A Ring Topology-based Optimization Approach for Federated Learning in D2D Wireless Networks

Zimu Xu, Wei Tian, Yingxin Liu, Wanjun Ning, and Jingjin Wu, Member, IEEE

Abstract—Federated learning (FL) is an emerging technique aiming at improving communication efficiency in distributed networks, where many clients often request to transmit their calculated parameters to an FL server simultaneously. However, in wireless networks, the above mechanism may lead to prolonged transmission time due to unreliable wireless transmission and limited bandwidth. This paper proposes an optimization approach to minimize the uplink transmission time for FL in wireless networks. The proposed approach consists of two major elements: namely a Ring All-reduce architecture that integrates D2D wireless communications to facilitate the FL process and a modified Ant Colony Optimization algorithm to identify the optimal composition of the Ring All-reduce architecture. Numerical results show that our proposed approach can significantly reduce the transmission time compared to large-scale transmissions where user devices are densely distributed, the reduction in transmission time compared to baseline policies can be over 50%.

Index Terms—Federated learning, Ring All-reduce, Communication efficiency, Ant Colony Optimization Algorithm

I. INTRODUCTION

Thanks to the rapid growth in the number and popularity of user devices (UDs) capable of collecting and processing data, artificial intelligence (AI) techniques are more commonly applied in many aspects of daily life. Federated learning (FL) [1] is a class of distributed machine learning techniques that keeps all actual training data on local UDIs while only exchanging specific model parameters with each other. By decoupling the training process to local UDIs, FL enables collaborative learning of AI models without storing data in the server. As a result, the privacy of UDIs is better preserved than traditional centralized mechanisms. This advantage in turns motivates more users to participate in FL and leads to a more accurate global model.

A base station (BS) can function as an FL server in wireless networks, while the UDIs are considered clients. One obstacle for wider application of FL in wireless networks is that it requires multiple rounds of model parameters exchange between the FL server and clients until the FL process converge to an accurate global model [2]. However, due to the nature of wireless communication, the reliability and quality of connections will be significantly deteriorated with a large number of simultaneous transmissions.

Specifically, in every training round, the BS updates the global model by aggregating the local parameters sent by UDIs generated from their respective local models. Then, the BS broadcasts the updated global model to the UDIs [3]. Therefore, most UDIs participating in the training round will transmit within a short period for synchronization purposes. In this paper, we focus on the uplink transmission with the orthogonal frequency division multiple access (OFDMA) scheme, where the average transmission time in a training round is approximately proportional to the number of UDIs participating in the round given the assumption that every participating UD transmits the same amount of data to the BS. As a result, the latency would become unacceptable for urban scenarios where a single BS needs to serve a high density of UDIs for the FL process.

There are two straightforward directions to tackle the above-mentioned problem in existing studies. One direction, referred as gradient compression, aims to reduce the data size of transmitted parameters to improve communication efficiency [4]. Another direction is to reduce the frequency of communication by restricting the number of training rounds such that fewer communications between the BS and UDIs would be required [5]. However, both approaches would sacrifice the accuracy of the final model to some extent.

It has been investigated in more recent mainstream studies that D2D communications can be an attractive alternative to improve the communication efficiency for FL in wireless networks, as it can effectively avoid the communication bottleneck problem when compared to the traditional server-client (star) topology. Most approaches aiming at maximizing the efficiency of wireless D2D communications involve optimal resource allocation or power control [6]. One study that focused on the training algorithm is [7], which proposed to implement the decentralized stochastic gradient descent (DSGD) in an FL D2D wireless network. However, the astringency of DSGD requires more communication rounds to achieve the same level of performance as in conventional algorithms such as FedAvg.

We take a different perspective in this paper, by proposing an optimization approach that incorporates the Ring All-reduce (RAR) architecture [8] into FL in D2D wireless networks to minimize the uplink transmission time. Unlike the approaches in [7], the RAR-based FL keeps the classical training algorithms and does not incur extra computation time. The RAR is based on a logical ring topology where each UD only transmits to and from its next neighbors.

