A Cooperative Analysis to Incentivize Communication-Efficient Federated Learning

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***Abstract*—*Federated Learning (FL)* has achieved state-of-the-art performance in training a global model in a decentralized and privacy-preserving manner. Many recent works have demonstrated that incentive mechanism is of paramount importance for the success of FL. Existing incentives to FL either neglect communication efficiency, or consider communication efficiency but design the incentive mechanisms using non-cooperative games under complete information assumption, or study incentive mechanism under incomplete information but only apply to the sequential interaction setting. We shed light on this problem from the cooperative perspective and propose an incentive mechanism for communication-efficient FL based on the Nash bargaining theory. Specially, we formulate our incentive mechanism as a one-to-many *concurrent bargaining* game among the aggregator and clients, and systematically analyze the Nash bargaining solution (NBS, game equilibrium) to design the incentive mechanism. It should be noted that the existing *sequential bargaining* is not suitable for incentivizing FL due to high (exponential) time complexity, which deteriorates the straggler problem in FL. Our formulated bargaining game is challenging due to the NP-hardness. We propose a probabilistic greedy-based client selection algorithm and derive an analytical payment solution as an approximate NBS. We prove the convergence guarantee of our incentive mechanism for communication-efficient FL. Finally, we conduct experiments over real-world datasets to evaluate the performance of our incentive mechanism.**

***Index Terms*—Federated learning, incentive mechanism, bargaining, communication efficiency.**

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I. Introduction

With the rapid development of Internet of Things (IoT) and the proliferation of edge devices, data continuously generated at the network edge has given rise to an explosive growth. The significant amount of generated data would be beneficial to smart applications (e.g., mobile health) and smart services (e.g., MLaaS) provisioning. However, it is prohibitive to move the Big Data to the central cloud server and perform data mining using machine learning due to 1) the constrained network bandwidth capacity, 2) the limited storage for the very large-scale data, and 3) the potential privacy disclosure concerns.

Fortunately, it has shown that the current edge devices are often equipped with the growing storage (e.g., 8GB–512 GB for smart phones) and computation capability (e.g., mobile CPUs/GPUs and embedded AI chip). The development of local computation capability has enabled the possibility of distributed on-device machine learning [1]. As new paradigm for distributed learning, Federated Learning (FL) [2], [3] overcomes the disadvantages of the traditional centralized machine learning by coordinating clients to collectively train a global model in a decentralized and privacy-preserving manner while keeping their data locally.

Generally speaking, the FL framework consists of a parameter server (a.k.a., aggregator) and a set of clients. The aggregator maintains the global model training process by orchestrating clients' participation. In each round, the aggregator first distributes the current model parameter to the selected clients. Then, the selected clients calculate the model updates regarding the current model using their local datasets, and then upload the model updates. After receiving the model updates from the participants, the aggregator aggregates the model updates based on FEDAVG policy [2] and derives the new model parameter. This process is periodically repeated round by round until the global model is converged (e.g., a targeted accuracy or the maximum number of rounds is achieved).

Despite the promising benefits, most of the existing works on FL mainly focus on learning performance (e.g., convergence, scheduling, and non-IID) and assume clients' voluntary participation. In practice, however, clients often participate in performing FL task at the price of consuming their computation and communication resources. Clients may not be willing to take part in performing FL task unless they can receive rewards to compensate their resource consumption. Since the success of FL is highly dependent on clients' participation, *it is indispensable for the aggregator to design an appropriate incentive mechanism to ensure clients' participation*. Most importantly, different clients have non-IID datasets and heterogeneous computation and communication resources. Training a global model over different clients in a distributed fashion requires model information exchanges among the aggregator and clients in multiple rounds, which becomes a significant communication bottleneck. In a network-constrained environment, uploading the whole parameter would exacerbate the communication burden. *It is crucial to incentivize a large number of high-quality clients to ensure their cooperation for communication-efficient FL.*

Unluckily, previous incentive mechanisms for FL [4], [5], [6], [7], [8], [9] do not jointly and fully take communication efficiency and clients' heterogeneity into account. In [4], an incentive mechanism is designed based on contract theory by considering the reputation of clients. In [5], [9], auction-based incentive mechanisms are studied with non-cooperative equilibrium analysis. In [6], a Stackelberg game is formulated to analyze the incentive mechanism. In [7], [8], Deep Reinforcement Learning (DRL) is applied to design the aggregator's price rule for incentivizing clients. These existing incentive mechanisms either neglect communication efficiency, or consider communication cost but design the incentive mechanisms using non-cooperative games. In this paper, we shed light on studying the strategic interactions between the aggregator and clients from the perspective of cooperation using cooperative bargaining game. Specially, we want to answer the questions in our incentive mechanism: 1) Whether should a client cooperate with the aggregator in round t? 2) How much should the aggregator pay the participating clients?

In this paper, we aim to solve the above questions based on *Nash bargaining theory*. Specifically, we model the incentive mechanism for communication-efficient FL as a one-to-many concurrent bargaining game. In this bargaining game, the aggregator determines the specific payments for the clients while a set of clients concurrently determine whether or not to participate in the FL training task based on their current communication resources. However, our bargaining-based incentive mechanism for FL has two key challenges: 1) The formulated one-to-many concurrent bargaining is essentially an NP-hard problem due to the combinatorial decision in the client selection sub-problem. 2) The non-IID issue in FL must be considered in the designed incentive mechanism. To this end, we first handle the combinatorial constraint of the client selection sub-problem and propose a probabilistic greedy-based client selection algorithm, which greedily assigns the selection probabilities of clients with more communication resources and larger local datasets. Then, we derive an analytical closed-form payment solution as an approximate Nash bargaining solution (NBS). In summary, the main contributions in this work are three-fold.

- We are the first to address the incentive mechanism design problem for communication-efficient FL from the cooperative perspective and design the incentive mechanism based on the Nash bargaining theory.
- We formulate our incentive mechanism as a one-to-many concurrent bargaining game and prove its NP-hardness. To derive the approximate NBS, we propose a probabilistic greedy-based client selection algorithm and derive the closed-form payment solution. We prove the convergence guarantee of our incentive mechanism in the general non-convex loss functions, i.e., $\mathcal{O}(1/\sqrt{MT})$ for M clients' (partial) participation and T communication rounds scenario.
- We conduct experiments over real-world datasets to evaluate the effectiveness and efficiency of our incentive mechanism.

The benefit of using cooperative models: 1) Compared to non-cooperative game-based incentive mechanisms, using cooperative game to model incentive mechanism problem in FL can characterize the unstructured interactions between the aggregator and participants. 2) Due to the property of the unstructured interactions, cooperative game-based incentive mechanisms are scalable to large-scale participant pool. 3) Moreover, the utility functions in our work is not supposed to include quadratic or logarithmic cost as in the existing literature of non-cooperative game-based incentive mechanisms, in order to guarantee the uniqueness of Nash Equilibrium. We use linear cost in the utility modeling, which is more appropriate in practice. For convenience, we summarize the differences between cooperative game and non-cooperative game in Table I.

The rest of this paper is organized as below. We conduct literature review about incentive mechanisms for FL in Section II. Then, we introduce our focused system model for the communication-efficient FL and formulate the incentive mechanism design problem for FL in Section III. In Section IV, we propose our bargaining-based incentive mechanism for communication-efficient FL and theoretically analyze its performance. In Section V, we carry out experiments to evaluate our proposed incentive mechanism for communication-efficient FL. Finally, we conclude our work in Section VI.

II. Related Work

A. Federated Learning

Since FL was first proposed in [2], considerable research attention has been paid to study FL from *performance* (e.g., convergence [10], [11], [12], [13]), *security and privacy-preserving* [14], [15], [16], and *efficiency* (e.g., client scheduling [17], [18], [19], incentive [7], [20], resource allocation [21], [22] and communication orchestration [23]). These existing works are either under the less practical scenario where clients voluntarily participate in FL without incentives, or under the practical scenario with strategic clients but neglect to jointly consider other issues like communication efficiency. In this paper, we bridge this gap by designing a bargaining-based incentive mechanism with taking communication efficiency into account.

B. Communication Efficiency for FL

There are many existing works studying how to improve communication efficiency for FL from model/gradient compression [23], [24] (e.g., sparsification [25], quantization [26],

TABLE I
DIFFERENCES BETWEEN COOPERATIVE GAME-BASED AND NON-COOPERATIVE GAME-BASED INCENTIVE MECHANISMS

Type	non-cooperative game-based	cooperative game-based
Interaction	structured	unstructured
Solution	Nash Equilibrium	Nash Bargaining Solution
Property	procedural	coalitional
Focus	How to optimally act individually	How to form a coalition

gradient blending [27]) and client scheduling [19]. These works individually study communication efficiency without considering clients' strategic behaviors due to the heterogeneous communication resources. In this paper, we study communication efficiency for FL from the perspective of incentive mechanism design. In this line, the most related work is [6]. Pandey et al. study a utility maximization problem for communication efficiency in FL and propose a two-stage Stackelberg game-based incentive mechanism, which is a complete information non-cooperative game scenario and essentially different from our bargaining-based incentive mechanism.

C. Incentive Mechanism

In [4], Kang et al. design an incentive mechanism for FL based on contract theory by considering the reputation of clients. In [9], Deng et al. propose a quality-aware auction-based incentive mechanism for FL. However, communication efficiency is not considered in [4], [9]. In [5], Zeng et al. propose a multi-dimensional auction-based incentive mechanism for FL and consider bidders' communication bidder as one of dimensions. In [6], Pandey et al. formulate a Stackelberg game to analyze the incentive mechanism for FL and consider communication cost in modeling the client's utility. In [7], [8], Zhan et al. apply Deep Reinforcement Learning (DRL) to determine the aggregator's price decision for incentivizing clients by considering communication cost in modeling the utilities. In [20], Tang et al. design an incentive mechanism for FL based on a non-cooperative game with perfect information where uploading and downloading costs are considered. Though communication issues are considered in the above works, their principle of designing incentive mechanisms for FL is the non-cooperative games and fundamentally different from our work where we study the incentive mechanism in the context of bargaining theory, which is a cooperative game.

In [28], Ding et al. propose a contract-theoretic incentive mechanism for FL while considering multi-dimensional information under incomplete information. However, the analytical study and experimental result show that the contract-theoretic incentive mechanism works well both under weakly incomplete information and complete information when the local datasets are IID. In the non-IID setting, the contract-theoretic incentive mechanism performs inferior. In [29], Khan et al. propose a Stackelberg-game-based incentive mechanism for FL while considering communication efficiency and clients' heterogeneity. However, it does not provide the closed-form of Stackelberg equilibrium but gives an iterative process to compute the Stackelberg equilibrium in each round. We note that: 1) Incentive mechanisms in [28], [29] are applicable to the sequential interaction setting while our concurrent bargaining-based incentive mechanism can be used to capture the concurrent and unstructured interaction setting. 2) Our incentive mechanism can work well in non-IID scenario while admitting a closed-form payment rule.

III. SYSTEM MODEL

In this section, we outline the system model of our FL scenario. We present the modeling for aggregator payoff and clients' payoffs. Particularly, we introduce the problem formulation of our incentive mechanism.

