Federated Learning for Cellular Networks: Joint User Association and Resource Allocation

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***Abstract*—Recent years have shown a remarkable interest in federated learning from researchers to make several Internet of Things applications smart. Although, federated learning offers users' privacy preservation, it has communication resources optimization challenge. In this paper, we consider federated learning for cellular networks. We formulate an optimization problem to jointly minimizes latency and effect of loss in federated learning model accuracy due to channel uncertainties. We decompose the main optimization problem into two sub-problems: resource allocation and device association sub-problems, due to the NP-hard nature of the main optimization problem. To solve these sub-problems, we propose an iterative approach which further uses efficient heuristic algorithms for resource blocks allocation and device association. Finally, we provide numerical results for the validation of our proposed scheme.**

***Index Terms*—Federated learning, cellular networks, machine learning, Internet of Things.**

I. Introduction

Recently, *federated learning (FL)* has been explored to train various machine learning models without loosing privacy. In FL, a local learning model is trained at end-devices, which is followed by sending of the local learning model parameters to the centralized edge/cloud server. Global model aggregation takes place at the edge/cloud server and finally, the global model updates are sent to the end-devices. This process of learning takes place in an iterative fashion until convergence [1], [2]. FL offers a key feature of privacy preservation, it has few challenges such as resource optimization, incentive mechanism, and learning algorithm design [3], [4]. In this paper, we consider the resource optimization perspective of FL. FL over wireless networks mainly uses two kinds of resources such as communication resources and computational resources. Several papers [3], [5]–[7] studied optimization of resources for FL. In [3], Khan *et al.* presented the key design aspects such as resource optimization, incentive mechanism design, and learning algorithm design for FL at edge networks. An incentive mechanism-based on the Stackelberg game was proposed. Additionally, few open research challenges and future research directions are presented. In another work [6], Tran *et al.* presented the optimization model for FL over wireless networks. On the other hand, adaptive FL for edge networks has been proposed in [5]. Khan *et al.* [7] proposed a self-organizing FL using device-to-device (D2D) communication.

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In this paper, we consider a cellular network that consists of several SBSs and a set of devices with local datasets. we define a cost function for FL over wireless networks. The cost functions jointly consider the effect packet error rate on the global FL model accuracy and latency. Then, we formulate an optimization problem and propose an efficient solution to minimize of global FL model cost. The summary of our main contributions are as follows:

- First, we formulated a cost function for the FL model over wireless networks. The formulated cost function considers jointly latency and effect due to packet error rate on the performance of FL. Moreover, we formulate an integer linear programming optimization problem for minimizing FL cost.
- Second, we decompose the main problem into two sub-problems: resource allocation sub-problem and device association sub-problem, due to the NP-hard nature of the main formulated problem. Furthermore, an iterative scheme is proposed to solve the sub-problems in an efficient way.
- Finally, numerical results are provided for performance evaluation.

II. System Model and Problem Formulation

Consider the system shown in Fig. 1 which consists of several small cell base stations (SBSs) and set of devices. Let the sets of S SBS and N devices are represented by $\mathcal{S}$ and $\mathcal{N}$, respectively. A set $\mathcal{R}$ of R resource blocks that are already in use by the cellular users are reused by the devices.

A. Federated Learning Model

Let the devices n has a dataset $\mathcal{D}_n = \{\boldsymbol{d}_{n1}, \boldsymbol{d}_{n2}, ..., \boldsymbol{d}_{nk_n}\}, \forall n \in \mathcal{N}$, where k_n denote the total number of data samples of device n. The size of the input samples and the number of outputs depends on the nature of the application. We assume a single output Θ_{n1} for a data sample $\boldsymbol{d}_{n1}$. The output Θ_{n1} is determined by weight w_n (i.e., $\Theta_{n1} = w_n \boldsymbol{d}_{n1}$). The goal of the FL is to minimize the following function.