In RAR, the slowest connection determines the transmission time for each training round. In wireless networks, with all other things equal, the transmission rate is negatively correlated with the distance due to path loss and fading. Hence, our focus is to find an
appropriate Hamilton circuit given the distribution of UDs, such that UDs can transmit with closer neighbors and shorten the average transmission time.

A major challenge is that, finding the Hamilton circuit itself is an NP-hard problem. Inspired by the classical Travelling Salesman Problem (TSP) that can identify the shortest Hamilton circuit, we propose a modified Ant Colony Optimization (ACO) algorithm to obtain the optimal topology of our RAR, where each ant calculates the transmission time corresponding to its explored circuit and updates the pheromone.

Our main contributions are summarized as follows,

- We incorporate the RAR architecture by D2D communications in OFDMA wireless networks to address a potential bottleneck problem caused by simultaneous transmissions that may hinder the large-scale application of FL in wireless networks.
- We propose an ACO-based algorithm to overcome the computational complexity in identifying the optimal composition of the RAR, which in turns gives the shortest transmission time amongst all possible ring topologies.
- We demonstrate by simulation results that our proposed method significantly outperforms existing FL approaches in terms of transmission efficiency. Particularly, in a scenario where the UDs are densely distributed, the reduction in transmission time can be over 50%. Also, within the RAR framework, our proposed modified ACO achieves a further 15% improvement over the baseline.

II. PRELIMINARIES AND SYSTEM MODEL

A. Federated learning model

We consider that a set of $V = \{1, \ldots, K\}$ of $K$ UDs are participating in an FL training round. Each UD $k \in V$ has its own dataset $D_k$ with size $|D_k|$. Let $x_i$ represent the input vector and $y_i$ represent the output vector of $i$th data sample of a UD. We denote $w$ as the model parameters, thus the loss function of each data sample $D$ has its own dataset participating in an FL training round. Each UD $k$ initializes their local model based on the global model updated at the $(j-1)$th round, that is

$$w_k^{(j,0)} = w_{global}^{(j-1)}.$$  \hfill (5)

Then, each UD takes $\tau$ stochastic gradient descent (SGD) iterations to train its local model before calculating the global model of round $j$. At the $t$-th iteration in the same round, UD $k \in V$ first executes a local update step by SGD based on its dataset $D_k$ is,

$$w_k^{(j,t)} = w_k^{(j,t-1)} - \eta^{(t)} \bigtriangledown w^{j,t},$$  \hfill (6)

where $\eta^{(t)}$ is the learning rate, $\bigtriangledown F_k(w^{(j,t)})$ is the estimated gradient obtained from a mini-batch dataset $D_t^{(j)} \subseteq D_t$, and it can be written as,

$$\bigtriangledown F_k(w_k^{(j,t)}) = \frac{1}{|D_t^{(j)}|} \sum_{i \in D_t^{(j)}} \bigtriangledown f_i(w_k^{(j,t)}).$$  \hfill (7)

Then, after all UDs finish $\tau$ SGD iterations, the global model of round $j$ can be updated by

$$w^{(j)}_{global} = \sum_{k \in V} \frac{|D_k|}{|D|} w_k^{(j,H)}.$$  \hfill (8)

We consider the uplink of an OFDMA wireless network. When FL is implemented in such networks with a traditional star topology, UDs synchronously send their locally trained parameters to the BS at the end of each training round. The BS then updates the global model as in (8) before broadcasting the updated model to UDs. The UDs in turns initialize their local model by (5) at the beginning of the next round.

B. The Ring All-reduce scheme

We now introduce the RAR and show how it implements (5) and (6) in a different way. In RAR, UDs form a logical ring where each UD has two neighbors. A UD will only send data to the “next” neighbor in the clockwise direction and receive data from the “last” neighbor in the counter-clockwise direction.

