How Much Does It Cost to Train a Machine Learning Model over Distributed Data Sources?

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Abstract—Federated learning (FL) is one of the most appealing alternatives to the standard centralized learning paradigm, allowing heterogeneous sets of devices to train a machine learning model without sharing their raw data. However, FL requires a central server to coordinate the learning process, thus introducing potential scalability and security issues. In the literature, server-less FL approaches like gossip federated learning (GFL) and blockchain-enabled federated learning (BFL) have been proposed to mitigate these issues. In this work, we propose a complete overview of these three techniques proposing a comparison according to an integral set of performance indicators, including model accuracy, time complexity, communication overhead, convergence time and energy consumption. An extensive simulation campaign permits to draw a quantitative analysis. In particular, GFL is able to save the 18% of training time, the 68% of energy and the 51% of data to be shared with respect to the CFL solution, but it is not able to reach the level of accuracy of CFL. On the other hand, BFL represents a viable solution for implementing decentralized learning with a higher level of security, at the cost of an extra energy usage and data sharing. Finally, we identify open issues on the two decentralized federated learning implementations and provide insights on potential extensions and possible research directions on this new research field.

Index Terms—decentralized learning, edge computing, federated learning, gossip learning, blockchain, energy efficiency, computational complexity, communication overhead

I. INTRODUCTION

Machine learning (ML) models, and in particular deep neural networks, require a substantial amount of data and computational power that might not be available on a single machine. As a consequence, ML operations are normally run at cloud servers (or data centers), where batteries of powerful processing units enable short training and inference computation times. However, training ML models in a data center requires moving data from the information sources (e.g., edge devices) to the central system. This approach runs into several issues:

- **Communication overhead.** Nowadays, the huge pervasiveness of mobile services, devices, and network infrastructures makes data sources mainly distributed. As testified recently by the Ericsson Mobility Report [1], mobile network data traffic grew exponentially over the last 10 years, with a remarkable increase of 42% between Q3 2020 and Q3 2021. Mobile data traffic is projected to grow by over 4 times to reach 288 EB per month by 2027 [1]. Moving such a big amount of data from distributed sources to a central location for ML operations may create network congestion and service outage.
- **Latency.** In several real-life scenarios, transmitting data requires a stable and reliable connection to minimize latency and ensure updated models, which cannot be always guaranteed. For example, minimizing communication latency in connected vehicles is essential to guarantee road safety [2].
- **Energy consumption.** Running ML models in cloud data centers consumes a significant amount of energy and cannot be considered sustainable from an environmental perspective. As reported in [3], from 2012 to 2018, the computations required for training a deep learning model have been doubling every 3.4 months, with an estimated increase of 30000x. Estimates show that training a state-of-the-art natural language processing model produces more CO2 than an average car in one year lifetime [4].
- **Privacy.** With the growing awareness of data privacy and security, it is often undesirable, or even unfeasible, to collect and centralize users’ data [5]. For instance, a single hospital may not be able to train a high-quality model for a specific task on its own (due to the lack of data), but it cannot share raw data due to various policies or regulations on privacy [6]. Another example could be the case of a mobile user that would like to employ a good next-word predictor model without sharing his/her private historical text data.

A. Edge AI and Federated Learning

To address the challenges that stem from cloud-based centralized ML, edge computing pushes cloud services to the network edge and enables distributed ML operations, i.e. the so-called edge intelligence [7]. In particular, AI on Edge [8] is the paradigm of running AI models with a device-cloud synergy. It allows to relax the massive communication requirements and privacy of cloud-based ML operations [9]. Moreover, distributing ML computation over the edge has been demonstrated to save up to the 25% of the energy consumption [10]. In fact, data may be directly processed at the edge with smaller and more energy efficient devices (no need of air conditioning systems) and the energy cost related to communication is limited due to unnecessary data transmission.

Among the several training paradigms enabled by edge intelligence, federated learning (FL) has emerged as a popular...
solution by providing low communication overhead, enhanced user privacy and security to distributed learning [11]. With FL, the ML model is trained cooperatively by edge devices without sharing local data, but exchanging only model parameters. The usual implementation envisions an iterative procedure whereby a central server collects local updates from the clients (e.g., edge devices) and returns an aggregated global model. In the rest of the paper, we refer to centralized FL (CFL) to the traditional server-dependent FL scenario. In this setting, the server has to wait for all the clients before returning a new global update. Therefore, high network latency, unreliable links, or straggled clients may slow down the training process and even worsen model accuracy [12]. In addition, the central server represents a single point of failure, i.e., if it is unreachable due to network problems or an attack, the training process cannot continue. Furthermore, it may also become a bottleneck when the number of clients is very large [13].

Decentralized and server-less solutions for federated learning have been introduced in the literature, mainly to overcome the single point of failure and the security problems [14], [15]. In [16] a decentralized FL mechanism was proposed by enabling one-hop communication among FL clients. Similarly, Gossip FL (GFL) extends device-to-device (D2D) communications to compensate for the lack of an orchestrating central server [17], [18]. It guarantees a low communication overhead thanks to the reduced number of messages [19].

Beyond, we find more sophisticated proposals, like blockchain-enabled federated learning (BFL), which adopts blockchain to share FL information among devices, thus removing the figure of the orchestrating central server. In this way, blockchain removes the single point of failure for the sake of openness and decentralization and provides enhanced security via tampered-proof properties [20].

B. Contributions

Despite in the literature it is possible to find papers comparing classical centralized learning in data center with CFL [21], [22], a comparison among the different federated learning approaches (centralized versus decentralized) is still missing.

In this work, we aim to fill this gap and, thus, we focus on two of the most popular and widely adopted approaches for decentralizing FL: GFL and BFL. In particular, we provide a comprehensive analysis of both methods and compare them to traditional FL, i.e., CFL. Note that we combine standard performance indicators for ML models, i.e., accuracy, with indicators that quantify the efficiency of these algorithms, i.e., time complexity, communication overhead, convergence time and energy consumption. With our comparison under fair conditions, we would like to provide the research community with a complete overview of the three approaches together with all the information to choose the best model according to the specific use cases.