A. Overview

We consider an FL scenario with an aggregator and a set $\mathcal{M} \triangleq \{1, 2, \ldots, M\}$ of clients. The goal of the aggregator is to learn a global model parameterized by a d-dimensional vector $\Theta \in \mathbb{R}^d$. In ML/DL, the global model can be represented as the empirical risk loss function $F(\Theta)$ over the whole dataset. Note that the loss function $F(\Theta)$ can be convex (e.g., in logistic regression models) or non-convex (e.g., in neural network models). Without accessing the dataset, the aggregator cannot obtain the (sub-)optimal model parameter Θ^* by directly minimizing $F(\Theta)$ via the typical SGD algorithm.

Let $\mathcal{D}_m = \{(\boldsymbol{x}_{m,i}, y_{m,i})\}_i$ be the local dataset owned by client m where $\boldsymbol{x}_{m,i}$ is the ith sample's feature vector and $y_{m,i}$ is the ith sample's label in local dataset $\mathcal{D}_m$. For the local dataset $\mathcal{D}_m$, the local loss function is defined as $F_m(\Theta) = \sum_{i=1}^{|\mathcal{D}_m|} L(\Theta; \boldsymbol{x}_{m,i}, y_{m,i})$ where $L(\cdot)$ is per-sample loss (e.g., 0/1 loss, hinge loss, cross-entropy loss). Denoted by $D = \sum_{m\in\mathcal{M}} |\mathcal{D}_m|$ the size of the whole dataset, the global model Θ^* is learnt by minimizing $F(\Theta)$ on the local datasets, i.e.,

$$\Theta^* = \arg\min_{\Theta} F(\Theta), \text{ s.t.}, F(\Theta) = \sum_{m\in\mathcal{M}} h_m F_m(\Theta), \quad (1)$$

h_m specifies the relative impact of client m with two natural settings, i.e., $h_m = 1/D$ (equally) or $h_m = |\mathcal{D}_m|/D$ (proportionally) [30]. In this paper, we set h_m that is inversely proportional to the selection probability given in (14).

To solve the federated optimization in (1), the aggregator manages an iterative procedure within T communication rounds. Let $\mathcal{M}_t \subseteq \mathcal{M}$ be the online clients in round $t \in [T] \triangleq \{1, 2, \ldots, T\}$. The operations in round t include,

- *model distribution*: The aggregator selects set $\mathcal{S}_t$ of clients and distributes the current model Θ_t to them.
- *local computation*: After receiving Θ_t, each selected client computes a model update based on the local dataset.
- *parameter uploading*: The selected clients upload the model updates after they complete the local computation.

In this paper, we consider a lightweight local computation scheme where each participating client m computes a stochastic gradient $\boldsymbol{g}_m^t$ using a batch of (or all of) its local data in round t. When a subset $\mathcal{S}_t \subseteq \mathcal{M}_t$ of clients upload their local gradients, the aggregator aggregates the local gradients by $\Delta_t = \sum_{m\in\mathcal{S}_t} h_m \boldsymbol{g}_m^t$, and update the global model with a (decayed) learning rate η, i.e., $\Theta_{t+1} = \Theta_t - \eta\Delta_t$.

Considering the strategic interaction, we introduce aggregator's strategy and clients' strategies for modeling their payoffs.

B. Client Modeling

On the one hand, client m's utility is the received payment $p_m^t \geq 0$ as a reward if she decides to participate in performing local computation for FL in round t. On the other hand, when client m participates in FL task in round t, she incurs a cost C_m^t including computation overhead $C_{m,t}^{\text{cmp}}$ and communication overhead $C_{m,t}^{\text{com}}$, i.e., $C_m^t = C_{m,t}^{\text{cmp}} + C_{m,t}^{\text{com}}$.

Let $b_m^t \in \{0,1\}$ be the boolean variable indicating whether client m joins FL task in round t: $b_m^t = 1$ if client m participates in FL task in round t, $b_m^t = 0$ otherwise. For any client m in round t, her payoff $V_m^t(b_m^t, p_m^t)$ depends on the payment she obtains and the cost she incurs, which can be calculated as,

$$V_m^t(b_m^t, p_m^t) = p_m^t - b_m^t C_m^t. \tag{2}$$

Note that b_m^t is client m's decision while p_m^t is the aggregator's decision. We can interpret the decisions as whether the aggregator and clients agree on the cooperation in terms of the FL task. When their decisions are made, their payoffs are revealed to themselves. Note that we use one-to-many concurrent bargaining to model the unstructured interaction between the aggregator and clients. A stable combination of decisions regarding the concurrent bargaining in our setting is referred to as Nash Bargaining Solution (NBS) [31]. A client cannot independently determine its optimal decision contained in an NBS. Our proposed incentive mechanism can derive an approximate NBS.

Remarks: From (2), it may be counter-intuitive that the non-participating client (i.e., $b_m^t = 0$) can receives the payment p_m^t, which leads to a exogenous transfer between the aggregator and clients. To eliminate the untruthfulness of malicious clients, we should impose a requirement that $p_m^t = 0$ whenever $b_m^t = 0$. We will explicitly consider this constraint in our incentive mechanism (see formulation).

C. Gradient Sparsification-Based Uploading Scheme

To reduce the communication overhead, we leverage the gradient sparsification scheme [32] to compress client m's local gradient $\boldsymbol{g}_m^t$ into a sparse vector with K_m ($< d$) non-zero elements (called sparse number). K_m is determined by client m based on her communication resource. A natural idea is to retain top-K_m elements in absolute values and drop out other elements of the local gradients. However, it requires sorting of the gradient magnitude values to identify the top-K_m elements, which is difficult because the size of gradients is often large in the large-scale model.

Alternatively, we calculate a sparsification probability vector $\mathcal{P} \in \mathbb{R}^d$ where $\mathcal{P}_i$ indicates the probability of keeping the ith element of the local gradient to be non-zero and $1 - \mathcal{P}_i$ indicates the probability of dropping out the ith element. With $\mathcal{P}$, randomly drop out elements of the local gradients and amplify the remaining elements appropriately to ensure that the sparsified gradient is unbiased.

Note that each selected client m individually calculates the sparsification probability vector $\mathcal{P}^m$ to sparsify the obtained local gradient $\boldsymbol{g}_m^t$ before uploading the model update. We calculate $\mathcal{P}_i^m$ as,

$$\mathcal{P}_i^m = \min\left\{\frac{K_m|\boldsymbol{g}_{m,i}^t|}{\sum_{i=1}^d |\boldsymbol{g}_{m,i}^t|}, 1\right\}, \tag{3}$$

where d is the dimension of the global model. Computing the probability vector $\mathcal{P}^m$ can be achieved within $\mathcal{O}(d)$ time complexity. Let $Z_i^m \in \{0,1\}$ be the boolean random variable whose value is realized based on probability $\mathcal{P}_i^m$. Then, we can define a sparsification operator $Q : \mathbb{R}^d \to \mathbb{R}^d$ as,

$$Q(\boldsymbol{g}_m^t) = \left[Z_i^m \frac{\boldsymbol{g}_{m,i}^t}{\mathcal{P}_i^m}\right]_{i=1}^d. \tag{4}$$

It is easy to verify $\mathbb{E}[Q(\boldsymbol{g}_m^t)] = \boldsymbol{g}_m^t$. Thus, sparsification operator $Q(\cdot)$ produces an unbiased estimator of local gradient $\boldsymbol{g}_m^t$. Operator $Q(\cdot)$ has $\mathcal{O}(d)$ time complexity. Thus, (4) is efficient to derive a sparse gradient while keeping the local gradient unbiased, which can guarantee convergence performance while improving communication efficiency.

D. Aggregator Modeling

As in the existing works [6], [20], we define the utility of the aggregator in round t as a function of the accuracy gain. Recall that the aggregator receives the sparse gradient with K_m non-zero elements from the participating client m. When the number $\sum_{m\in\mathcal{M}_t} b_m^t K_m$ of the received parameter of sparse gradients increases, the accuracy $\epsilon(\sum_{m\in\mathcal{M}_t} b_m^t K_m)$ of the global model will increase [23], [32], [33], [34]. Without receiving any gradients, the accuracy $\epsilon(0)$ remains unchanged. Thus, the accuracy gain regarding the receiving gradients is $\epsilon(\sum_{m\in\mathcal{M}_t} b_m^t K_m) - \epsilon(0)$ and the utility of the aggregator is defined as,

$$f_t\left(\sum_{m\in\mathcal{M}_t} b_m^t K_m\right) = \lambda\left(\epsilon\left(\sum_{m\in\mathcal{M}_t} b_m^t K_m\right) - \epsilon(0)\right), \tag{5}$$

where the gain coefficient λ can be interpreted as the aggregator's valuation on the accuracy gain, e.g., the unit revenue obtained from provisioning MLaaS with the global model.

For the aggregator's cost C_0^t, it contains communication cost and payment cost. We assume that the aggregator has sufficient communication resources and suffers from a fixed communication consumption C_0^{com} to communicate with a client. Thus, the total communication cost for the aggregator is $\sum_{m\in\mathcal{M}_t} b_m^t C_0^{\text{com}}$. For client m, the aggregator will provide payment $p_m^t \in \mathbb{R}$ to her for participating FL in round t. Clearly, $p_m^t = 0$ whenever $b_m^t = 0$, i.e., there is no payment for the non-participating client. For ease of exposition, we define participation vector $\boldsymbol{b}^t \triangleq (b_m^t)_{m\in\mathcal{M}_t}$ and payment vector $\boldsymbol{p}^t \triangleq (p_m^t)_{m\in\mathcal{M}_t}$. Based on participation vector $\boldsymbol{b}^t$ and payment vector $\boldsymbol{p}^t$, the aggregator's payoff is,

$$\begin{aligned} U(\boldsymbol{b}^t, \boldsymbol{p}^t) &= f_t\left(\sum_{m\in\mathcal{M}_t} b_m^t K_m\right) - C_0^{\text{com}} \mathbf{1}^T \boldsymbol{b}^t - \mathbf{1}^T \boldsymbol{p}^t \\ &= f_t\left(\sum_{m\in\mathcal{M}_t} b_m^t K_m\right) - \sum_{m\in\mathcal{M}_t} b_m^t C_0^{\text{com}} - \sum_{m\in\mathcal{M}_t} p_m^t. \end{aligned} \tag{6}$$

The first term is the utility the aggregator obtains from receiving the number $\sum_{m\in\mathcal{M}_t} b_m^t K_m$ of the elements of sparse gradients from clients $\mathcal{M}_t$ in round t and the last two terms are the overall cost C_0^t incurred by the aggregator.

In this paper, we focus on the monetary incentive mechanism [35] where the payment mean the monetary reward that the participating clients obtain from cooperating with the aggregator and participating in FL training tasks. Since the aggregator compensates the costs that clients incur in the training procedure, the cost can be regarded as monetary. In our proposed incentive mechanism, after the participating clients return the local sparse gradients to the aggregator in each round, the aggregator calculates the payment based on our designed rule in (19) in Corollary 1. Then, the aggregator directly transfers the payment to client m in the FL system. Note that the developed incentive mechanism can be incorporated into a specific FL system that implements the payment procedure according to our payment rule. For example, when the FL system is enabled by blockchain, the payment procedure is easily implemented by directly transferring the bitcoin into the participating clients' accounts and store the transaction into the blockchain [36], [37].