Two key steps to implement the RAR mechanism are scatter-reduce and all-gather. Assume that there are $N$ UDs, each UD divides their local model parameters (i.e. $w_k^{(j,L)}$ in (6)) into $N$ chunks. If we choose an arbitrary UD as UD 0, and number the other UDs in ascending order according to the transmission direction, then the two steps can be described as follows,

- **Scatter-reduce**: in the $n$th round, UD $k$ sends $[(k-n) \mod N]$-th chunk of its weighted local model to its next neighbor, and receives and its last neighbor’s $[(k-n-1) \mod N]$-th chunk. Each UD then accumulates the received chunk.
- **All-gather**: in each round, each UD receives an accumulated chunk from its last neighbor and

The FedAvg algorithm [10] has been commonly applied in solving (4) and computing the optimal $w^*$. At the beginning of the $j$th training round, each UD $k$ initializes their local model based on the global model updated at the $(j-1)$th round, that is

$$w_k^{(j,0)} = w_{global}^{(j-1)}.$$  \hfill (5)

Therefore, the global loss function is

$$F(w) = \sum_{k \in V} \frac{|D_k|}{|D|} F_k(w),$$  \hfill (3)

where $|D| = \sum_{k=1}^{K} |D_k|$.

The objective of FL is to identify the optimal model parameter $w^*$ such that

$$w^* = \arg \min_w F(w).$$  \hfill (4)
overwrites the chunk, then sends the chunk to its next neighbor in the next round.

The entire implementation consists of \( N - 1 \) steps of \textit{scatter-reduce} followed by \( N - 1 \) steps of \textit{all-gather}. An example of the process is shown in Fig. [1]. By the end of the process, all UDs obtain a global model accumulated by all local models, thus achieving \([4]\) and \([5]\).

C. Communication model

For uplink OFDMA systems, it is reasonable to consider the Signal-to-Noise Ratio (SNR) to measure the quality of transmissions. Consider a transmission from UD \( i \) to UD \( j \) (we consider the BS as a special UD with index 0 hereafter), the uplink SNR is \( \text{SNR}_{ij} = (d_{ij}^{-\alpha} p_i) / N_0 \), where \( \alpha \) is the path loss exponent, \( d_{ij} \) is the distance between transmitter \( i \) and receiver \( j \), \( p_i \) is the transmission power of UD \( i \), and \( N_0 \) represents the noise power. Then, the data rate \( R_{ij} \) of transmitter \( i \) to receiver \( j \) can be represent by \( R_{ij} = B_i \log(1 + \text{SNR}_{ij}) \), where \( B_i \) is the allocated bandwidth for UD \( i \).

In terms of OFDMA, if we consider a worst-case scenario where all UDs request to transmit simultaneously, the allocated bandwidth should be constrained by

\[
\sum_{i \in V} B_i \leq B,
\]

where \( B \) is the total bandwidth allocated for FL.

D. Analysis of transmission time

Recall the procedure of the FedAvg, \([6]\) of \( j \)th round can only be processed after \([2]\) of \((j - 1)\)th round and \([3]\) of \( j \)th round. Hence, in traditional communication scheme, the BS should wait for all UDs to finish their transmissions. Then the uplink transmission time of each round in the traditional scheme is

\[
T_{uStar} = \frac{M}{\min_{i \in V} R_{i,0}},
\]

where \( M \) is the model size. The total transmission time of each round is \( T_{star} > T_{uStar} \) considering downlink transmission time.

In RAR scheme, each UD transmits \( 2(N - 1) \) chunks in the implementation process. Since each chunk contains \( \frac{1}{N} \) of model parameters, the transmission time of each round is

\[
T_{ring} = \frac{2(N - 1)M}{N \min_{k \in V} R_{r(i)}},
\]

where \( r(i) \) represents the index of the next neighbour of UD \( i \) in the ring.

