, N. C. Luong, D. Niyato, D. I. Kim, and L.-C. Wang, "Efficient training management for mobile crowd-machine learning: A deep reinforcement learning approach," *IEEE Wireless Commun. Letters*, vol. 8, no. 5, pp. 1345–1348, May 2019.

[13] C. T. Dinh, N. H. Tran, M. N. H. Nguyen, C. S. Hong, W. Bao, A. Y. Zomaya, and V. Gramoli, "Federated learning over wireless networks: Convergence analysis and resource allocation," *IEEE/ACM Trans. on Netw.*, vol. 29, no. 1, pp. 398–409, Nov. 2021.

[14] M. Chen, H. V. Poor, W. Saad, and S. Cui, "Convergence time optimization for federated learning over wireless networks," *IEEE Trans. on Wireless Commun.*, vol. 20, no. 4, pp. 2457–2471, Dec. 2021.

[15] M. Chen, Z. Yang, W. Saad, C. Yin, H. V. Poor, and S. Cui, "A joint learning and communications framework for federated learning over wireless networks," *IEEE Trans. on Wireless Commun.*, vol. 20, no. 1, pp. 269–283, Oct. 2021.