E. Problem Formulation

In this subsection, we formulate the incentive mechanism design problem for the communication-efficient FL. We consider the incentive mechanism for the interaction in each round. Therefore, our incentive mechanism can work in the dynamic setting where the client set is volatile. Generally speaking, the incentive mechanism design problem consists of two subproblems: client selection and payment determination.

For the client selection problem, the objective is to maximize the social welfare, which is a widely adopted objective in mechanism design [38], [39] and defined as the overall payoff of the aggregator and all clients. Denoted by $\Psi(\boldsymbol{b}^t, \boldsymbol{p}^t)$ the social welfare in round t, we can calculate $\Psi(\boldsymbol{b}^t, \boldsymbol{p}^t)$ as,

$$\Psi(\boldsymbol{b}^t, \boldsymbol{p}^t) = f_t\left(\sum_{m\in\mathcal{M}_t} b_m^t K_m\right) - \sum_{m\in\mathcal{M}_t} b_m^t \left(C_0^{\text{com}} + C_m^t\right). \tag{7}$$

As the payments $\boldsymbol{p}^t$ are cancelled out, we rewrite the social welfare as $\Psi(\boldsymbol{b}^t) \triangleq \Psi(\boldsymbol{b}^t, \boldsymbol{p}^t)$ which is only conditioned on the participation vector $\boldsymbol{b}^t$. From (7), we can see that the social welfare in round t can be interpreted as the utility gain of the aggregator over the total transmission cost between the aggregator and the participating clients. However, the aggregator usually faces the cardinality constraints when solving the client selection problem, especially in communication-efficient FL where it is impossible to select all clients to participate in training task in each round due to limited communication resources. Therefore, the total number of the selected clients is no more than B, i.e., $\sum_{m\in\mathcal{M}_t} b_m^t \le B$. Formally, we can formulate the client selection problem as,

$$\max_{\boldsymbol{b}^t} \ \Psi(\boldsymbol{b}^t), \ \text{s.t.,} \ \begin{cases} \mathbf{1}^T \boldsymbol{b}^t \le B, \\ \boldsymbol{b}^t \in \{0,1\}^{|\mathcal{M}_t|}, \end{cases} \tag{8}$$

For the payment determination problem, we compute a payment vector $\boldsymbol{p}^t$ for the optimal $\boldsymbol{b}^{*t}$ determined from Problem (8) such that the participating clients and aggregators have positive payoffs, i.e., $V_m^t(b_m^{*t}, p_m^t) > 0$ for $b_m^{*t} = 1$ and $U(\boldsymbol{b}^t, \boldsymbol{p}^t) > 0$. When determining the payments $\boldsymbol{p}^t$ for the clients in round t, we have to consider the budget constraints since the aggregator impossibly has unlimited budgets to compensate the clients. Suppose that the budget in round t is P_t, the budget constraint imposed in round t is $\mathbf{1}^T \boldsymbol{p}^t \le P_t$.

By addressing the client selection problem and payment determination problem, the incentive mechanisms for FL largely aim to achieve the following design goals:

- *Social optimality:* The best clients with less computation and communication costs are selected to train the global model and achieve the highest accuracy gain.
- *Individual rationality:* Both the aggregator and clients have non-negative payoffs.
- *Budget feasibility:* The aggregator's budget constraints are not violated in all rounds.
- *Computational efficiency:* The incentive mechanism runs in real-time, which requires the proposed algorithms to avoid exponential computational complexity.

Remarks: When communication efficiency and computation efficiency are mentioned in this paper, their meanings are different in terms of FL. In this paper, we aim to address the problem of how to improve communication efficiency *for FL* from the incentive perspective, rather than addressing *FL's* computation efficiency issue. We specify *the criteria of efficiency as follows.* 1) The communication efficiency in this paper is characterized by sparse number K_m, which means to sparsify client m's local gradient by retaining K_m significant non-zero elements. 2) The computational efficiency in this paper mean that our proposed bargaining-based incentive mechanism is computation-efficient, which can be run in polynomial time complexity $\mathcal{O}(|\mathcal{M}_t|)$, i.e., the number of participants.

IV. Mechanism Design

In this section, we present our bargaining-based incentive mechanism for communication-efficient FL. First, we provide some basics of Nash bargaining theory and reformulate our incentive mechanism as a bargaining game. Then, we introduce how our incentive mechanism works in the elementary one-to-one bargaining case. Finally, we extend the one-to-one bargaining to the practical one-to-many bargaining case where the aggregator bargains with multiple clients in each round.

A. The Basics of Nash Bargaining and Reformulation

Suppose a set $\mathcal{N} = \{1, 2, \ldots, N\}$ of n players bargaining with each other in a cooperative game. The game is captured by a tuple $(\mathcal{C}, \boldsymbol{c}_0)$ where $\mathcal{C} \subseteq \mathbb{R}^N$ is a compact and convex set, and $\boldsymbol{c}_0 \in \mathcal{C}$. Given set $\mathcal{C}$, its element describes the payoffs that N players can simultaneously accrue when they reach an agreement. Point $\boldsymbol{c}_0$ is called the disagreement point where it gives the payoffs that N players fail to cooperate with each other. Game $(\mathcal{C}, \boldsymbol{c}_0)$ is said to be feasible whenever there exists a point $\boldsymbol{v} \in \mathcal{C}$ such that $\boldsymbol{v} \succ \boldsymbol{c}_0$, and infeasible otherwise.

For a feasible bargaining game $(\mathcal{C}, \boldsymbol{c}_0)$, a reasonable bargaining solution will satisfy four axioms: 1) *Pareto optimality*, 2) *Invariance under affine transformations*, 3) *Symmetry* and 4) *Independence of irrelevant alternatives*. However, Nash proved that there is a unique solution satisfying the four axioms in any feasible bargaining game below.

Theorem 1 (NBS [31]): For any feasible bargaining game $(\mathcal{C}, \boldsymbol{c}_0)$, there is a unique solution satisfying the above axioms, called Nash Bargaining Solution (NBS). NBS can be derived by maximizing the product of all players' payoff gains over the disagreement point, i.e., $\max_{\boldsymbol{v}\in\mathcal{C}} \prod_{i\in\mathcal{N}}(v_i - c_{0,i})$.

Due to the intractable product objective, we directly solve the following equivalent convex optimization for NBS,

$$\max_{\boldsymbol{v}} \sum_{i\in\mathcal{N}} \log(v_i - c_{0,i}), \quad s.t. \quad \boldsymbol{v} \in \mathcal{C}. \tag{9}$$

B. One-to-One Bargaining Case

In this subsection, we apply NBS to the special case where there is only one client in each round. Then, we extend the analysis to the more general one-to-many bargaining case where there are multiple clients in each round.

Taking client 1 as an example, client 1's payoff in round t is $V_1^t(b_1^t, p_1^t)$. The aggregator's payoff in round t is $U(b_1^t, p_1^t)$. If client 1 does not participate in performing FL task in round t (i.e., $b_1^t = 0$), the aggregator will not offer any payment to client 1 (i.e., $p_1^t = 0$). Therefore, the disagreement point is $(V_1^t(0,0), U(0,0)) = (0,0)$. According to Theorem 1, the one-to-one bargaining for FL can be formulated as,

$$\begin{aligned} &\max_{b_1^t, p_1^t} \ \left(V_1^t(b_1^t, p_1^t) - V_1^t(0,0)\right) \cdot \left(U(b_1^t, p_1^t) - U(0,0)\right) \\ &s.t. \quad \begin{cases} V_1^t(b_1^t, p_1^t) - V_1^t(0,0) \geq 0, \\ U(b_1^t, p_1^t) - U(0,0) \geq 0, \\ b_1^t \in \{0,1\}, p_1^t \geq 0, p_1^t \in \mathbb{R}. \end{cases} \end{aligned} \tag{10}$$

We assume that the budget P_t is sufficient, and hence we do not consider budget constraints in the one-to-one bargaining case. The objective is concave in p_1^t. When variable $b_1^t = 0$, the payment also $p_1^t = 0$. Thus, we can solve the above problem by setting $b_1^t = 1$ and checking the first-order condition of the objective and the feasibility of constraints. We present the closed-form optimal solution in the following theorem.

Theorem 2: In one-to-one bargaining case, the client 1's optimal participation decision b_1^{*t} and aggregator's optimal pricing decision p_1^{*t} are determined as follows,

$$\begin{aligned} &(b_1^{*t}, p_1^{*t}) \\ &= \begin{cases} \left(1, \frac{f_t(K_1) - C_0^{\text{com}} + C_1^t}{2}\right), & \text{if } f_t(K_1) - C_0^{\text{com}} + C_1^t > 0, \\ (0,0), & \text{otherwise.} \end{cases} \end{aligned}$$

Proof: To prove this theorem, we need to analyze whether there exists a case where the payment p_1^{*t} is positive. To do this, we first replace the objective with the terms $V_1^t(1, p_1^t)$ and $U(1, p_1^t)$ according to (2) and (6). We obtain the objective function $F(p_1^t)$ as

$$\begin{aligned} F(p_1^t) &\triangleq (p_1^t - C_1^t) \cdot \left(f_t(K_1) - C_0^{\text{com}} - p_1^t\right) \\ &= -(p_1^t)^2 + p_1^t\left(f_t(K_1) - C_0^{\text{com}} + C_1^t\right) \\ &\quad - C_1^t(f_t(K_1) - C_0^{\text{com}}). \end{aligned}$$

Then, we obtain the first-order condition $F'(p_1^t) = 0$ that characterizes the optimality of the objective function $F(p_1^t)$. Solving $F'(p_1^t) = 0$ gives the maximizer $p_1^{*t} = (f_t(K_1) - C_0^{\text{com}} + C_1^t)/2$. However, when $f_t(K_1) - C_0^{\text{com}} + C_1^t > 0$, the optimal payment p_1^{*t} can be positive. Otherwise, it would be zero and client 1 will not participate in FL (i.e., $b_1^{*t} = 0$). □

Remarks: Theorem 2 indicates that client 1 and the aggregator reach an agreement in terms of performing FL task in round t if and only if $p_1^{*t} = \frac{f_t(K_1) - C_0^{\text{com}} + C_1^t}{2} > 0$ holds and the budget can support p_1^{*t}. Otherwise, they fail to reach an agreement in terms of performing the FL task in round t. By pricing the payment $p_1^{*t} = \frac{f_t(K_1) - C_0^{\text{com}} + C_1^t}{2}$, the payoffs $V_1^t(1, p_1^{*t}) = U(1, p_1^{*t}) = (f_t(K_1) - C_0^{\text{com}} - C_1^t)/2 = \Psi(1)/2$. This implies that client 1 and the aggregator split the social welfare by pricing the optimal payment $p_1^{*t} = \frac{f_t(K_1) - C_0^{\text{com}} + C_1^t}{2}$.