Since the transmission time of each round is always determined by the slowest connection, we may optimally allocate the bandwidth to minimize the transmission time. In other words, if not all connections are transmitting at the same rate, we can adjust the bandwidth allocation of the slowest and the fastest connections until they have the same transmission rate. Hence, the optimal bandwidth allocation and transmission time can be expressed as

\[
B_i^* = \frac{B}{\sum_{k \in V} C_k} \quad \forall i \in V
\]

\[
T_{uStar}^* = \frac{M}{B} \sum_{k \in V} \frac{1}{C_k},
\]

\[
T_{ring}^* = \frac{2(N - 1)M}{NB} \sum_{k \in V} \frac{1}{C_k},
\]

where \( C_k = \log(1 + \text{SNR}_{k,0}) \) for the traditional scheme in \([13]\), and \( C_k = \log(1 + \text{SNR}_{k,r(k)}) \) for RAR in \([14]\).

Next, we show that the transmission time in the traditional scheme is approximately linearly correlated with the density of UDs participating in FL in the area, given that the distribution of UDs follows a spatial Poisson Point Process (PPP) \([11]\). If the UDs are distributed in a circular area with a radius \( R \), with the BS at the center, and the minimum distance between UD and BS is set to 1, the expectation of transmission time is

\[
\mathbb{E}[T_{star}] > \mathbb{E}[T_{uStar}^*] = \frac{M}{B} \mathbb{E} \left[ \frac{1}{C_k} \right]
\]

\[
= \frac{M}{B} \sum_{n=1}^{\infty} \frac{\lambda \pi R^2 n e^{-\lambda \pi R^2} n!}{n!} \mathbb{E} \left[ \frac{1}{C_k} \right]
\]

\[
= \frac{\lambda \pi R^2 M}{B} \mathbb{E} \left[ \frac{1}{C_k} \right],
\]

where \( \lambda \) is the intensity of PPP, \( p \) is the transmission power of each UD, and

\[
\mathbb{E} \left[ \frac{1}{C_k} \right] = \mathbb{E} \left[ \left( \log \left( 1 + \frac{p d_{k,0}^{-\alpha}}{N_0} \right) \right)^{-1} \right]
\]

\[
= \int_{x = 0}^{R} \frac{2 \pi x}{\pi R^2 \log(1 + \frac{p x - \alpha}{N_0})} dx
\]

\[
= \frac{2}{R^2} \int_{x = 0}^{R} \frac{x dx}{\log(1 + \frac{p x - \alpha}{N_0})}
\]

By substituting \([16]\) into \([15]\), we have

\[
\mathbb{E}[T_{star}] > \mathbb{E}[T_{uStar}^*] = \frac{\lambda \pi R M}{B} \frac{2}{R^2} \int_{x = 0}^{R} \frac{x dx}{\log(1 + \frac{p x - \alpha}{N_0})}
\]

Hence, the lower bound of \( \mathbb{E}[T_{star}] \) also increases linearly with \( \lambda \).
III. CONNECTION SCHEME OPTIMIZATION

In this section, we demonstrate the algorithm to identify the best ring to minimize (14), i.e. to find the next neighbor \( r(k) \) for each UD \( k \) such that

\[
\min_{\text{T}_{\text{ring}}^*} \quad \text{s.t.} \quad r(i) \neq r(j), \quad i, j \in V, i \neq j \\
\text{r}(n) (k) = k, \quad k \in V.
\]  
(18)

Since (18) has the same constraints as the TSP and is also NP-hard, we propose an algorithm based on ACO, which is the most commonly used method for the TSP, to solve this problem. The completed modified ACO algorithm is presented as Algorithm 1, while the key steps of the algorithm are summarized as follows,