The contributions of this paper may be summarized as follows:

- We overview the traditional FL setting and delve into two approaches for decentralizing it. They are selected since are two of the most popular in the literature and are kind of diverging into two completely different solutions, which are based on gossip communication and blockchain technology, respectively.
- We provide a thorough analysis to derive the running time complexity, the communication overhead and the convergence time of each overviewed mechanism for FL, including CFL, BFL, and GFL.
- We provide an energy model to measure the energy consumption of each solution, based on the associated communication and computation overheads.
- We assess the performance of each method (CFL, GFL, and BFL) through extensive simulations on widely used TensorFlow libraries [23].
- We delve into the open aspects of decentralized FL and provide insights on potential extensions and considerations for GFL and BFL.

The rest of the paper is structured as follows: Section II reviews the related work. Section III describes the three studied algorithms (CFL, BFL and GFL). Section IV analyzes their time complexity, the communication cost, and introduces the communication model and the convergence time. Section V provides the energy model used in this paper. Then, Section VI compares the three mechanisms through simulation results. In Section VII we provide some open issues of GFL and BFL, and we discuss on the correspondent optimizations and future research directions. Finally, Section VIII concludes the paper with final remarks.

II. RELATED WORK

Distributing and decentralizing ML operations at the edge has been embraced as an appealing solution for addressing the issues of centralization (connectivity, privacy, and security) [24]. With FL, different devices collaborate to train an ML model by sharing local updates obtained from local and private data. The traditional FL algorithm (FedAvg), referred to as CFL in this paper, is introduced in [25]. In [11], the authors propose techniques to improve its communication efficiency. Nevertheless, CFL still requires a central server responsible for clients orchestration and model aggregation. The star topology is a weak aspect of CFL, since the central entity represents a single point of failure, it may limit the number of devices that can participate in the training process, augments the communication cost of the learning process, and presents privacy concerns [13], [26].

To address these challenges, decentralized federated learning has been proposed in [16]. The authors present a fully decentralized model, in which each device can communicate only with its one-hop neighbors. The authors also provide a theoretical upper bound on the mean square error. Ormandi et al. [17] introduce Gossip FL, a generic approach for Peer-to-peer (P2P) learning on fully distributed data, i.e., every device has only a single input sample to process at each round. The
same algorithm has been tested in \cite{13} under real-world conditions, i.e., devices have multiple input samples available (rather than only one point, as originally stated in \cite{17}), restricted communication topology and, heterogeneous communication and computation capabilities.

Another prominent solution to decentralize FL is blockchain-enabled FL \cite{27,29}. A blockchain system allows clients to submit and retrieve model updates without the central server. Additionally, the usage of blockchain guarantees security, trust, privacy, and traceability, however, it introduces delays due to the distributed ledger technology. An analysis of end-to-end latency and the effects of blockchain parameters on the training procedure of BFL is proposed in \cite{20}.

In the literature, there exist some comparisons across FL techniques. The authors of \cite{30} compare GFL and CFL with a logistic regression model in terms of convergence time, proportion of the misclassified examples in the test set (0-1 error), and used communication resources. When nodes have a random subset of the learning samples, GFL performance is comparable with CFL; instead, CFL converges faster when a node has only labels from one class. Another comparison is proposed in \cite{31}, where the performance of FL algorithms that require a central server, e.g., FedAvg and Federated Stochastic Reduced Gradient are analyzed. Results show that FedAvg achieves the highest accuracy among the FL algorithms regardless of how data are partitioned. In addition, the comparison between FedAvg and the standard centralized algorithm shows that they are equivalent when independent and identically distributed (IID) datasets are used.

In \cite{19}, the authors compare GFL with the standard centralized data center based architecture in terms of accuracy and energy consumption for two radio access network use-cases. To achieve this goal, they use the machine learning emission calculator \cite{32} and green algorithms \cite{33}. In \cite{21}, the authors compare centralized data center based learning and CFL in terms of carbon footprint using different datasets. The assessment is done by sampling the CPU and GPU power consumption. In \cite{22}, the authors propose a framework to evaluate the energy consumption and the carbon footprint of distributed ML models with focus on industrial Internet of Things applications. The paper identifies specific requirements on the communication network, dataset and model size to guarantee the energy efficiency of CFL over centralized learning approaches, i.e., bounds on the local dataset or model size. Differently from our work, the authors do not consider Blockchain-enabled FL and evaluate the algorithm performance in scenarios with limited number of devices (i.e., 100). Moreover, we also empirically measure the energy consumption of the devices based on the real load of the computations realized during the training phase; we provide a communication model to estimate overheads and convergence time. Additionally, here we introduce an analysis on the computational complexity of the three federated algorithms under study.

In summary, in this paper, we bridge the gap in the literature by providing a thorough comparison including performance analysis and cost of the different federated approaches listed above, i.e., CFL, BFL and GFL. Differently from the other works in the literature, we combine standard metrics, i.e., accuracy, with indicators of the efficiency of these algorithms, i.e., computational complexity, communication overhead, convergence time and energy consumption. Our final aim is to contribute to the development of Green AI \cite{34}.

III. FEDERATED LEARNING IMPLEMENTATIONS

Let us consider a set of $N$ clients (or devices) $\mathcal{N} = \{1, ..., N\}$ with their datasets $D_1, ..., D_N$. Each local dataset $D_i, \forall i \in \mathcal{N}$, contains pairs $(x_i, y_i)$, where $x_i$ is the feature vector, and $y_i$ its true label. The goal of a federated setting is to train a global model (e.g., a set of weights $w$), that minimize the weighted global loss function:

$$\ell = \sum_{i=1}^{N} \ell_i(w, x_i, y_i), \quad (1)$$

where $\ell_i$ is the local loss experienced by client $i$. In this scenario, devices do not share raw local data with other devices. Instead, they exchange model parameters updates, computed during several iterations by training the global model on local data.

In this paper we study three different implementations to solve the federated problem stated above, namely: CFL, BFL, and GFL. The investigated solutions are depicted in Fig. 1 and we will introduce them in what follows.