C. One-to-Many Bargaining Case

Based on the one-to-one bargaining results, we consider a more general but harder one-to-many bargaining case where one aggregator bargains with multiple clients and selects at most B clients to participate in FL task each round.

When the aggregator bargains with multiple clients $\mathcal{M}_t$ in round t, the first challenge is which bargaining protocol is appropriate to our FL scenario. The existing bargaining protocols for one-to-many bargaining include *sequential bargaining* [38], [40] and *concurrent bargaining* [39], [41], [42]. In the sequential bargaining, the aggregator bargain with all clients $\mathcal{M}_t$ sequentially in round t, in a predefined order. On the contrary, the aggregator concurrently bargains with all clients $\mathcal{M}_t$ in round t. We note that the sequential bargaining framework is inappropriate to the FL scenario because of its high computational complexity (i.e., $\mathcal{O}(3^{|\mathcal{M}_t|})$ [43]) due to the redundant computation in the backward induction [38], [40]. When $|\mathcal{M}_t|$ is large, the sequential bargaining framework cannot compute the optimal client selection decision $\boldsymbol{b}^{*t}$ and the optimal payment determination decision $\boldsymbol{p}^{*t}$ in a real-time fashion, which slows down the overall training latency of FL. Therefore, we use the concurrent bargaining framework as the bargaining protocol to design the incentive mechanism for FL.

In the concurrent bargaining, we can view the bargaining process as $|\mathcal{M}_t|$ aggregator-client pair of one-to-one bargainings happen simultaneously. To formulate the NBS in the concurrent one-to-many bargaining for FL in round t, we first analyze the payoffs of the aggregator and any client in $\mathcal{M}_t$ in the disagreement point.

For any client $m \in \mathcal{M}_t$, she will receive no payment (i.e., p_m^t) and incur no cost (i.e., $C_m^t = 0$) if she does not participate in FL (i.e., $b_m^t = 0$). Under this circumstance, client m's payoff is zero, i.e., $V_m^t(0,0) = 0$. When there is no any client participating in FL (i,e., $\boldsymbol{b}^t = \mathbf{0}$), the aggregator will set the payments $\boldsymbol{p}^t = \mathbf{0}$ and the model's accuracy cannot be improved (hence $f_t(0) = 0$). Therefore, the aggregator's payoff is also zero (i.e., $U(\mathbf{0}, \mathbf{0}) = 0$). And the disagreement point is the origin, i.e., $\boldsymbol{c}_0 = \mathbf{0}$.

Consider that the aggregator and clients $\mathcal{M}_t$ reach agreements in $(\boldsymbol{b}^t, \boldsymbol{p}^t)$. Then the aggregator's payoff and client m's payoff are $U(\boldsymbol{b}^t, \boldsymbol{p}^t)$ and $V_m^t(b_m^t, p_m^t)$, respectively. Here $b_m^t \in \boldsymbol{b}^t$ and $p_m^t \in \boldsymbol{p}^t$. Since the disagreement point is $\mathbf{0}$, $U(\boldsymbol{b}^t, \boldsymbol{p}^t)$ and $V_m^t(b_m^t, p_m^t)$ can represent the payoff gain from the bargaining. According to Theorem 1, we can formulate the concurrent bargaining as the following optimization problem:

$$\max_{\boldsymbol{b}^t, \boldsymbol{p}^t} \; \left(U(\boldsymbol{b}^t, \boldsymbol{p}^t) - U(\mathbf{0}, \mathbf{0})\right) \prod_{m \in \mathcal{M}_t} \left(V_m^t(b_m^t, p_m^t) - V_m^t(0,0)\right)$$
$$s.t. \quad \text{Constraint (12)}, \tag{11}$$

where the constraint (12) is,

$$\begin{cases} V_m^t(b_m^t, p_m^t) - V_m^t(0,0) \geq 0, \\ U(\boldsymbol{b}^t, \boldsymbol{p}^t) - U(\mathbf{0}, \mathbf{0}) \geq 0, \\ \mathbf{1}^T \boldsymbol{b}^t \leq B, \\ \mathbf{1}^T \boldsymbol{p}^t \leq P_t \\ b_m^t \in \{0,1\}, p_m^t \geq 0, p_m^t \in \mathbb{R}, \forall m \in \mathcal{M}_t. \end{cases} \tag{12}$$

To derive the NBS in the concurrent bargaining, we transform the problem (11) into the following equivalent convex optimization by taking the logarithm over the objective, i.e.,

$$\max_{\boldsymbol{b}^t, \boldsymbol{p}^t} \; \log\left(U(\boldsymbol{b}^t, \boldsymbol{p}^t)\right) + \sum_{m \in \mathcal{M}_t} \log\left(V_m^t(b_m^t, p_m^t)\right)$$
$$s.t. \quad \text{Constraint (12)}. \tag{13}$$

We have the following lemma to characterize the concurrent bargaining problem in our setting.

Lemma 1: The concurrent bargaining for FL is NP-hard.

Proof: From (11) and in (13), we can see that the concurrent bargaining for FL is mixed-integer convex programming (MICP), actually a type of combinatorial optimization problem, which is a classical NP-hard problem [44], [45], [46]. □

Remarks: Lemma 1 indicates that the concurrent bargaining problem is still challenging to derive the NBS, though the concurrent bargaining framework can overcome the issue of sequential bargaining. Even if the concurrent bargaining is NP-hard, it is difficult to design an approximation algorithm with theoretical approximation guarantee, largely because global model utility $f_t(\sum_{m \in \mathcal{M}_t} b_m^t K_m)$ and communication overhead C_0^{com} and C_m^t are revealed only after the decisions are made. In fact, only for the case with two integer variables, does there exist a efficient approximate algorithm for MICP with theoretical approximation factor [45]. However, the aggregator usually bargains with more than 2 clients in practical FL setting. Therefore, we turn our focus to design a heuristic algorithm for our incentive mechanism. To tackle these issues, we propose a heuristic algorithm to derive the approximate NBS within polynomial time complexity. Our heuristic algorithm for the concurrent bargaining includes two key processes: client selection and payment determination.

Client selection: We consider non-uniform probabilistic sampling distribution to design client selection due to the convergence guarantee of non-uniform probabilistic sampling [47]. We use a probabilistic greedy policy to design the client selection routine. Our heuristics is established on the fact that uploading more parameters will increase the value of $f_t(\sum_{m \in \mathcal{M}_t} b_m^t K_m)$ with high probability [23], [32], [33], [34]. This is because $f_t(\cdot)$ is non-decreasing in K_m. Specifically, we consider the sizes of the local datasets and greedily assign each client with a non-zero probability of selection, to handle the non-IID issue, which guarantees the convergence of the global model [19]. We use the Softmax function to determine the selection probability $\mathbb{P}_m^t$ of client m based on parameters K_m and $|\mathcal{D}_m|$,

$$\mathbb{P}_m^t = \exp(K_m + |\mathcal{D}_m| - C_m^{t-1}) / \sum_{n \in \mathcal{M}_t} \exp(K_n + |\mathcal{D}_n| - C_n^{t-1}). \tag{14}$$

Remarks: 1) *The intuition behind (14) is supported by the observation:* When client m has a higher sparse number K_m and a larger local dataset, client m could have a significant contribution to speed up the convergence of the global model. Thus, our bargaining-based incentive mechanism should enforce the cooperation with these clients with a higher sparse number K_m and a larger local dataset. To this end, we should correspondingly enlarge the selection probability of this kind of clients in proportion to the sparse number K_m and the size $|\mathcal{D}_m|$ of the local dataset. 2) *The reason why use the Softmax function to determine the selection probability:* Note that the sparse number K_m and the size $|\mathcal{D}_m|$ of the local dataset can be unbounded values. Thus, it is difficult to directly incorporate them into the selection rule. Inspired by deep learning's logit layer that use Softmax operator to transform the unbounded output into the bounded range [0,1], which can be interpreted as prediction probability, in this paper, we choose Softmax function to generate probabilities, and normalize the impact of the sparse number K_m and the size $|\mathcal{D}_m|$ of the local dataset on selection probability. Similar idea can be seen in control action selection in decision-making models [48]. 3) *Calculation with different units*. In (14), When parameters K_m, $|\mathcal{D}_m|$ and C_m^{t-1} have different units, it is still possible to use them together to calculate the client selection probability. The reasons are three-fold: First, their monotonic relationship with the probability $\mathbb{P}_m^t$ is well-captured in (14), which a client with higher K_m and $|\mathcal{D}_m|$ and lower C_m^{t-1} will have larger probability to be selected. Second, the Softmax function can accurately re-shift the different scale brought by the different unit. Third, to keep the same unit, it suffices to find the factors to discount their effects in (14). However, the underlying factors will not significantly change the selection probability using the Softmax function. Finding the factors is not the focus in this paper. Actually, both analytical selection

Algorithm 1: Probabilistic Greedy Client Selection in Round t.

Input: $\mathcal{M}_t$, B, $\{K_m\}$, $\{|\mathcal{D}_m|\}, \forall m \in \mathcal{M}_t$
Output: Participation vector $\tilde{\boldsymbol{b}}^t$
1: Initialize variables $b_m^t = 0, \forall m \in \mathcal{M}_t$
2: **if** $|\mathcal{M}_t| \leq B$ **then**
3: Set $b_m^t = 1, \forall m \in \mathcal{M}_t$
4: **else**
5: Greedily assign client m's selection probability $\mathbb{P}_m^t$ using Softmax in (14)
6: Sample B clients with $\{\mathbb{P}_m^t\}_{\forall m}$ and obtain set $\mathcal{S}$
7: Let $b_m^t = 1, \forall m \in \mathcal{S}$
8: **end if**
9: Construct vector $\tilde{\boldsymbol{b}}^t = (b_m^t)_{m \in \mathcal{M}_t}$
10: **return** $\tilde{\boldsymbol{b}}^t$.

probability [19] and learning-based selection probability [49] use the parameters with different units in the existing works. 4) *About truthfully reporting clients' costs.* Note that we establish the client selection rule in (14) to incorporate the clients' costs based on the Myerson theorem [50], which has truthfulness guarantee. We have the following lemma to show this point.

Lemma 2: Our bargaining-based incentive mechanism for FL is truthful.

Proof: According to the Myerson theorem [50], we need to prove that the client selection rule in our bargaining-based incentive mechanism is monotonous and the payment rule in our bargaining-based incentive mechanism is determined by the critical value. 1) For any $\tilde{C}_m^{t-1} \leq C_m^{t-1}$, inequality $\mathbb{P}_m^t(\tilde{C}_m^{t-1}) \geq \mathbb{P}_m^t(C_m^{t-1})$ holds. It indicates the selection probability is reduced when a client reports a higher cost. Thus, our client selection rule satisfies monotonicity. 2) If a client reports a higher cost, the selection probability is reduced and the client loses the chance to be selected. If a client reports a lower cost, the client obtains less payment. That means, the mis-reporting cost will not produce a higher payment that is not the critical value. Therefore, a rational client will truthfully report the cost. □

Remarks: About truthfully reporting the size $|\mathcal{D}_m|$ of the local dataset. In our proposed FL-oriented bargaining-based incentive mechanism, *each potential participants will report and upload their local datasets' sizes to the server in the initial stage*. We highlight that our proposed mechanism can ensure that each client m will truthfully report the size $|D_m|$ of local dataset D_m. The reason is the *truthfulness dependence* between costs C_m^t and size $|D_m|$. Recall that each client m truthfully reports their costs C_m^t to the aggregator in each round, which gives the optimal selection probability to earn the payment. As demonstrated in reference [51], client's cost is linear in $|D_m|$ with a unit cost factor. Therefore, the truthfulness of C_m^t leads to the truthfulness of $|D_m|$.