$$\min_{\boldsymbol{w}_1, \boldsymbol{w}_2, ..., \boldsymbol{w}_N} \frac{1}{K} \sum_{n=1}^{N} \sum_{k=1}^{k_n} f(\boldsymbol{w}_n, \boldsymbol{d}_{nk}, \Theta_{nk}), \tag{1a}$$

$$s.t. \boldsymbol{w}_1 = \boldsymbol{w}_2 = ... = \boldsymbol{w}_N = \boldsymbol{z}, \tag{1b}$$

where $\boldsymbol{z}$ and K denote the global FL model and the total

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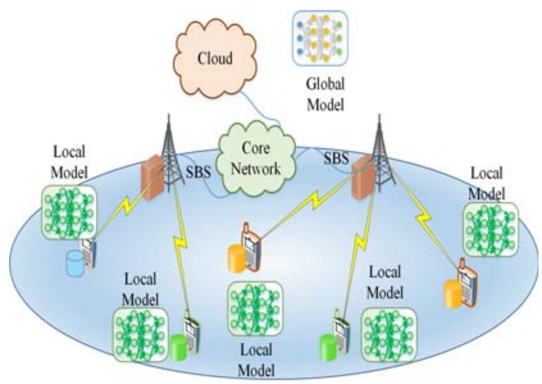

Figure 1: System model

number of devices data samples, respectively. The global FL model is given by:

$$z = \frac{\sum_{n=1}^{N} k_n \boldsymbol{w}_n}{K}. \tag{2}$$

In FL, first of all, local learning models are computed which are then transferred to the centralized edge/cloud server for aggregation. However, the wireless channel uncertainties cause degradation in quality of the received local learning model updates at the centralized server. Therefore, the signal with a high error rate might not be considered during the computation of the global model computation. Let the binary variable Q_n denote the whether the local learning model parameters are considered in global model computation (i.e., Q_n=1) or not (i.e., $Q_n = 0$). (3) can be rewritten as:

$$z = \frac{\sum_{n=1}^{N} k_n \boldsymbol{w}_n Q_n}{\sum_{n=1}^{N} k_n Q_n}. \tag{3}$$

B. Channel Model

The set of orthogonal resource blocks already in use by cellular users are reused for communication by devices. All the devices are assigned different resource blocks, and thus they will not receive interference from other devices. However, cellular users will cause interference to the devices. Let define the association variable $x_{n,s} = 1$ if device n is associated with s and 0 otherwise. Similarly, we can define the resource block allocation variable $y_{n,r} = 1$, if device n is assigned r and 0 otherwise. Every resource block must not be assigned to more than one device, i.e., $\sum_{n\in\mathcal{N}} y_{n,r} \le 1, \forall r \in \mathcal{R}$. On the other hand, every device must be associated with a maximum of one SBS, i.e., $\sum_{s\in\mathcal{S}} x_{n,s} \le 1, \forall n \in \mathcal{N}$. All the SBS has limitations in terms of processing capabilities. Therefore, the maximum number of devices assigned to a particular SBS must not exceed the maximum limit, $\sum_{n\in\mathcal{N}} x_{n,s} \le \Delta_s, \forall s \in \mathcal{S}$. The signal-to-interference-plus-noise ratio (SINR) for the device n assigned a resource block r is given by:

$$\Gamma_{n,r} = \frac{p_{n,r} h_{n,r}}{\sum_{c\in\mathcal{C}_r} h_{c,r} P_{c,r} + \sigma^2}, \tag{4}$$

where $p_{n,r}$ and $h_{n,r}$ denote the up-link transmission power of device n and channel gain between the device n and SBS s, respectively. The term $\sum_{c\in\mathcal{C}_r} h_{c,r} P_{c,r}$ represent the interference due to cellular users. The up-link achievable data rate for device n assigned a resource block r of bandwidth B_r is given by:

$$\delta_{n,r} = B_r \log_2(1 + \Gamma_{n,r}). \tag{5}$$

C. Problem Formulation

In this section, we formulate the problem to jointly minimize the effect of packet error rate on FL model accuracy and FL model computation time. To study the effect of performance degradation due to channel uncertainties on the performance of FL, we can consider the packet error rate. The packet error rate for devices can be given by:

$$E_p(\boldsymbol{X}, \boldsymbol{Y}) = \sum_{n\in\mathcal{N}} x_{n,s} y_{n,r} \left(\digamma\right), \tag{6}$$

where $\digamma = 1 - \exp\left(\frac{-\vartheta(\sum_{y\in\mathcal{Y}_r} h_{c,r} P_{c,r} + \sigma^2)}{p_{n,r} h_{n,r}}\right)$ and ϑ denote the waterfall threshold. The cost function that counts for the effect of the packet error rate on the performance of FL model accuracy can be given by [8].