![Fig. 1: Overview of the different FL scenarios.](image)

A. Centralized Federated Learning (CFL)

At the beginning of a round $t$, a random subset of $m$ devices $S^t \subseteq \mathcal{N}$ is selected, and the server sends the current global model to the parties. Each client makes $E$ epochs on the local dataset with a mini-batch size of $B$, updates its local model $w_{k}^{t+1}$ and send it to the server. The server aggregates the local
updates and generates the new global model by computing the weighted average of the local updates as follows:

\[ w^{t+1} = \sum_{k \in S^t} \frac{|D_k|}{|D|} w_k^{t+1}, \tag{2} \]

where \(|D| = \sum_{k \in S^t} |D_k|\). The process is repeated until the model reaches convergence, e.g., the loss function does not improve across subsequent epochs or a specific number of training rounds have been executed. In this work, we consider the FedAvg algorithm [25] as a merging method to generate global model updates.

Algorithm 1 describes the CFL with FedAvg mechanism. The procedure MAIN is executed by the server that coordinates the whole training process. Each client executes the procedure CLIENTUPDATE and applies the stochastic gradient descent (SGD) algorithm on its local dataset with a learning rate \(\eta\).

Algorithm 1 CFL

1: procedure MAIN
2: initialize \(w_0\)
3: \(t \leftarrow 0\)
4: while convergence is not reached do
5: \(S^t \leftarrow \text{random set of } m \text{ clients}\)
6: for each client \(k \in S^t\) in parallel do
7: Download the global model \(w^t\)
8: \(w_k^{t+1} \leftarrow \text{CLIENTUPDATE}(k, w^t)\)
9: Send \(w_k^{t+1}\) to the server
10: end for
11: \(w^{t+1} \leftarrow \sum_{k \in S^t} \frac{|D_k|}{|D|} w_k^{t+1}\)
12: \(t \leftarrow t + 1\)
13: end while
14: end procedure

B. Blockchain-enabled Federated Learning (BFL)

BFL is based on distributed ledger technology, which collects data in form of transactions and organizes it in blocks. Indeed, a blockchain is a sequence of blocks chained one after the other through advanced cryptographic techniques. Each block contains the hash value of the previous one, leading to a tampered-proof sequence and providing properties that are essential to building trust in decentralized settings, such as transparency and immutability. In a blockchain, a set of participant nodes (miners) apply certain mining protocols and consensus mechanisms to append new blocks to the blockchain and agree on the status of the same. This procedure allows devices to write concurrently on a distributed database and guarantees that any malicious change on data would not be accepted by the majority, so that data in a blockchain is secured.

When a blockchain is applied to a federated setting, the process is going as follows [20]:

1) Each device submits its local model updates in the form of transactions to the blockchain peer-to-peer (P2P) network of miners.
2) The transactions are shared and verified by miners.
3) Miners execute certain tasks to decide which node updates the chain. One of the most popular mining mechanisms, and studied in this paper, is Proof-of-Work (PoW) [35], whereby miners spend their computational power (denoted by \(\lambda\)) to solve computation-intensive mathematical puzzles.
4) As a result of the concurrent mining operation, a new block is created and propagated throughout the P2P blockchain network every \(BI\) seconds (on average). The block size \(S_B\) is selected such that can include a maximum of \(m\) transactions, each one representing a local model submitted by a client.
5) Clients download the latest block from its associated miner (as in [27], [36]), which would allow performing on-device global model aggregation and local training.

An important consequence of the blockchain decentralized consensus forking. A fork occurs when two or more miners generate a valid block simultaneously (i.e., before the winning block succeeds to be propagated). The existence of forks can be seen as a waste of resources, as it may lead to extra computation and delay overheads [17].

In this work, we consider the version of BFL reported in Algorithm 2 [20], which entails the participation of Multi-Access Edge Computing (MEC) servers and edge devices. Each client downloads the updates \(w^t_k\) contained in the latest block, computes the new global \(w^{t+1}\), and trains it on its local dataset with the CLIENTUPDATE procedure described in Section III-A. The parameters of the new updated model \(w_k^{t+1}\) are then submitted with the method SUBMITLOCALUPDATE, where \(St_r\) is the transaction size. Once all the local updates are uploaded to the blockchain, a new block \(b^{t+1}\) is mined with MINEBLOCK, where the block generation rate \(\lambda\) is derived from the total computational power of blockchain nodes. Finally, the new block is shared across all the blockchain nodes with the procedure PROPAGATEBLOCK, which depends on the size of block \(b^{t+1}\) (fixed to \(S_B\)). The process is repeated until convergence.

C. Gossip Federated Learning (GFL)

GFL is an asynchronous protocol that trains a global model over decentralized data using a gossip communication algorithm [17], [18].

We consider the general skeleton proposed in [18]. Overall, the participating clients start from a common initialization. The global model is then trained sequentially on local data.
Algorithm 2 BFL

1: procedure Main
2:  \( t \leftarrow 0 \)
3:  initialize \( w_0 \)
4:  while convergence is not reached do
5:      \( S^t \leftarrow \) random set of \( m \) clients
6:      for each client \( k \in S^t \) in parallel do
7:          Download the latest block, \( b^t \)
8:          \( w^t_k \leftarrow \sum_{j \in b^t} \frac{|D_j|}{|T_j|} w_j^t \)
9:          \( w^t_{k+1} \leftarrow \) CLIENT_UPDATE(\( k, w^t_k \))
10:     end for
11:  end procedure

and following a given path (e.g., random walk) of visiting clients.

Algorithm 3 describes the GFL procedure. At each round \( t \), \( m \) nodes are randomly selected and ordered in a sequence \( S^t = [k_1, \ldots, k_m] \). Every node \( k_i \in S^t \) receives the model \( w^t_{k_{i-1}} \) from the previous node in the sequence and performs the steps below, also reported in Fig. 2 for a better understanding:

1) Run the procedure MERGE to combine \( w^t_{k_{i-1}} \) and the model saved in its local cache, lastModel\( _{k_i} \), i.e., the model from the previous round in which the node has been selected.