Based on this greedy policy, we design a probabilistic client selection routine and show its pseudo-code in Algorithm 1. Algorithm 1 inputs client set $\mathcal{M}_t$, selection budget B and the number of uploading model update $\{K_m\}$, the size of local datasets $\{|\mathcal{D}_m|\}, \forall m \in \mathcal{M}_t$, and outputs the participation vector $\boldsymbol{b}^t$. In line 1, we first initialize all elements to be zero, i.e., $b_m^t = 0, \forall m \in \mathcal{M}_t$. If the size of client set $\mathcal{M}_t$ is smaller than B, we select all clients in $\mathcal{M}_t$ to participate in FL (line 2–4). Otherwise, we greedily assign clients' selection probability using the Softmax policy in (14) (line 5). Then, we randomly sample B clients using the assigned selection probabilities and obtain set $\mathcal{S}$ (line 6). Finally, we obtain the participation vector $\tilde{\boldsymbol{b}}^t$. The time complexity is $\mathcal{O}(|\mathcal{M}_t|)$. Thus, our designed client selection routine is computational efficiency.

Payment determination: After making the participation decision $\tilde{\boldsymbol{b}}^t$ (corresponding the selected clients $\mathcal{S}_t = \{m | b_m^t = 1, m \in \mathcal{M}_t\}$), the selected clients will perform FL local training tasks. At the end of round t, the model utility $f_t(\sum_{m \in \mathcal{M}_t} b_m^t K_m)$ and communication overhead C_0^{com} and C_m^t are revealed. Then, the aggregator has to solve the payment determination problem to derive the payment pricing decision $\tilde{\boldsymbol{p}}^t$.

Given the participation decision $\tilde{\boldsymbol{b}}^t$, we define two constants $A \triangleq f_t(\sum_{m \in \mathcal{M}_t} b_m^t K_m) - \sum_{m \in \mathcal{M}_t} b_m^t C_0^{\text{com}} \geq 0$ and $E_m^t \triangleq b_m^t C_m^t \geq 0$. With these notations, the problem (13) can be transformed to the following maximization,

$$\max_{\boldsymbol{p}^t} \; \log\left(A - \sum_{m \in \mathcal{S}_t} p_m^t\right) + \sum_{m \in \mathcal{S}_t} \log\left(p_m^t - E_m^t\right)$$
$$s.t. \quad \begin{cases} p_m^t - E_m^t \geq 0, \\ A - \sum_{m \in \mathcal{S}_t} p_m^t \geq 0, \\ \sum_{m \in \mathcal{S}_t} p_m^t \leq P_t, \\ p_m^t \geq 0, p_m^t \in \mathbb{R}, \forall m \in \mathcal{S}_t. \end{cases} \tag{15}$$

In order to solve the above optimization problem, we simplify the constraints by combining the same class constraints (e.g., the first constraint and the fourth constraint, the second constraint and the third constraint). We further obtain the following equivalent optimization,

$$\min_{\boldsymbol{p}^t} \; -\log\left(A - \sum_{m \in \mathcal{S}_t} p_m^t\right) - \sum_{m \in \mathcal{S}_t} \log\left(p_m^t - E_m^t\right)$$
$$s.t. \quad \begin{cases} \sum_{m \in \mathcal{S}_t} p_m^t \leq G, \\ p_m^t \geq E_m^t, p_m^t \in \mathbb{R}, \\ \forall m \in \mathcal{S}_t. \end{cases} \tag{16}$$

where $G \triangleq \min\{A, P_t\}$. Note that problem (16) is still convex optimization due to the convexity-preserving transformation. Thus, it suffices to characterize its optimal solution $\tilde{\boldsymbol{p}}^t$ by the Karush–Kuhn–Tucker (KKT) conditions [52]. We present the optimal solution $\tilde{\boldsymbol{p}}^t$ to the payment determination in the following theorem.

Theorem 3: In the concurrent bargaining for FL, given the clients $\mathcal{S}_t$ selected by Algorithm 1, we can price the optimal payments for them according to the following equation,

$$\tilde{p}_m^t = \frac{A + E_m^t - \sum_{n \in \mathcal{S}_t \setminus \{m\}} \tilde{p}_n^t}{2}, \forall m \in \mathcal{S}_t. \tag{17}$$

For the non-participating client m, her payment $\tilde{p}_m^t = 0$. Thus, the optimal payments $\tilde{\boldsymbol{p}}^t = (\tilde{p}_m^t)_{m \in \mathcal{M}_t}$.

Proof: To construct the KKT conditions, we introduce Lagrange multipliers $\theta \geq 0$ for constraint $\sum_{m \in \mathcal{M}_t} p_m^t \leq G$ and $\boldsymbol{\nu} = [\nu_1, \ldots, \nu_m, \ldots, \nu_{|\mathcal{M}_t|}] \succeq \mathbf{0}$ for constraints $p_m^t \geq E_m^t, \forall m \in \mathcal{M}_t$. By KKT conditions, we have,

$$\begin{cases} \frac{1}{A - \sum_{m \in \mathcal{M}_t} p_m^t} - \frac{1}{p_m^t - E_m^t} + \theta - \nu_m = 0, \forall m \in \mathcal{M}_t, \\ \sum_{m \in \mathcal{M}_t} p_m^t \leq G, \\ \theta \geq 0, \\ \theta(G - \sum_{m \in \mathcal{M}_t} p_m^t) = 0, \\ p_m^t \geq E_m^t, \forall m \in \mathcal{M}_t, \\ \nu_m(p_m^t - E_m^t) = 0, \forall m \in \mathcal{M}_t, \\ \nu_m \geq 0. \end{cases} \tag{18}$$

Solving the above KKT condition equations, we can obtain the closed form of payment in (17). Thus, we can conclude this theorem. □

Remarks: From Theorem 3, we can see that the client uploading more parameters of model update and incurring more costs will receive more payment. However, the total payments will not exceed the augmented budget G. Intuitively, the clients with more computation and communication resources are competing to participate in FL and obtain the aggregator's budget G. From this perspective, our incentive mechanism can improve the computation and communication efficiency of FL when scheduling the distributed clients to collectively complete the learning task. Based on Theorem 3, we can derive the closed-form payment for client $m \in \mathcal{S}_t$ by solving (17), which is shown in the following corollary.

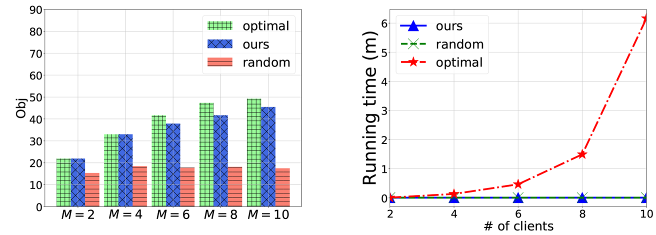
Corollary 1: The payment $\tilde{p}_m^t$ for the selected client $m \in \mathcal{S}_t$ can be calculated as,

$$\tilde{p}_m^t = \frac{A + E_m^t}{|\mathcal{S}_t| + 1}. \tag{19}$$

Remarks: As we can see, when the number of the selected clients is large, the payment is decreased. Thus, our incentive mechanism incentivizes the clients to compete for the payments by participating in the FL tasks. However, the competition is beneficial to the aggregator. The payment $\tilde{p}_m^t$ in (19) also indicates that the aggregator and clients $\mathcal{S}$ share the social welfare $A + E_m^t$, which coincides with the bargaining outcome.

Approximate performance: We carry out numerical experiment to evaluate the approximate performance of our proposed approach to derive approximate NBS for the concurrent one-to-many bargaining in (13). We consider two baselines: `optimal` and `random`. In `optimal`, we first enumerate the binary selection decision $\boldsymbol{b}^t$ and correspondingly invoke the convex optimization solver to solve the payment decision $\boldsymbol{p}^t$, namely we employ brute force policy to implement `optimal`. In `random`, we randomly set the binary selection decision $\boldsymbol{b}^t$ and the payment decision $\boldsymbol{p}^t$ according to the uniform distribution.

We set the aggregator's communication cost as $C_0^{\text{com}} = 50$ and configure clients' cost using uniform distribution over interval [50,100]. The unit valuation of model accuracy gain is set as $\lambda = 5,000$ by default while the maximum model accuracy gain is considered as sampling from [0.7,0.95]. As it is extremely



(a) Approximate performance. (b) Running time performance.

Fig. 1. Performance of our approximate NBS.

Algorithm 2: `BargainingFL`.

Input: T, $\mathcal{M}$, B, λ, C_0^{com}, η
Output: Global model Θ_T
Initialize global model Θ_0, evaluate initial accuracy $\epsilon(0)$
for $t = 1, 2, \ldots, T$ **do**
  Observe active clients $\mathcal{M}_t$
  Collect sparse number K_m from client $m, \forall m \in \mathcal{M}_t$
  Call $\tilde{\boldsymbol{b}}^t \leftarrow$ Algorithm 1$(\mathcal{M}_t, B, \{K_m\}_{\forall m \in \mathcal{M}_t})$
  Select participants $\mathcal{S}_t = \{m | b_m^t = 1, b_m^t \in \tilde{\boldsymbol{b}}^t\}$
  Send the current global model Θ_t to $\mathcal{S}_t$
  Each client $m \in \mathcal{S}_t$ calculates local gradient $\boldsymbol{g}_m^t$
  Each client $m \in \mathcal{S}_t$ calculates $\mathcal{P}^m$ based on (3) and sparsifies $\boldsymbol{g}_m^t$ based on (4).
  Each client $m \in \mathcal{S}_t$ uploads the sparse gradient $Q(\boldsymbol{g}_m^t)$
  Aggregate: $\Delta_t = \frac{1}{M} \sum_{m \in \mathcal{S}_t} Q(\boldsymbol{g}_m^t) / \mathbb{P}_m^t$
  $\Theta_{t+1} = \Theta_t - \eta \Delta_t$
  Observe the cost C_m^t from client $m, \forall m \in \mathcal{S}_t$
  Evaluate the accuracy $\epsilon(\sum_{m \in \mathcal{M}_t} b_m^t K_m)$
  Calculate $f_t(\sum_{m \in \mathcal{M}_t} b_m^t K_m)$ based on (5)
  Define $A = f_t(\sum_{m \in \mathcal{M}_t} b_m^t K_m) - \sum_{m \in \mathcal{M}_t} b_m^t C_0^{\text{com}}$ and $E_m^t = b_m^t C_m^t$
  Calculate payment $\tilde{p}_m^t$ based on (19)
end for
return Θ_T.

difficult for `optimal` in large-scale problem, we consider the experimental setting regarding client size as $M \in \{2, 4, 6, 8, 10\}$. For each M, we accordingly run our method (given by Algorithm 1 and (19)) and `random` to obtain the performance metrics.