$$E_p(\boldsymbol{X}, \boldsymbol{Y}) = \sum_{n\in\mathcal{N}} e_n(\boldsymbol{X}, \boldsymbol{Y}). \tag{7}$$

On the other hand, the time required for uplink transmission local learning model parameters is given by:

$$T(\boldsymbol{X}, \boldsymbol{Y}) = \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} \sum_{r\in\mathcal{R}} \frac{x_{n,s} y_{n,r} g_n}{\delta_{n,r}}, \tag{8}$$

where g_n denote the size of the local learning model parameters of device n. The total cost of the global FL model computation can be given by:

$$C_{FL}(\boldsymbol{X}, \boldsymbol{Y}) = \alpha E_P(\boldsymbol{X}, \boldsymbol{Y}) + (1-\alpha) T(\boldsymbol{X}, \boldsymbol{Y}), \tag{9}$$

where α is the tuning parameters that adjust between the effect due to packet error rate and latency. Now, we formulate our optimization problem as follows:

$$\mathbf{P1}: \min_{\mathbf{X},\mathbf{Y}} \; C_{FL}(\boldsymbol{X}, \boldsymbol{Y}) \tag{11}$$

subject to:

$$\sum_{r\in\mathcal{R}} y_{n,r} \le 1, \forall n \in \mathcal{N}, \tag{10a}$$

$$\sum_{n\in\mathcal{N}} y_{n,r} \le 1, \forall r \in \mathcal{R}, \tag{10b}$$

$$\sum_{s\in\mathcal{S}} x_{n,s} \le 1, \forall n \in \mathcal{N}, \tag{10c}$$

$$\sum_{n\in\mathcal{N}} x_{n,s} \le \Delta_s, \forall s \in \mathcal{S}, \tag{10d}$$

$$x_{n,s} \in \{0,1\} \quad \forall n \in \mathcal{N}, s \in \mathcal{S}, \tag{10e}$$

$$y_{n,r} \in \{0,1\} \quad \forall n \in \mathcal{N}, r \in \mathcal{R}. \tag{10f}$$

The above-formulated problem is an integer linear programming problem and has combinatorial nature. Constraint 10a restricts the allocation of a maximum one resource block to a device. Constraint 10b represents that every resource block must not be assigned to more than one device. Constraint 10c restricts the association of a device to a maximum of one SBS. The maximum number of devices that can be associated with the SBS is limited by the constraint 10d. Finally, constraints

10e and 10f denote that variables $x_{n,s}$ and $y_{n,r}$ can take only binary values.

III. Proposed Solution

The formulated problem has combinatorial nature and it becomes NP-hard for a large number of devices. To solve the problem, we decompose the problem into two problems and propose an iterative approach. The sub-problems are device association problem and resource allocation problem. For fix device association matrix, the resource allocation sub-problem can be given by:

$$\mathbf{P2}: \min_{\mathbf{Y}} \quad C_{FL}(\boldsymbol{Y}) \tag{11}$$

subject to:

$$\sum_{r \in \mathcal{R}} y_{n,r} \leq 1, \forall n \in \mathcal{N}, \tag{11a}$$

$$\sum_{n \in \mathcal{N}} y_{n,r} \leq 1, \forall r \in \mathcal{R}, \tag{11b}$$

$$y_{n,r} \in \{0,1\} \quad \forall n \in \mathcal{N}, r \in \mathcal{R}. \tag{11c}$$

Next, we discuss the device association sub-problem for fix resource allocation matrix.

$$\mathbf{P3}: \min_{\mathbf{X}} \quad C_{FL}(\boldsymbol{X}) \tag{11}$$

subject to:

$$\sum_{s \in \mathcal{S}} x_{n,s} \leq 1, \forall n \in \mathcal{N}, \tag{12a}$$

$$\sum_{n \in \mathcal{N}} x_{n,s} \leq \Delta_s, \forall s \in \mathcal{S}, \tag{12b}$$

$$x_{n,s} \in \{0,1\} \quad \forall n \in \mathcal{N}, s \in \mathcal{S}, \tag{12c}$$

To solve the sub-problems, we use an iterative approach. Our approach fix one variable (e.g., association variable) and computes the other one (e.g., resource allocation variable) and vice versa. Next, we presents the efficient heuristic algorithms resource allocation and device association algorithms in the subsequent sections.