2) Train the model generated in 1) on the local dataset with the procedure CLIENT_UPDATE described in Section III-A.

3) Update the local cache (lastModel\( _{k_i} \)) with the model received from the previous node \( w^t_{k_{i-1}} \).

4) Share the model trained on the local dataset \( w^t_{k_i} \) with the following node in the sequence.

A round is completed when the model has visited all the nodes in the sequence. The algorithm stops when convergence is reached (after a given number of rounds).

IV. COMPUTATIONAL AND COMMUNICATION COSTS

In this section, we introduce the mathematical statements for the calculation of the time complexity of the three federated algorithms considered in Section III. We elaborate also on the data overhead due to the communication of the different model updates during the several rounds of the process of each implementation. Finally, we derive the equations for the calculation of the time to reach the convergence of the three analyzed federated approaches. The results proposed hereafter are derived using the following assumptions:

1) Scalar operations (sums and products) cost \( O(1) \).

Algorithm 3 GFL

1: procedure Main
2:  initialize lastModel\( _k \) for each client \( k \)
3:  \( t \leftarrow 0 \)
4:  while convergence is not reached do
5:      \( S^t \leftarrow \) random set of \( m \) clients
6:      \( [k_1, \ldots, k_m] \leftarrow \) GET_SEQUENCE(\( S^t \))
7:      for \( i = 1, \ldots, m \) do
8:          \( w^t_{k_{i-1}} \) \( \triangleright \) Model trained by the previous node in the sequence
9:      end for
10:     \( w^t_k \leftarrow \) MERGE(\( w^t_{k_{i-1}}, \) lastModel\( _k \))
11:     \( w^t_k \leftarrow \) CLIENT_UPDATE(\( k_i, w^t_k \))
12:     lastModel\( _k \leftarrow w^t_k \)
13:     Send model to the next client
14:     end procedure
15:  \( t \leftarrow t + 1 \)
16: end while
17: end procedure
18: procedure MERGE(\( w, w' \))
19:  \( w \leftarrow \frac{w + w'}{2} \)
20: return \( w \)
21: end procedure
22: procedure GET_SEQUENCE(\( S^t \))
23:  \( [k_1, \ldots, k_m] \) i.i.d. \( U(S^t) \)
24: return \( [k_1, \ldots, k_m] \)
25: end procedure

Fig. 2: Overview of the operations executed by a node in the GFL algorithm.

2) The time complexity of the matrix multiplication is linear with the matrix size, i.e., \( A \in \mathbb{R}^{i \times j} \) and \( B \in \mathbb{R}^{j \times k} \), the cost of the product is \( O(i \cdot j \cdot k) \).

3) For a single input pair \( (x_i, y_i) \), the time complexity required to compute \( \nabla \ell \) is linear with the number of model’s weights, \( O(|w|) \).

4) During the mining process, with the PoW, a miner computes the nonce of a block using brute force until finding
a hash value lower or equal to a certain threshold \[38\], referred to as the mining difficulty. Assume that the hash value has \(b\) bits, and that its solution should be smaller than \(2^{b-l}\) bits (being \(l\) a value determined by the mining difficulty), if the miner samples the nonce values at random, the probability of a valid value is \(2^{-l}\). Henceforth, \(2^l\) sampling operations are required for mining a block. The time complexity is \(O(2^l)\).

5) The set of nodes that have a local copy of the blockchain is \(N_B = \{1, ..., N_B\}\), without loss of generality, is assumed to be \(N' \cap N_B = \emptyset\).

6) We assume that convergence of the FL training procedure is reached after \(R\) rounds.

Theorem 1. The time complexity of CFL is:

\[
O(RmE[D_{max}|w]),
\]

where \(D_{max} = \max_{k \in N}[D_k]\). The communication overhead is given by

\[
2Rm|w|
\]

Proof. See Appendix A

Theorem 2. The time complexity of BFL is:

\[
O(R(|w|m^2 + E[D_{max}|w]|m + 2^l + m|w|N_B)),
\]

where \(N_B\) is the number of nodes that have a local copy of the blockchain and \(l\) is related to the PoW difficulty (see Assumption 4). Its communication overhead is

\[
R \left(|w|m^2 + |w|m + m|w|N_B\right)
\]

Proof. See Appendix A

Theorem 3. The time complexity of GFL is

\[
O(RmE[D_{max}|w|])
\]

and its communication overhead is

\[
Rm|w|
\]

Proof. See Appendix A

The three algorithms have a time complexity that depends on the dataset size \(|D_{max}|\). Additionally, the time complexity of BFL \([5\)] is also a function of the blockchain parameters \(N_B\) and \(l\). In particular, the dominant term in \([5\)] is \(R2^l\). Hence, the time complexity of BFL is exponential in the PoW difficulty \(l\), while for CFL and GFL is polynomial in \(RmE[D_{max}|w|]\). Table II summarizes the different results obtained for time complexity and communication overhead.

To finalize our analysis, we compute the total execution time of each algorithm till convergence (convergence time) as a function of the delay introduced by the communication rounds and the computational operations. To do that, we characterize the links whereby the different types of nodes exchange information (e.g., local model updates, blocks), having in mind the topology introduced in Fig. I. We classify two different types of connections: cloud (solid arrows) and edge (dotted and dashed arrows). Cloud connections (assumed to be wired) are used by miners in the blockchain; instead, edge connections (assumed to be wireless) are used by edge nodes to upload/download models. Given its popularity and easiness of deployment, we adopt IEEE 802.11ax links for edge connections \([39\)]. Since edge devices are often energy-constrained, we consider different values of transmission power for the edge connections. The central server and blockchain node use a transmission power of \(P_{TX}^c\), instead, edge devices use \(P_{TX}^e\), with \(P_{TX}^c \leq P_{TX}^e\). The wired connection has a capacity \(C_{P2P}\). Additionally, we identify three main types of computational operations during the federated learning processes: local model training, model parameters exchange, and blockchain data sharing. Based on this, we can compute the convergence time of CFL, BFL, and GFL as follows:

\[
T_{CFL} = T_{train} + Rm(T_{TX}^c + T_{c/e}^c),
\]

\[
T_{BFL} = T_{BC} + T_{train} + Rm(T_{TX}^c + T_{TX}^e),
\]

\[
T_{GFL} = T_{train} + RmT_{c/e}^e
\]

where \(T_{train}\) is the total amount of time spent for training the ML model locally, \(T_{TX}^c\) is the transmission time of the central server/blockchain node \((c)\) or the edge device \((e)\), and computed according to the model detailed in Appendix B. \(T_{BC}\) is the delay introduced by blockchain and described in steps 2-4 of the process in Section III-B.