1) Initialize a ants on each UD.
2) Each ant starts travelling from the current UD and constructs a ring by repeatedly applying the state transition rule,

\[
P_{ij} = \frac{h_{ij}^\beta R_{ij}^\gamma}{\sum_{k} h_{ik}^\beta R_{ik}^\gamma},
\]  
(19)

where \( V \) contains UDs that have not been visited.
3) Each ant calculates (14) corresponding to the ring, and updates the pheromone by

\[
h_{ij} = \rho (h_{ij} + \Delta h_{ij}) + (1 - \rho) \frac{1}{T^*_{\text{ring}}},
\]  
(20)

where \( \text{ring}^* \) is the so-far best ring that achieves minimum transmission time, and \( \Delta h_{ij} \) is the sum of \( \frac{1}{T^*_{\text{ring}}} \) of all ants.
4) Stop the algorithm if it reaches the maximum iterations, else go to step 1).

IV. EXPERIMENTAL RESULTS

A. Simulation setup

We consider a 200m x 200m squared area with a single BS. The positions of the BS and UDs are uniformly and independently distributed in the area. We consider that all UDs have same transmission power \( p = 0.1W \). Other relevant network parameters are set as \( M = 0.1\text{Mb}, B = 10\text{MHz}, \alpha = 4 \) and \( N_0 = -90\text{dBm} \).

We consider two baseline policies star and greedy. In star, we consider the traditional communication approach where all UDs only communicate with the BS to exchange the model parameters. In greedy, we consider a ring topology where the connection scheme is constructed by repeatedly connecting to the closest UD that has not been visited. We here reiterate that, our approach focuses on the communication scheme of FL in wireless networks and does not alter the training algorithm (FedAvg) itself. Therefore, we can compare the performances of our proposed scheme and the baselines only by the transmission time of each round. Besides, we apply the optimal bandwidth allocation policy to every scenario to guarantee a more fair comparison. In the previous section, we have explained that the transmission time will not be longer than any other bandwidth allocation methods (e.g., all UDs are evenly allocated bandwidth) under all schemes.

Algorithm 1 Modified ACO

Input: \( K \): the number of UDs;
\( d \): distance matrix;
\( r^* : V \to V \), i.e. the optimal connection scheme of the ring;
Output: \( \text{r}^* : V \to V \);

1: initialize \( h = 1 \)
2: repeat
3: initialize a ants on each UD;
4: for each ant do
5: construct a ring by repeatedly applying (19);
6: calculate the transmission time \( T^*_{\text{ring}} \);
7: if \( T^*_{\text{ring}} < T^*_{\text{ring}^*} \) then
8: \( \text{ring}^* = \text{ring} \), i.e. \( r^* (\cdot) = r (\cdot) \);
9: \( \Delta h_{ij} = \frac{1}{T^*_{\text{ring}}} \);
10: update the pheromone by (20);
11: until reach the maximum iteration
For the modified ACO, we set $\beta = 2$, $\gamma = 2$ and $\rho = 0.95$. We initialize $\alpha = 10$ ants for each UD in each iteration, and perform 200 iterations in total.

B. Numerical results

We use $T^*_\text{star}$ as a lower-bound representation for $T^*_\text{RAR}$ in the following results. We simulate 50 cases for each scenario with the same number of UDs, and comparisons of averaging transmission time per round are demonstrated in Fig. 2. We can conclude from the results that the RAR scheme conducted by modified ACO outperforms the other two schemes in most of scenarios. The gaps between the transmission time of star and RAR schemes (including greedy and modified ACO) become larger as the number of UDs increase. In these scenarios, the modified ACO reduces about 15% on average of transmission time comparing to greedy, and over 50% comparing to star. In fact, the traditional communication scheme is only superior in scenarios where UDs are very sparsely distributed, which is not the common case in FL applications.