A. Resource Allocation Algorithm

In this sub-section, we propose an efficient heuristic algorithm to enable efficient resource allocation. The resource allocation scheme is summarized in Algorithm 1. Algorithm 1 consists of two main phases such as initialization and allocation phase. In initialization phase, matrix $C_{FL}(\boldsymbol{X})$ is computed for all possible resource allocations (line 6). In the allocation phase, all the devices are allocated resource blocks based on the cost matrix $C_{FL}(\boldsymbol{X})$. First of all, the allocation of a resource block to a device with the lowest value of cost is performed. Then, the next allocation of resource block is performed based on the next lowest (greater than the first lowest value). This process works in an iterative fashion until all devices are allocated with resource blocks (lines 10-17).

Algorithm 1 Resource Allocation Algorithm

1: ***Inputs***
2: Device association matrix $\boldsymbol{X}$, Devices matrix $\mathcal{N}$, Resource blocks matrix $\mathcal{R}$, $t = 0$.
3: ***Output***
4: Resource allocation matrix $\boldsymbol{Y}$
5: ***Step 1: Initialization phase***
6: Compute the matrix $C_{FL}(\boldsymbol{X})$ $\forall n \in \mathcal{N}, r \in \mathcal{R}$
7: $G^{(0)} \leftarrow C_{FL}$ for input $\boldsymbol{X}$ and all possible associations.
8: ***Step 2: Allocation phase***
9: **repeat**
10:     $t \leftarrow t + 1$
11:     Compute $l^{(t)} = min(G^{(t)})$
12:     For $l^{(t)}$, propose corresponding resource block $r^{(t)}$
13:     **if** $|r^{(t)}| = \emptyset$ **then**
14:         $\boldsymbol{Y}^{(t)}(n) \leftarrow$ corresponding r ; $G^{(t)}(n,:) \leftarrow \emptyset$
15:     **else**
16:         $G^{(t)}(n,r) \leftarrow \emptyset$
17:     **end if**
18: **until** All devices are allocated resource blocks.

B. Device Association Algorithm

In this sub-section, we present the device association scheme for FL over cellular networks. The summary of the proposed association scheme is given in Algorithm 2. Similar to Algorithm 1, Algorithm 2 has two main phases such as initialization and association phase. In the initialization phase, cost matrix $C_{FL}(\boldsymbol{Y})$ is computed for all possible associations between the devices and SBSs. Next, in the association phase, all the devices are associated with the SBS in an iterative manner. First of all the device is associated with the SBS using the lowest value of cost matrix $C_{FL}(\boldsymbol{Y})$. Then, the next association is performed between the device and the SBS. It must be noted all the SBS can be associated with a maximum number of devices indicated by $\Delta_s, \forall s \in \mathcal{S}$. The association phase of Algorithm 2 works in an iterative manner until all the devices are associated with SBSs.

IV. Numerical Results

In this section, we present numerical results to evaluate the performance of our proposed joint devices association and resource algorithm for FL over cellular networks. We consider an area of $1000 \times 1000m^2$ with 3 SBSs and a single MBS. Other simulation parameters are given similar to [9]. In all results, C_{FL} denotes the average cost of FL for all devices for 1000 runs. For each run, the position of marco base station and SBSs remain the same, whereas devices and cellular users are positioned randomly. We compared the performance of our proposed scheme with two baselines, such as baseline-1 and baseline-2. The baseline-1 uses random device association and proposed resource allocation scheme, whereas baseline-2 uses random resource allocation and proposed device association scheme. The variations in FL cost C_{FL} for the proposed scheme with iterations are shown in Fig. 2 for a different number of devices. The word ”iterations” denotes the global iteration which includes running of both resource allocation and device association algorithm. The values of FL cost C_{FL} shows fast convergence (up to 6 iterations) for a different number of devices for the proposed scheme. The cost C_{FL}