V. ENERGY FOOTPRINT

In this section, we define the models used to characterize the energy consumption that results from the FL operations. Driven by \([9\), \([10\) and \([11]\), the total amount of energy consumed in each scenario is:

\[
\mathcal{E}_{CFL} = \mathcal{E}_{train} + Rm(\mathcal{E}_{TX}^c + \mathcal{E}_{c/e}^c),
\]

\[
\mathcal{E}_{BFL} = \mathcal{E}_{BC} + \mathcal{E}_{train} + Rm(\mathcal{E}_{TX}^c + \mathcal{E}_{TX}^e),
\]

\[
\mathcal{E}_{GFL} = \mathcal{E}_{train} + Rm\mathcal{E}_{e/e}^e
\]

where \(\mathcal{E}_{train}\) is the energy consumed by each node during the local training, and \(\mathcal{E}_{TX}^c\) the energy required to transmit the model through the IEEE 802.11ax wireless links, from either a central server/blockchain node \((c)\) or an edge device \((e)\). \(\mathcal{E}_{train}\) is calculated as:

\[
\mathcal{E}_{train} = \sum_{r=0}^{R-1} P_{cpu}^r \Delta r,
\]

where \(P_{cpu}^r\) is the average power consumed by the CPU and DRAM during a round \(r\), and \(\Delta r\) is the duration of the operation. As described in Section IV we may have two types of communication links: cloud and edge. Considering that cloud links are wired, we assume that their energy consumption is negligible. Instead, we compute the energy consumption of the edge connections according to the following equation:

\[
\mathcal{E}_{TX}^c = T_{TX}^c P_{TX}^c,
\]

\[
\mathcal{E}_{TX}^e = T_{TX}^e P_{TX}^e,
\]

\[
\mathcal{E}_{c/e}^e = T_{TX}^e P_{TX}^e.
\]
where $T_{Tx}^{c/e}$ and $P_{Tx}^{c/e}$ are the transmission time and power of a central server/miner ($c$) or an edge device ($e$). The additional term $E_{BC}$ for BFL is associated to mining operations of the PoW. We measure that consumed energy based on the model proposed in [40] and according to the following equation:

$$E_{BC} = P_h \frac{1}{\lambda},$$

where $P_h$ is the total hashing power of the network and $\lambda$ is the block generation rate.

VI. PERFORMANCE EVALUATION

In this section, we first describe the experimental settings adopted to compare the three federated approaches and then, we present numerical results.

A. Simulation Setup

We use the Extended MNIST (EMNIST) dataset available on Tensorflow Federated (TFF) library [41]. The input features are black and white images that represent handwritten digits in $[0, 9]$, coded in a matrix of $28 \times 28$ pixels. Considering only digits, it contains 341,873 training examples and 40,832 test samples, both divided across 3,383 users. The training and the test sets share the same users’ list so that each user has at least one sample. In the EMNIST dataset, all the clients have a rich number of samples for all the classes, thus data distribution across them can be considered as IID. To evaluate the targeted federated mechanisms in more challenging settings, we create a new version of the EMNIST dataset, called EMNISTp, by randomly restricting each client dataset to 3 classes only. Fig. 3 shows the available samples of the first 4 clients, for both versions of the dataset.

To correctly classify these samples we choose a feedforward neural network (FFNN) with an input layer of 784 neurons, two hidden layers of 200 neurons activated with the rectified linear unit (ReLU) function, and an output layer of 10 neurons with Softmax activation function. In total, the number of trainable parameters $|w|$ is 199,210. Assuming that each parameter requires 4 bytes in memory, i.e., size of a float32 variable, the total amount of space required ($S_w$) is 796.84 kB. We opted for a FFNN to reproduce a realistic scenario where edge devices might not have enough computational power to train more sophisticated deep learning mechanisms, like NNs based on convolutional architectures. Despite its simplicity, the selected FFNN model accurately classifies the digits of the EMNIST dataset, as shown next.

The three FL algorithms are implemented with Tensorflow [23], Tensorflow Federated [42] and Keras [43] libraries. We have extended the Bitcoin model provided by BlockSim [44] to simulate the blockchain behavior. BlockSim is an event-based simulator that characterizes the operations carried out to store data in a blockchain, from the submission of transactions to mining blocks and reaching consensus in a decentralized manner. Accordingly, BlockSim allows simulating the delays added by the blockchain in a BFL application, i.e., the $T_{BC}$ parameter defined in Section IV.

We create a validation set by choosing a subset of 200 clients from the test set. The accuracy is computed at the end of each learning round using the global model on the training and validation sets. At the end of each simulation, we evaluate the performance on the test set.

As for $E_{train}$ and $T_{train}$, we have used Carbontracker [45], a Python library that periodically samples the hardware energy consumption and measures the execution time. Moreover, $P_{Tx}^c$ is set to 20 dBm and $P_{Tx}^e = 9$ dBm. Table 2 reports all the other parameters used in our simulations. We note here that we have used the same FL parameters for a fair comparison, being the number of rounds $R$ of CFL and GFL equivalent to the main chain’s length ($N_{chain}$) in BFL. In such a way, we guarantee that the number of global rounds of each learning algorithm is the same.