![Fig. 2. Performance comparison of different schemes in terms of a) transmission time per round vs. the number of participants, and b) CDF of transmission time per round with 30 UDs.](image)

Then, we simulate 1000 cases for the moderate density scenario with 30 UDs. Fig. 3 shows the cumulative distribution functions (CDF) of the transmission time by three schemes in this scenario. As shown in Fig. 3, the modified ACO has the minimum mean value and variance, showing that our proposed approach is both efficient and robust. On the other hand, star has the maximum mean value and a rather high variance, indicating that the performance of the traditional scheme is not satisfactory on average, and also sensitive to the relative position of BS and UDs.

![Fig. 3. Performance comparison of RAR and DSGD.](image)

In addition, we compare the performance between RAR and DSGD, an existing approach we mentioned earlier aiming to improve the communication efficiency of FL by revising the FedAvg algorithm [7]. In DSGD, each UD broadcasts its local model to other UDs within a preset distance, of which the value would affect the communication efficiency. For more intuitive comparisons, we tune the parameters of DSGD to achieve the same training accuracy as RAR and compare their communication time in Fig. 3a, where results show that RAR requires shorter time. Similarly, in Fig. 3b, we keep the total communication time of RAR and DSGD equal, and show that RAR obtains higher accuracy. To summarize, while the performance of DSGD depends on the values of its parameters, RAR with FedAvg is a superior approach under all circumstances.

V. CONCLUSION AND FUTURE WORK

The paper investigated to improve the communication efficiency for FL of OFDMA wireless networks. We showed that the traditional star communication scheme for FL was inefficient when UDs were densely distributed. To overcome the problem, we proposed the RAR scheme with D2D communications and optimized the connection scheme of the ring. Simulation results showed that our proposed approach achieved significant improvement in the communication efficiency.

One potential future research direction is integrating spectrum resources allocation and interference management with power control in the existing framework.

REFERENCES

[1] Q. Yang, Y. Liu, T. Chen, and Y. Tong, “Federated machine learning: Concept and applications,” ACM TIST, vol. 10, no. 2, pp. 1–19, 2019.

[2] T. Li, A. K. Sahu, A. Talwalkar, and V. Smith, “Federated learning: Challenges, methods, and future directions,” IEEE Signal Processing Mag., vol. 37, no. 3, pp. 50–60, 2020.

[3] 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. Wirel. Commun., vol. 20, no. 1, pp. 269–283, 2020.

[4] H. Sun, X. Ma, and R. Q. Hu, “Adaptive federated learning with gradient compression in uplink NOMA,” IEEE Trans. Veh. Technol., vol. 69, no. 12, pp. 16 325–16 329, 2020.

[5] Z. Zhao, J. Xia, L. Fan, X. Lei, G. K. Karagiannidis, and A. Nallanathan, “System optimization of federated learning networks with a constrained latency,” IEEE Trans. Veh. Technol., vol. 71, no. 1, pp. 1095–1100, 2021.

[6] Y. Jiang, Q. Liu, F. Zheng, X. Gao, and X. You, “Energy-efficient joint resource allocation and power control for D2D communications,” IEEE Trans. Veh. Technol., vol. 65, pp. 6119–6127, 2015.

[7] H. Xing, O. Simeone, and S. Bi, “Federated learning over wireless device-to-device networks: Algorithms and convergence analysis,” IEEE J. Sel. Areas Commun., vol. 39, no. 12, pp. 3723–3741, 2021.

[8] A. Gibiansky, “Bringing HPC techniques to deep learning,” Baidu Research technical blog, 2017. [Online]. Available: https://andrew.gibiansky.com/blog/machine-learning/baidu-allreduce/.

[9] M. Dorigo and L. M. Gambardella, “Ant colonies for the traveling salesman problem,” Biosystems, vol. 43, pp. 73–81, 1997.

[10] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, “Communication-efficient learning of deep networks from decentralized data,” in AISTATS 2017, pp. 1273–1282.

[11] A. Baddeley, I. Bárány, and R. Schneider, Stochastic Geometry: lectures given at the CIME Summer School held in Martina Franca, Italy, September 13–18, 2004. Springer, 2007.