We focus on the approximate performance and time consumption performance. The approximate performance implies evaluating the difference from `optimal` regarding the objective value (as in (13)) and the time consumption performance implies the running time when deriving a solution. We present the results in Fig. 1. As we can observe in Fig. 1(a), our method obtains the same objective value in cases with $M = 2$ and $M = 4$. In other client size, our method achieves more than 95% optimal objective while `random` performs worse than our method. In Fig. 1(b), we can see that the running time of `optimal` increases exponentially while our method and `random` remain stable running time less than 1 s. Therefore, we can empirically conclude that our method have better approximate performance with near real-time calculation performance.

D. Bargaining for Communication-Efficient FL

In this subsection, we present our bargaining-based incentive mechanism for communication-efficient FL. The previous analyses lead to the algorithm for incentivizing communication-efficient FL. We show the pseudo-code in Algorithm 2.

Algorithm 2 inputs the total training rounds T, client set $\mathcal{M}$, selection budget B, the unit valuation of model accuracy gain λ, the aggregator's communication cost C_0^{com}, learning η, and outputs the global model Θ_T. In line 1, we randomly initialize the global model Θ_0 and accordingly evaluate initial model accuracy $\epsilon(0)$. The T-round FL procure takes place in line 2–18. In each round t, the aggregator first selects clients $\mathcal{S}_t$ by invoking Algorithm 1 (line 3–7). Then, the selected clients perform local training to compute the local sparse gradients and upload them to the aggregator (line 8–10). When receiving the model updates, the aggregator aggregates these gradients and updates the global model, then calculates the payments $\tilde{p}_m^t$ using our pricing rule in (19) (line 11–17). After T-round training, we obtain the global model Θ_T. Note that the final obtained global model Θ_T is unbiased, i.e., Θ_T solves the FL problem given in (1) in expectation, because of: 1) the unbiasedness of our sparse local gradients produced by the sparsification operator $Q(\cdot)$, 2) the non-uniform client sampling rule in (14), and 3) $\mathcal{O}(1/\sqrt{MT})$ convergence rate as shown in Theorem 5. Moreover, our `BargainingFL` can a dynamic communication environment where the sparse number K_m changes in each round. If the K_m change in each round, we can directly replace K_m in (14) and (19) without affecting the correctness.

Remarks: About the aggregator's truthfulness. It is impossible that the server deliberately lowers the value of the ϵ function for the sake of saving its payment. Actually, the participating clients can compute the value of the ϵ function because the global model is distributed to them. Recall that the accuracy gain regarding the receiving gradients is $\epsilon(\sum_{m\in\mathcal{M}_t} b_m^t K_m) - \epsilon(0)$. In round 0, when the clients received the global model, $\epsilon(0)$ can be calculated by evaluating the global mode over testing dataset. In any round t, the previous gradients was aggregated. And the accuracy $\epsilon(\sum_{m\in\mathcal{M}_t} b_m^t K_m)$ can be also calculated. Therefore, it is impossible for the server to fool the clients in our framework. On the other hand, deploying blockchain with FL and implementing the payment computation using smart contract can also avoid this issue.

We present the incentive guarantee of our incentive mechanism `BargainingFL` as follows.

Theorem 4: Our incentive mechanism `BargainingFL` is approximate socially optimal, individually rational, budget-feasible, computation-efficient and communication-efficient.

Proof: We begin to prove this theorem one by one as follows,

- *Approximate Socially optimal*: Recall that the social welfare focused in our setting is $\Psi(\boldsymbol{b}^t) \triangleq \Psi(\boldsymbol{b}^t, \boldsymbol{p}^t)$, as defined in (7). The social welfare objective is non-decreasing in client m's K_m and decreasing in client m's C_m^t. Our probabilistic greedy policy in (14) depends on K_m and C_m^t, which approximately maximizes the social welfare $\Psi(\boldsymbol{b}^t)$ in expectation. Recall that $\Psi(\boldsymbol{b}^t)$ is non-decreasing in client m's K_m and decreasing in client m's C_m^t. Meanwhile, the pure greedy policy greedily selects client m based on sorting clients in the descending order of K_m and in the ascending order of C_m^t under budget B, which leads to the approximate-optimal social welfare $\Psi(\boldsymbol{b}^t)$. Due to this observation, we integrate client m's K_m and C_m^{t-1} into our designed selection probability rule in (14). Let $\tilde{\boldsymbol{b}}^t = (b_m^t)_{m\in\mathcal{M}_t}$ be the decision yielded by our probability $\mathbb{P}_m^t$ and b_m^{*t} be the decision yielded by the pure greedy policy. $\mathbb{E}[b_m^t] = b_m^{*t}$ holds due to the observation that $\Psi(\boldsymbol{b}^t)$ is non-decreasing in client m's K_m and decreasing in client m's C_m^{t-1}. Therefore, we have $\mathbb{E}[\Psi(\tilde{\boldsymbol{b}}^t)] = \Psi(\boldsymbol{b}^{*t})$. Thus, this property holds in our incentive mechanism.
- *Individually rational*: When participants $\mathcal{S}_t$ is selected based on our probabilistic greedy policy, we have ensure that the payments from our incentive mechanism leads to non-negative utilities for clients and the aggregator, i.e., $V_m^t(b_m^t, p_m^t) - V_m^t(0,0) \geq 0$ and $U(\boldsymbol{b}^t, \boldsymbol{p}^t) - U(\mathbf{0}, \mathbf{0}) \geq 0$. It should be noted that the payment rule in (19) Corollary 1 is derived from the formulation (11), which takes the non-negative utilities as constraints.
- *Budget-feasible*: The budget constraint $\mathbf{1}^T\boldsymbol{b}^t \leq B$ (the maximum number of the selected clients is no more than B) is incorporated into our designed Algorithm 1.
- *Computation-efficient*: Algorithm 1 has $\mathcal{O}(M)$ time complexity while Algorithm 2 has $\mathcal{O}(Td)$ time complexity, which are both polynomial computational complexity. Thus, our incentive mechanism is computation-efficient.
- *Communication-efficient*: The selection rule and payment rule are both monotone on client m's sparse number K_m, which means our incentive mechanism incentivizes high-quality clients with more communication resources to participate in training tasks.

□

We present the convergence guarantee of our incentive mechanism `BargainingFL` for the non-convex case as follows. To ensure the convergence in the non-convex case, we assume the objectives are L-smooth, which is widely assumed in the literature.

Theorem 5: When the global model $F(\Theta)$, local models $F_m(\Theta)$ are L-smooth, and the uploading sparse gradients are unbiased and bounded (i.e., $|\boldsymbol{g}_{m,i}^t| \leq J, \forall m, i, t$), the sequence $\{\Theta_t\}_{t=1}^T$ derived by `BargainingFL` satisfies,

$$\frac{\sum_{t=1}^T \mathbb{E}\left[\|\nabla F(\Theta_t)\|^2\right]}{T} \leq \frac{F(\Theta_1)}{\eta T} + \frac{L\eta}{2\,M^2\,T}\sum_{t=1}^T \sum_{m\in\mathcal{M}} \frac{(K_m J)^2}{\mathbb{P}_m^t}.$$

Specifically, $\sum_{t=1}^T \mathbb{E}[||\nabla F(\Theta_t)||^2]/T = \mathcal{O}(1/\sqrt{MT})$ when the learning rate is $\eta = \mathcal{O}(\sqrt{M}/\sqrt{T})$.

Proof: According to the L-smoothness of loss functions $F(\Theta)$ [52], we begin to bound the following expression in round t,

$$F(\Theta_{t+1}) - F(\Theta_t) \leq \langle \nabla F(\Theta_t), \Theta_{t+1} - \Theta_t \rangle + \frac{L}{2}\|\Theta_{t+1} - \Theta_t\|^2. \tag{20}$$

Recall line 12 in Algorithm 2 and the gradient sparsification-based aggregation rule, we have,

$$\Theta_{t+1}-\Theta_t=-\eta\Delta_t=\frac{-\eta}{M}\sum_{m\in\mathcal{M}}\frac{\mathbb{I}(m,t)}{\mathbb{P}_m^t}Q(\boldsymbol{g}_m^t), \tag{21}$$

where indicator function $\mathbb{I}(m,t)$ indicates whether client m is selected in round t. By definition, we have $\mathbb{E}[\mathbb{I}(m,t)]=\mathbb{P}_m^t$.

Plugging (21) into (20) and taking expectation derive,

$$\mathbb{E}\left[F(\Theta_{t+1})-F(\Theta_t)\right]\le\underbrace{-\eta\left\langle\nabla F(\Theta_t),\frac{1}{M}\sum_{m\in\mathcal{M}}\mathbb{E}\left[Q(\boldsymbol{g}_m^t)\right]\right\rangle}_{\text{(A)}}+\underbrace{\frac{L\eta^2}{2M^2}\mathbb{E}\left[\left\|\sum_{m\in\mathcal{M}}\frac{\mathbb{I}(m,t)}{\mathbb{P}_m^t}Q(\boldsymbol{g}_m^t)\right\|^2\right]}_{\text{(B)}}. \tag{22}$$

For (A), we find that the sparse gradient $Q(\boldsymbol{g}_m^t)$ is the unbiased estimate of $\nabla F_m(\Theta_t)$ and $\nabla F(\Theta_t)=\frac{1}{M}\sum_{m\in\mathcal{M}}\nabla F_m(\Theta_t)$. Thus, we have

$$-\eta\left\langle\nabla F(\Theta_t),\frac{1}{M}\sum_{m\in\mathcal{M}}\mathbb{E}\left[Q(\boldsymbol{g}_m^t)\right]\right\rangle=-\eta\left\|\nabla F(\Theta_t)\right\|^2. \tag{23}$$

To bound (B), we have,

$$\begin{aligned}&\frac{L\eta^2}{2M^2}\mathbb{E}\left[\left\|\sum_{m\in\mathcal{M}}\frac{\mathbb{I}(m,t)}{\mathbb{P}_m^t}Q(\boldsymbol{g}_m^t)\right\|^2\right]\\&\overset{(a)}{\le}\frac{L\eta^2}{2M^2}\sum_{m\in\mathcal{M}}\mathbb{E}\left[\left\|\frac{\mathbb{I}(m,t)}{\mathbb{P}_m^t}Q(\boldsymbol{g}_m^t)\right\|^2\right]\\&=\frac{L\eta^2}{2M^2}\sum_{m\in\mathcal{M}}\frac{\mathbb{E}\left[\mathbb{I}(m,t)\right]}{(\mathbb{P}_m^t)^2}\mathbb{E}\left[\left\|Q(\boldsymbol{g}_m^t)\right\|^2\right]\\&=\frac{L\eta^2}{2M^2}\sum_{m\in\mathcal{M}}\frac{1}{\mathbb{P}_m^t}\mathbb{E}\left[\left\|Q(\boldsymbol{g}_m^t)\right\|^2\right]\overset{(b)}{\le}\frac{L\eta^2}{2M^2}\sum_{m\in\mathcal{M}}\frac{(K_mJ)^2}{\mathbb{P}_m^t},\end{aligned} \tag{24}$$