B. Result Analysis

Fig. 4 reports the accuracy of each algorithm implementation on the two considered datasets. CFL and BFL achieve the best accuracy (both close to 0.9), instead, GFL presents lower values. This result validates the claim that, under similar setups as in our simulations (i.e., each block contains $m$ local updates organized in transactions), the central parameter server of CFL can be replaced by a blockchain network, properly

| Algorithm | Time complexity | Communication Overhead |
|-----------|----------------|-----------------------|
| CFL       | $O(RmE|D_{max}||w|)$ | $\frac{2Rm|w|}{p}$ |
| BFL       | $O(R(|w|m^2 + E|D_{max}||w|m + 2 + m|w|N_B))$ | $\frac{R(|w|m^2 + |w|m + m|w|N_B)}{Rm|w|}$ |
| GFL       | $O(RmE|D_{max}||w|)$ | $\frac{2Rm|w|}{p}$ |

TABLE 1: Computational complexity and communication overhead for CFL, BFL and GFL.
TABLE 2: Simulation parameters.

| Parameter | Description | Value |
|-----------|-------------|-------|
| $|w|$ | Number of model parameters | 199,210 |
| $S_w$ | Model parameters size | 796.84 kB |
| $η$ | Learning rate | 0.2 |
| $N$ | Number of total clients | 3362 |
| $E$ | Local epochs number | 5 |
| $R$ | Number of rounds | 200 |
| $m_t$ | Number of clients for each round | 200 |
| $B$ | Batch size | 20 |
| $t_0$ | Local loss function | Sparse Cat. Crossentropy |

Fed. Learning

| $N_{DAWN}$ | Number of nodes in the main chain | 200 |
| $BI$ | Block interval | 15 s |
| $N_0$ | Number of blockchain nodes | 200 |
| $N_m$ | Number of miners | 10 |
| $C_{2P2P}$ | Capacity of 2P2P links | 100 Mbps |
| $S_H$ | Block header size | 25 KB |
| $S_B$ | Block size | 166,368 MB |
| $S_T$ | Transaction size | 796.84 KB |

Blockchain

| $P_{tx}$ | Tx power for edge devices | 9 dBm |
| $P_c$ | Tx power for a central server | 20 dBm |
| $σ_{OFDM}$ | Legacy OFDM symbol duration | 4 µs |
| $N_u$ | Number of subcarriers (20 MHz) | 234 |
| $N_s$ | Number of spatial streams | 1 |
| $T_e$ | Empty slot duration | 9 µs |
| $T_{SIFS}$ | SIFS duration | 16 µs |
| $T_{DIFS}$ | DIFS duration | 34 µs |
| $T_{Preamble}$ | Preamble duration | 20 µs |
| $T_{IEEE}$ | IEEE single-user field duration | 100 µs |
| $L_s$ | Size OFDM symbol | 24 bits |
| $L_{RTS}$ | Length of an RTS packet | 160 bits |
| $L_{CTS}$ | Length of a CTS packet | 112 bits |
| $L_{ACK}$ | Length of an ACK packet | 240 bits |
| $L_{SF}$ | Length of service field | 16 bits |
| $L_{MAC}$ | Length of MAC header | 320 bits |
| $CW$ | Contention window (fixed) | 15 |

Communication (IEEE 802.11ac)

| $P_{tx}$ | Tx power for edge devices | 9 dBm |
| $P_c$ | Tx power for a central server | 20 dBm |
| $σ_{TX}$ | Legacy OFDM symbol duration | 4 µs |
| $N_u$ | Number of subcarriers (20 MHz) | 234 |
| $N_s$ | Number of spatial streams | 1 |
| $T_e$ | Empty slot duration | 9 µs |
| $T_{SIFS}$ | SIFS duration | 16 µs |
| $T_{DIFS}$ | DIFS duration | 34 µs |
| $T_{Preamble}$ | Preamble duration | 20 µs |
| $T_{IEEE}$ | IEEE single-user field duration | 100 µs |
| $L_s$ | Size OFDM symbol | 24 bits |
| $L_{RTS}$ | Length of an RTS packet | 160 bits |
| $L_{CTS}$ | Length of a CTS packet | 112 bits |
| $L_{ACK}$ | Length of an ACK packet | 240 bits |
| $L_{SF}$ | Length of service field | 16 bits |
| $L_{MAC}$ | Length of MAC header | 320 bits |
| $CW$ | Contention window (fixed) | 15 |

VII. OPEN ISSUES AND RESEARCH DIRECTIONS

A. Open Aspects of GFL

As described before, GFL is not able to achieve the same accuracy level as CFL and BFL. We identify two possible reasons for this behavior:

1) The number of rounds is not enough to converge: the number of visited nodes might not be sufficient to hit an acceptable accuracy.

2) The merge step negatively impacts the performance of the learning algorithm: the model received in the previous round and stored in the local cache slows down the learning process.

To verify the first hypothesis, we execute GFL algorithm changing the number of rounds ($R = \{200, 400, 800\}$) and varying the number of local computations ($E = \{5, 10\}$). Table 4 shows the results obtained. Considering the EMNIST dataset, the best results are achieved with $R = 800$ and $E = \{5, 10\}$, i.e., a higher test accuracy of 0.66, but still lower than CFL and BFL. Moreover, the model is overfitting with $R = 800$ rounds; hence, a regularization method would be needed, when increasing the number of rounds. On the EMNISTp dataset, the accuracy is even lower for each combination of the hyperparameters tested.

To verify the second hypothesis, we run GFL algorithm without the merge step (GFL-NM). The pseudocode of this algorithm is the same in Algorithm 3 but replacing the old Line 10 with the new command $w_{k+1}^d \leftarrow w_{k+1}^d$. Thus, in GFL-NM, given a sequence of clients $S_t$, the model is trained incrementally on the client’s datasets. GFL-NM achieves a
proposes an iterative continual learning algorithm, where a single round on the edge devices using the entire local dataset, and, hence, without requiring any merge step. Similarly, \[46\] encourages by our results, the investigation of new methods for merging the model updates from the distributed sources to reach the best performance on the test set. These results suggest that the M
\[47\] (EMNISTp) dataset (see Fig. 5), higher than CFL and BFL. The performance of a blockchain, typically measured in transactions per second (tps), together with the granted degree of security, strongly depends on the nature of the blockchain (e.g., degree of visibility, type of consensus, mining protocol), its configurable parameters (e.g., block interval, difficulty), and the size of the P2P network maintaining it. Furthermore, the necessary energy to maintain a blockchain is correlated to its performance in tps and security, thus leading to the well-known performance, security, and energy trilemma.