Algorithm 2 Device Association Algorithm

Inputs
Resource block allocation matrix $\boldsymbol{Y}$, Devices matrix $\mathcal{N}$, SBS matrix $\mathcal{S}$, $t=0$.
Output
Device association matrix $\boldsymbol{X}$
Step 1: Initialization phase
Compute the matrix $C_{FL}(\boldsymbol{Y})\ \forall n \in \mathcal{N}, s \in \mathcal{S}$
$G^{(0)} \leftarrow C_{FL}$ for input $\boldsymbol{Y}$ and all possible resource allocations.
Step 2: Association phase
repeat
  $t \leftarrow t+1$
  Compute $l^{(t)} = min(G^{(t)})$
  For $l^{(t)}$, propose corresponding SBS $s^{(t)}$
  if $|s^{(t)}| \leq \Delta_s$ **then**
    $\boldsymbol{X}^{(t)}(n) \leftarrow$ corresponding s ; $G^{(t)}(n,:) \leftarrow \emptyset$
  else
    $G^{(t)}(n,s) \leftarrow \emptyset$
  end if
until All devices are associated

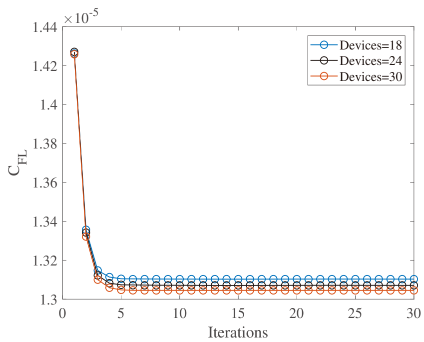

Figure 2: C_{FL} vs. iterations for proposed scheme with $\alpha=0.5$.

shows low values for a greater number of devices. The reason for this trend is because of the fact that increasing the number of devices increases the probability of association with the nearest SBS. Association of a device with nearest SBS causes an increase in throughput which subsequently decrease the cost C_{FL}.

Fig. 3 shows C_{FL} vs. SBS for fixed number of devices using proposed, baseline-1, and baseline-2 schemes. The proposed scheme results in the lowest cost C_{FL} for different numbers of SBS. The reason for the best performance of the proposed scheme is joint resource allocation and device association. Baseline-1 has the worst performance in terms of the highest cost C_{FL} for different numbers of SBSs among the three algorithms. Baseline-1 only uses the proposed resource allocation algorithm, whereas baseline-2 only uses the proposed device association algorithm. Therefore, it is clear from Fig. 3 that device association has more impact on cost C_{FL} optimization than resource allocation. On the other hand, a decreasing trend in cost C_{FL} has been observed for different schemes. The reason for this behavior is increasing the number of SBS for a fixed area results in a high probability for devices

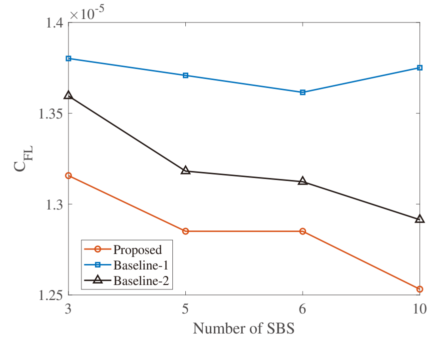

Figure 3: C_{FL} vs. SBSs for $\alpha=0.5$.

to get connected to nearby SBS. Connecting with the nearby SBS results in more cost C_{FL} reduction than association with a remote SBS.

V. Conclusions

In this paper, we have discussed FL for cellular networks. We defined the cost function to jointly consider latency and loss in FL model accuracy due to packet error rate. An optimization problem has been formulated to minimize the cost function via resource allocation and device association. Due to the NP-hard nature of the formulated, we decomposed the main problem into two sub-problems: resource allocation sub-problem and association sub-problem. Furthermore, we have proposed an iterative scheme to jointly optimize the devices association and resource allocation. We have compared the performance of our proposed scheme with two baselines. Numerical results confirmed the superior performance of our proposed scheme compared to baselines.

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