(a) is due to Jensen's inequality. (b) is due to the sparse parameter K_m and the assumption of $|\boldsymbol{g}_{m,i}^t|\le J,\forall m,i,t$. Plugging (23) and (24) into (25), rearranging terms and taking telescope sum $t\in[T]$, dividing ηT on both sides, we obtain,

$$\begin{aligned}&\sum_{t=1}^{T}\left\|\nabla F(\Theta_t)\right\|^2/T\\&\le\frac{\mathbb{E}\left[F(\Theta_1)-F(\Theta_T)\right]}{\eta T}+\frac{L\eta}{2M^2T}\sum_{t=1}^{T}\sum_{m\in\mathcal{M}}\frac{(K_mJ)^2}{\mathbb{P}_m^t}\\&\le\frac{F(\Theta_1)}{\eta T}+\frac{L\eta}{2M^2T}\sum_{t=1}^{T}\sum_{m\in\mathcal{M}}\frac{(K_mJ)^2}{\mathbb{P}_m^t}.\end{aligned} \tag{25}$$

To minimize the r.h.s of (25), we set $\eta=\sqrt{\frac{2M^2F(\Theta_1)}{L\sum_{t=1}^{T}\sum_{m\in\mathcal{M}}\frac{(K_mJ)^2}{\mathbb{P}_m^t}}}=\mathcal{O}(\sqrt{M}/\sqrt{T})$. Thus, $\sum_{t=1}^{T}\|\nabla F(\Theta_t)\|^2/T=\mathcal{O}(1/\sqrt{MT})$, which concludes the theorem. □

V. Experiments

A. Experimental Setup

We implement our proposed bargaining-based incentive mechanism for FL (i.e., Algorithm 2) using an open-source FL framework, Plato (https://github.com/TL-System/plato), which is developed based on Pytorch. With Plato, we can simulate clients using threads. Moreover, we can customize the non-IID datasets by controlling the concentration parameter in the Dirichlet distribution. We modify the framework's server code to implement the FL procedure using Algorithm 2.

Setting: Our simulation setting consists of one aggregator (i.e., the server in Plato) and 100 clients (i.e., the 100 threads). We set the total training rounds $T=4000$ by default. In each round t, we activate 20 clients, i.e., $|\mathcal{M}_t|=20$. The aggregator's communication cost is set as $C_0^{\text{com}}=50$. We configure clients' cost using uniform distribution over interval [50,100]. We set the unit valuation of model accuracy gain $\lambda=5{,}000$ and the learning rate $\eta=0.1$. The minibatch size is set to be 32 to derive the local gradient.

Datasets and model: We consider two classic datasets for FL, i.e., MNIST and CIFAR-10. MNIST includes 70,000 Gy-scale images of handwritten digits with size 28×28 where the number of classes is 10. CIFAR-10 includes 60,000 color images of different objects with size $32\times32\times3$ where the number of classes is also 10. We generate the non-IID local datasets by setting the concentration parameter to be 0.2. In the both datasets, we aim to train a convolutional neural network (CNN) as the global models with over $400{,}000$ weight parameters (i.e., $d>400{,}000$). In each round, we randomly set K_m over $[10^3,10^4]$ for client m.

Baseline: we consider 6 baselines for fair comparison:

- *RandomIncentive:* This baseline randomly generates payments in each round.
- *FixedIncentive:* This baseline provides fixed payments in each round.
- *StackelbergIncentive* [29]: This baseline calculates payments according to the Stackelberg equilibrium in each round. Given the aggregator payment strategy R and client m's decision e_m, *StackelbergIncentive* can be formulated as the multi-objective bilevel optimization,

$$\begin{aligned}\max_{R}\quad & u_0^t(\boldsymbol{e}^*(R),R)\\ \text{s.t.}\quad & R\ge0, \end{aligned}\tag{26a}$$

$$\max_{\boldsymbol{e}}\quad u_1^t(e_1,\boldsymbol{e}_{-1},R),\ldots,u_M^t(e_M,\boldsymbol{e}_{-M},R) \tag{26b}$$

$$\text{s.t.}\quad e_m\ge0,\forall m\in\mathcal{M}, \tag{26c}$$

where $u_0^t(\cdot,\cdot)$ is the utility function of the aggregator in round t, $u_i^t(\cdot,\cdot,\cdot)$ is the utility function of client $m\in\mathcal{M}$,

$\boldsymbol{e}_{-m}$ is other clients' decision excluding client m, and $\boldsymbol{e}^*(R)$ is the best response of clients given the aggregator's strategy R.

- *ContractIncentive* [28]: This baseline provides the elaborated contract items (i.e., payment-type items) in each round. Let $\boldsymbol{\phi} = \{\phi_i\}_{i=1}^I$ be the contract set where I contract items are designed. Each contract item $\phi_i \triangleq (e_i, p_i)$ gives the map of client i's decision e_i and the corresponding payment p_i. *ContractIncentive* can be formulated as the following optimization,

$$\min_{\boldsymbol{\phi}} \quad W(\boldsymbol{\phi})$$

$$\text{s.t.} \quad p_i \geq 0, \forall i \in \mathcal{M}, \tag{27a}$$

$$e_i \geq 0, \forall i \in \mathcal{M}, \tag{27b}$$

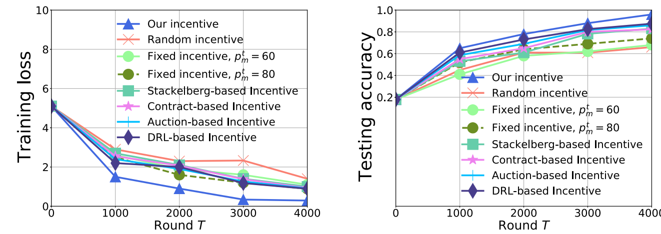
$$U(\theta_i, e_i, p_i) \geq 0, \forall i \in \mathcal{M}, \tag{27c}$$

$$U(\theta_i, e_i, p_i) \geq U(\theta_i, e_j, p_j), \forall i, j \in \mathcal{M}, \tag{27d}$$

where $W(\boldsymbol{\phi})$ is the cost function regarding contract items $\boldsymbol{\phi}$, $U(\theta_i, e_i, p_i)$ is the utility of client i with type θ_i. Eq. (27c) and (27d) correspond to individual rationality (IR) constraint and incentive compatibility (IC) constraint, respectively.
- *AuctionIncentive* [5]: This baseline first selects winning clients and calculates payments using VCG rule [53]. Generally speaking, *AuctionIncentive* is formulated as winning determination rule and payment calculation rule. Let $\tilde{C}_m^t$ be client m's bid (i.e., claimed cost), and p_m^t be the payment calculated for client m. Then, *AuctionIncentive* can be formulated as the social welfare maximization with the winning bids, i.e., formulation (8)

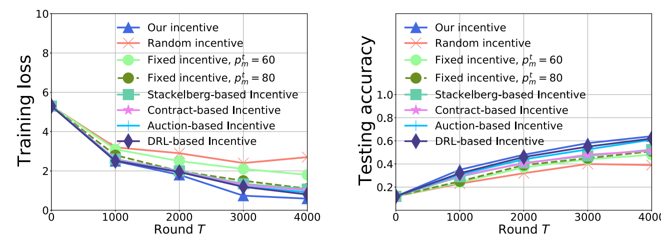
$$\max_{\boldsymbol{b}^t} \ \Psi(\boldsymbol{b}^t, \{\tilde{C}_m^t\}_m), \ \text{s.t.}, \ \begin{cases} \boldsymbol{1}^T \boldsymbol{b}^t \leq B, \\ \boldsymbol{b}^t \in \{0,1\}^{|\mathcal{M}_t|}. \end{cases}$$

Then, the payment is determined by a critical value according to Myerson law [50]. One of critical value assigning rule is VCG rule with truthfulness guarantee (i.e., $\tilde{C}_m^t = C_m^t$). Based on the VCG rule where the payment to client m is the social welfare loss to other clients when selecting client m, i.e., $p_m^t = \Psi(\boldsymbol{b}^t, \{\tilde{C}_m^t\}_m | b_m^t = 1) - \Psi(\boldsymbol{b}^t, \{\tilde{C}_m^t\}_m | b_m^t = 0)$.
- *DRLIncentive* [7], [8]: This baseline calculates the payments using DRL policy and learns the optimal payments in each round. *DRLIncentive* can be formulated as a Markov Decision Process (MDP) where, in round t, the action is $\boldsymbol{a}_t = (\boldsymbol{b}^t, \boldsymbol{p}^t)$ while the space is the historical incentive results. Suppose the past L rounds' historical information is considered, then the state in round t can be represented as $\boldsymbol{s}_t = (\boldsymbol{b}^{t-1}, \boldsymbol{p}^{t-1}, \text{acc}^{t-1}; \boldsymbol{b}^{t-2}, \boldsymbol{p}^{t-2}, \text{acc}^{t-2}; \ldots; \boldsymbol{b}^{t-L}, \boldsymbol{p}^{t-L}, \text{acc}^{t-L})$ where acc^{t-1} is the accuracy of the global model in round $t-1$. When taking action $\boldsymbol{a}_t$ under state $\boldsymbol{s}_t$, the aggregator observes a reward signal $r_t = \Psi(\boldsymbol{b}^t) + \gamma \text{acc}^t$, which is the social welfare $\Psi(\boldsymbol{b}^t)$ regularized by the accuracy acc^t with factor $\gamma > 0$. The goal of *DRLIncentive* is to learn a decision policy $\Phi: \boldsymbol{s}_t \rightarrow \boldsymbol{a}_t$ parameterized by a deep neural network such that an optimal action can be predictd given a current state, in terms of maximizing the cumulative reward in expectation.



(a) Training loss. (b) Testing accuracy.

Fig. 2. Convergence performance results on MNSIT.



(a) Training loss. (b) Testing accuracy.

Fig. 3. Convergence performance results on CIFAR-10.

From the formulation and the solution above, we can observe that baselines either have static participant selection rules which fail to overcome the non-IID issue and slow down the convergence of the global model (i.e., *StackelbergIncentive*, *ContractIncentive*, *AuctionIncentive*), or select participant based on a specific probability distribution but have no closed-form payment rule, which require additional process to learn the payment rule (i.e., *DRLIncentive*, *RandomIncentive*). Moreover, these baselines do not only neglect the communication cost, but also leave the transmitted parameters uncompressed.

Performance metrics: We adopt the training loss and testing accuracy to evaluate the convergence performance of our incentive mechanism for FL. To evaluate the communication efficiency, we focus on the total communication rounds. We also use payoff as matric to verify the incentive performance.