To showcase the effect of using different types of blockchain networks, Fig. 6 shows the total delay incurred by the blockchain to the FL operation to generate up to 200 blocks under different blockchain configurations. Notice that, in the proposed setting, each block is equivalent to an FL round. In particular, we vary the total number of miners ($N = \{1, 10, 100\}$) and the block interval ($BI = \{5, 15, 600\}$ s), which affect the time required to achieve consensus.

First, a higher number of miners leads to a higher fork probability, provided that more nodes need to agree on the same status of the ledger. By contrast, a higher block interval allows mitigating the effect of forks, since the probability that two miners mine a block simultaneously is lower \[47\].

As shown in Fig. 6, the blockchain delay increases with the block interval ($BI$), which indicates the average time for mining a block. Notice that, in a PoW-based blockchain, the block interval is fixed by tuning the mining difficulty according to the total computational power of miners. As for the impact of $N$ on the delay, its effects on the delay are more noticeable for low $BI$ values. In particular, a higher fork probability is observed as $N$ increases, thus incurring additional delays to the FL application operating on top of the blockchain.

To optimize the performance of a blockchain, a widely adopted approach consists of finding the best block generation rate \[27\], which is controlled by tuning the mining difficulty. Other approaches consider optimizing the block size \[48\], which fits better scenarios where the intensity of transactions arrivals depends on the nature of the application running on

| R   | E  | Acc. Training | Acc. Validation | Acc. Test | Conv. Time (s) | Comp. Energy (%) | Tot. Energy (kWh) | Comm. Overhead (GB) |
|-----|----|---------------|-----------------|-----------|----------------|------------------|-------------------|---------------------|
| 200 | 5  | 0.44 (0.36)   | 0.42 (0.12)     | 0.41 (0.11) | 36401.67       | 1.88e − 03       | 9.46 (9.46)       | 946.08 (946.07)     |
| 400 | 5  | 0.55 (0.41)   | 0.51 (0.16)     | 0.5 (0.15) | 72791.81       | 1.85e − 03       | 9.39 (9.39)       | 1892.17 (1892.15)   |
| 800 | 5  | 0.85 (0.64)   | 0.67 (0.19)     | 0.66 (0.17) | 145653.71      | 1.87e − 03       | 9.38 (9.38)       | 3784.34 (3784.34)   |
| 200 | 10 | 0.57 (0.58)   | 0.4 (0.09)      | 0.41 (0.1)  | 37377.47       | 2.59e − 03       | 1.22e (1.22e)     | 946.09 (946.08)     |
| 400 | 10 | 0.66 (0.37)   | 0.47 (0.17)     | 0.48 (0.16) | 74989.72       | 2.59e − 03       | 1.22e (1.22e)     | 1892.18 (1892.16)   |
| 800 | 10 | 0.94 (0.58)   | 0.67 (0.3)      | 0.67 (0.29) | 149448.14      | 2.59e − 03       | 1.22e (1.22e)     | 3784.36 (3784.31)   |

**Table 4:** Simulation results of GFL on EMNIST (EMNISTp) datasets with higher number of rounds and local computations.

In conclusion, we have seen that both 1) and 2) influence the achieved accuracy. Moreover, GFL-NM solves the accuracy problem of standard GFL and reaches the best performance from all the metrics point of view. In our opinion, and encouraged by our results, the investigation of new methods for merging the model updates from the distributed sources to achieve faster and higher accuracy is an interesting and open research line. To the best of our knowledge, there are still very few works that go in this direction in the literature. In \[19\], the authors implement an incremental version of GFL with a single round on the edge devices using the entire local dataset, and, hence, without requiring any merge step. Similarly, \[46\] proposes an iterative continual learning algorithm, where a model is trained incrementally on the local datasets without applying any merge operation.
methods, like the poor accuracy achieved by GFL and the blockchain overhead in BFL. Regarding GFL, we have argued that the main drawback lays in the method used to merge model updates across the algorithm steps. We have demonstrated that with an incremental approach, the modified version of GFL is able to outperform CFL and BFL. As for BFL, we have indicated that possible optimizations go in the direction of finding the best block generation rate and block size. Moreover, we have reasoned on the possibility of reducing the time complexity by including the global model in a block, which is aggregated by the same miner building the block. Finally, we have pointed out the importance of further studies on the implication of model inconsistencies due to the fact that the blockchain cannot be perfectly shared and accessed by (all) the FL devices.

APPENDIX A
PROOFS

A. Proof of Theorem I

Let us consider the procedure ClientUpdate, whose time complexity is $E \left( |D_{max}|w| + 2\frac{|D_{max}|w|}{B} \right)$. In fact, a single client $k$ performs the training phase on its local dataset $D_k$ along $E$ local epochs and updates the model parameters. The first operation has a time complexity of $|D_k|w|$ and the second $2|D_k|w|$. The update it is executed a number of times equal to $|D_k|$, and requires a product and a sum. Each client performs $E$ local epochs, so the total cost is:

$$
\sum_{k \in S_t} E \left( |D_k|w| + 2\frac{|D_k|w|}{B} \right)
$$

(18)

To obtain an upper bound that does not depend on $k$, we can use $|D_{max}|$ as an upper bound of $|D_k|$:

$$
\sum_{k \in S_t} E \left( |D_k|w| + 2\frac{|D_{max}|w|}{B} \right) \leq m E \left( |D_{max}|w| + 2\frac{|D_{max}|w|}{B} \right)
$$

(19)

We can divide the MAIN procedure in Algorithm 1 into two blocks. The first, up to Line 10 has a cost upper bounded by

$$
m E \left( |D_{max}|w| + 2\frac{|D_{max}|w|}{B} \right) + 2|w|m
$$

(20)

In parallel every client downloads the global model, executes ClientUpdate, and sends the updated parameters back to the server. The download and upload operations have a time complexity proportional to $|w|$. Considering that the same procedure is repeated by $m$ clients, the upper bound in (20) easily follows. The second block starts from Line 10 where the server aggregates the local updates and computes the new global model. The number of arithmetical operations performed is:

$$
2|w|m
$$

(21)

Combining (20) and (21), and considering the number of total
rounds $R$ required to reach convergence, the total cost of CFL is given by:

$$R \left[ mE \left( |D_{\text{max}}| w + 2 \frac{|D_k|}{B} |w| \right) + 4m|w| \right] =$$

$$R mE |D_{\text{max}}| |w| + 2RmE \frac{|D_k|}{B} |w| + 4Rm|w|$$

(22)

The first addend in (22) is the dominant term for the asymptotic time analysis, so this completes the proof to obtain (3).

When it comes to the communications overhead of CFL, the result easily follows considering that, for each round, each clients downloads and uploads the model parameters.

B. Proof of Theorem II

In each algorithm’s round, every client in $S^t$ has to download the latest block from the closest edge server (miner) to obtain the current global model. These operations, as described before, have a cost of $|w|m$ and $2|w|m$, respectively. Then, after running the CLIENTUPDATE procedure in Algorithm 2, clients submit the new model weights with a cost of $|w|$. These steps are done by each node in $S^t$ (in total, $m$ nodes), so the total cost is:

$$m \left( 2|w|m + |w|m + E|D_{\text{max}}||w| + 2E \frac{|D_{\text{max}}|}{B} |w| + |w| \right)$$

(23)

When all the local updates have been computed, it is necessary to create a block, reach consensus throughout the mining operation, and propagate the block across all the blockchain nodes. The cost of these operations is given by:

$$2^t + m|w|N_B$$

(24)

If we combine together (23) and (24), we obtain the total time complexity of the algorithm

$$R \left( 3|w|m^2 + E|D_{\text{max}}||w|m + 2E \frac{|D_{\text{max}}|}{B} |w|m + 2^t + m|w|N_B \right)$$

(25)

The dominant addends are reported in (3).

The communication overhead of BFL can be easily derived from the algorithm description.

In this analysis, we considered the less efficient implementation, whereby each client has to perform the computation of the new global model given the updates in the latest block. To improve this, we can move the instruction in Line 8 outside the for loop and execute it before the MineBlock procedure. In this way, the new block has size $|w|$, since it contains only the parameters of the new model. Following the same analysis described before, the computational complexity is:

$$O(R(mE|D_{\text{max}}||w| + 2^t + N_B|w|))$$

(26)

And the communication overhead is:

$$R(2|w|m + N_B|w|)$$

(27)

C. Proof of Theorem III

Let $k_i$ be a client in the sequence $[k_1, ..., k_m]$. Following the steps of Algorithm 3, three main operations are performed: 1) MERGE, 2) CLIENTUPDATE and 3) send of the model parameters to the next client of the sequence. The first one is the average of two model parameters, so its cost is $2|w|$. The cost of the second operation has already been computed in (19) and the cost of parameter sharing is $|w|$. By summing up these contributions we obtain:

$$m \left[ E \left( |D_{\text{max}}||w| + 2 \frac{|D_{\text{max}}|}{B} |w| \right) + 3|w| \right]$$

(28)

This process is repeated for $R$ rounds, so the time complexity is:

$$Rm \left[ E \left( |D_{\text{max}}||w| + 2 \frac{|D_{\text{max}}|}{B} |w| \right) + 3|w| \right],$$

(29)

where the first addend is the dominant one.

Given that each client shares its local model only with the following node in the sequence, the communication overhead is given by (8).

APPENDIX B

EDGE CONNECTION MODEL

To compute the duration for transmitting model weights, we assume IEEE 802.11ax channel access procedures [39], which also include the overheads to carry out the Distributed Coordination Function (DCF) operation. In particular, the duration of a packet transmission is defined as:

$$T_{\text{Tx}} = T_{\text{RTS}} + T_{\text{SIFS}} + T_{\text{CTS}} + T_{\text{DATA}} + T_{\text{SIFS}} + T_{\text{ACK}} + T_{\text{SIFS}} + T_{\text{e}},$$

(30)

where $T_{\text{RTS}}$ is the duration of the Ready-to-Send (RTS) control frame, $T_{\text{SIFS}}$ is the Short Interframe Space (SIFS) duration, $T_{\text{CTS}}$ is the duration of the Clear-to-Send (CTS) control frame, $T_{\text{DATA}}$ is the duration of the data payload, $T_{\text{ACK}}$ is the duration of the acknowledgement (ACK) frame, and $T_{\text{e}}$ is the duration of an empty slot.

To compute the duration of each type of IEEE 802.11ax control frame, i.e., RTS, CTS, and ACK, we compute them as:

$$T_{\text{RTS/CTS/ACK}} = T_{\text{PHY}} + \left[ \frac{L_{\text{SF}} + L_{\text{RTS/CTS/ACK}}}{L_{s}} \right] \sigma_{\text{leg}},$$

(31)

where $T_{\text{PHY}}$ is the duration of the PHY preamble, $L_{\text{SF}}$ is the length of the service field (SF), $L_{\text{RTS/CTS/ACK}}$ is the length of the control frame, $L_{s}$ is the length of an Orthogonal Frequency Division Multiplexing (OFDM) symbol, and $\sigma_{\text{leg}}$ is the duration of a legacy OFDM symbol.

As for the duration of the data payload, it is computed as:

$$T_{\text{DATA}} = T_{\text{HE-SU}} + \left[ \frac{L_{\text{SF}} + L_{\text{MAC}} + L_{\text{DATA}}}{L_{s}} \right] \sigma,$$

(32)
where $T_{\text{HE-SU}}$ is the duration of the high-efficiency (HE) single-user field, $L_{\text{MAC}}$ is the length of the MAC header, $L_{\text{DATA}}$ is the length of a single data packet (in our case, it matches with the model size, $S_w$), and $\sigma$ is the duration of an OFDM symbol. The number of bits per OFDM symbol will vary, so as the effective data rate, based on the employed modulation and coding scheme (MCS), which depends on the transmission power used.

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