B. Performance Results

In this subsection, we demonstrate the extensive experimental results to validate the effectiveness of our incentive mechanism for FL in terms of convergence performance, communication performance and incentive performance.

Convergence performance: We run our bargaining-based incentive mechanism and baselines for FL up to 4,000 rounds. We set the payments to be $p_m^t = 60$ and $p_m^t = 80$ to produce two counterparts of FixedIncentive. The global models are trained on MNIST and CIFAR-10. In each round, we report the training losses and evaluate the testing accuracy results of the global models for all mechanisms. The maximum number of the selected clients is $B = 5$. The results for MNIST and CIFAR-10 are shown in Figs. 2 and 3, respectively. We have the following

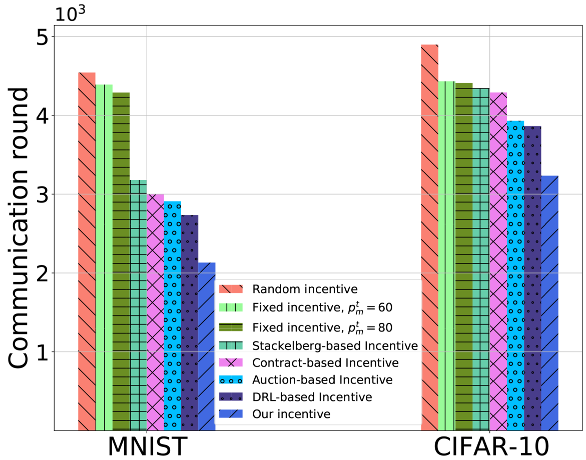
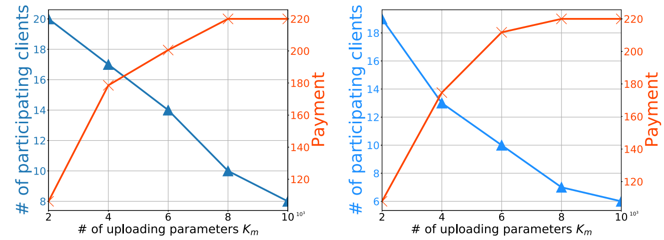
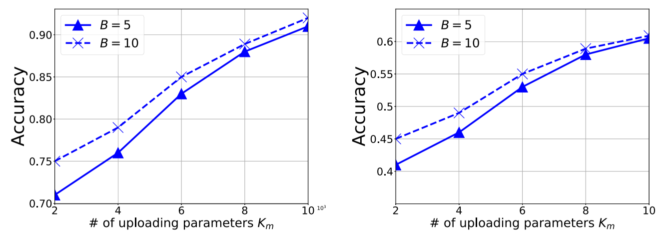


Fig. 4. Communication performance comparison.



(a) MNSIT. (b) CIFAR-10.

Fig. 5. Incentive performance in different K_m.



(a) MNSIT. (b) CIFAR-10.

Fig. 6. Impact of K_m on accuracy performance.

observations: First, all incentive mechanisms for FL achieve a lower training loss and a higher testing accuracy when the training rounds increase. This is because more training rounds enable the participation of more clients. The *RandomIncentive* has a fluctuating trend due to the randomness that slows down the convergence. Second, our incentive mechanism outperforms the baselines in terms of the training loss and the testing accuracy over MNIST and CIFAR-10. For instance, our incentive mechanism achieves more $10\% - 30\%$ testing accuracy than the second-best DRL-based incentive mechanism, given the same training rounds. This is largely because DRL uses more training rounds to learn the optimal payment policy. All these results verify that our incentive mechanism significantly motivates more clients' participation to contribute to training the global models.

Communication performance: To evaluate the communication efficiency of our incentive mechanism, we set the target accuracy to be 80% for MNIST and 60% for CIFAR-10, respectively. When the target accuracies are achieved, we report the communication rounds consumed by different mechanisms. The results are shown in Fig. 4. We see that our incentive mechanism significantly reduces the communication rounds to achieve the target accuracies. Compared to our incentive mechanism, baselines almost require 1.2–2.0x communication rounds. The reasons might be two-fold: 1) FL's non-IID issue slows down the convergence of the global model. That means, an FL algorithm will incur more communication rounds to train the global model when failing to mitigate the effect of non-IID issue. To overcome the non-IID challenge, the existing FL frameworks (e.g., FEDAVG [2]) usually select a subset of clients at random in each round, according to a selection *probabilistic distribution*, e.g., uniform distribution. The existing work [47] also shows the convergence guarantee with probabilistic client sampling. As to the baselines, *StackelbergIncentive*, *ContractIncentive*, and *AuctionIncentive* belong to the static participant selection rules, which tend to select a specific set of clients and lead to more communication rounds. Compared to these baselines, our proposed incentive mechanism consider probabilistic client selection, which significantly addresses non-IID issue and results in fewer communication rounds to train the global model. 2) Different clients have different communication resources, which lead to heterogeneous communication cost. When other probabilistic baselines like *DRLIncentive*and *RandomIncentive* can address non-IID issue and use relatively fewer communication rounds, they cannot optimize the payment and fail to incentivize high-quality clients' contribution. In fact, *ContractIncentive*, *AuctionIncentive* and *DRLIncentive* only guarantee the non-negativity of clients' utilities, rather than optimize clients' utilities via the payment. Therefore, our proposed incentive mechanism can achieve the best communication performance, compared to baselines. These results validate that our incentive mechanism for FL is communication-efficient.

Incentive performance: We evaluate the incentive performance of our incentive mechanism on different clients characterized by the sparsity number of uploading model updates (i.e., K_m). We set the payment budget $P_t = 220$. In a round, we run our incentive mechanism and report the bargaining process. From Fig. 5, we observe that the payment for a client with a larger sparsity number K_m is higher but no more than the payment budget 220. However, the number of clients is less when the sparsity number K_m is larger, which corresponds to the case where our incentive mechanism efficiently incentivizes the high-quality clients with more computation and communication resources to participate in FL. In Fig. 6, we can see that the accuracies for the global models increase when more model update parameters (i.e., larger K_m) are updated. When the selection budget B is large, the accuracies are improved. This is because our incentive mechanism is allowed to select more clients with limited computation and communication resources.

C. Discussion

1. How can our results be easily applied in practice to improve the performance of FL systems, especially with the massive number of clients and many bargaining? The theoretical and empirical results of our proposed incentive mechanism can be easily applied in practice to improve the performance of FL systems from the following perspective: communication performance, convergence performance and incentive performance. 1) *Communication performance*: When training a global model with large-scale parameters under practical network-constrained scenario (e.g., IoT and edge computing), our bargaining-based incentive mechanism can be easily deployed to improve the performance of FL systems largely because our bargaining-based incentive mechanism can incentivize the high-quality clients with more computation and communication resources to participate in FL, which directly improve the communication performance of FL systems. 2) *Convergence performance*: Due to the non-uniform probabilistic sampling in client selection, our incentive mechanism effectively addresses non-IID issue in the practical FL systems and has convergence guarantee for the practical FL systems. 3) *Incentive performance*: The client selection algorithm in our bargaining-based incentive mechanism has polynomial time complexity with efficient approximate guarantee (approximate Nash bargaining solution) and the payment rule in our bargaining-based incentive mechanism has closed-form. Thus, our incentive mechanism works effectively with the massive number of clients and many bargaining.

2. Why does the utility of the aggregator (or accuracy gain) only depend on the number of the received parameter of sparse gradients? In this paper, we aim to address the problem of how to improve communication efficiency for FL from the incentive perspective. Therefore, it is necessary to capture the dependence of aggregator's utility on the communication efficiency. The utility of the aggregator might be affected by other factors. However, it is not focus of this paper. Recall that the communication efficiency in this paper is characterized by sparse number K_m, which means to sparsify client m's local gradient by retaining K_m significant non-zero elements (i.e., the number of the received parameter of sparse gradients). Note that K_m is determined by client m based on client m's communication resource. The more participating clients with sufficient communication resources, the more communication-efficient the FL becomes. Therefore, in this paper, we aim to design an incentive mechanism to incentivize high-quality clients (i.e., with larger K_m) to take part in FL tasks. The utility of the aggregator should capture the heterogeneity of communication resources.

3. Why does our incentive mechanism outperform baselines in terms of communication performance? Our proposed incentive mechanism have better communication performance than baselines, largely because our client selection rule is probabilistic, which essentially non-IID issue in FL. To overcome the non-IID challenge, the existing FL frameworks (e.g., FEDAVG [2]) usually select a subset of clients at random in each round, according to a selection probabilistic distribution, e.g., uniform distribution. The existing work [47] also shows the convergence guarantee with probabilistic client sampling (Theorems 2 and 3). However, these existing works either use uniform distribution or consider the impact of non-uniform sampling distribution without specifying the selection probability [47]. In this paper, we consider non-uniform sampling distribution and take client m's communication capability (characterized by sparse number K_m) and local dataset into account, which results in the selection probability (our sampling rule) in (14). Therefore, our incentive mechanism for FL can achieve high convergence performance when training the global model. When the global model is trained at a fast convergence rate, it can achieve higher accuracy with less communication rounds. Instead, the comparing baselines are deterministic or near-deterministic, which fails to address the non-IID issue. This is why our incentive mechanism for FL has better accuracy and communication performance, compared to baselines.

4. Why is the final global model unbiased and converged? 1) The impact weight h_m of client m's local loss does not affect the unbiasedness of the final global model. Actually, the formulation with h_m weight in (1) is the general form of FL formulation. When setting $h_m = 1/M$, it becomes the specific FL formulation in the existing FL works. In fact, this kind of FL formulation with impact weight is more general to indicate the impact of the non-IID issue in FL, which is commonly used in the existing works [47]. 2) To guarantee the unbiasedness of the final global model, FL with different impact weight h_m determinations will have different selection distributions. For example, FEDAVG randomly selects clients using uniform distribution where $h_m = 1/M$. 3) In our work, we consider non-uniform distribution for the client selection where the selection probability $\mathbb{P}_m^t$ is related to the sparse number K_m, the size of local dataset $|\mathcal{D}_m|$ and the communication cost C_m^t, as shown in (14), which are the studied factors in this work. Although the factor in the aggregated gradient seems to be time-variant, it can guarantee the final global model converged in expectation when $h_m = 1/M$. This is because our gradient descent is equivalent stochastic gradient descent.

VI. Conclusion

In this paper, we design a bargaining-based incentive mechanism for communication-efficient FL to incentivize heterogeneous clients with different computation and communication resources to contribute to FL. The bargaining-based incentive mechanism design problem is proved to be NP-hard and approximately solved using Nash bargaining solution theory. Our incentive mechanism enables clients to upload the different number of model updates and obtain the corresponding payments while guaranteeing the convergence of FL. With extensive experiments, we verify the convergence, communication and incentive performance of our incentive mechanism.

Future work includes 1) exploring a theoretical approximation for one-to-many concurrent bargaining, 2) extending to differentially private FL setting and considering privacy budgets.

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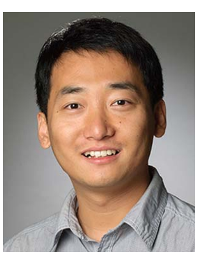

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