Report - AFCFL: Adaptive Fairness Compensation-based Federated Learning

Asif Ahmed Utsa
Mobaswirul Islam
0423052090@grad.cse.buet.ac.bd
0424052053@grad.cse.buet.ac.bd
Bangladesh University of Engineering & Technology
Dhaka, Bangladesh

1 INTRODCUTION

Artificial Intelligence is advancing quickly because there's a huge amount of data coming from many different devices and sources. To use this data effectively, we need systems that can collect, process, and train AI models across many locations smoothly and efficiently. Federated Learning (FL) is a way of training machine learning models that involves a central server and many clients (like devices or users). The key idea is that the server can learn a shared global model without actually seeing or accessing the private data stored on each client. Because the data stays on the local devices and only updates are shared, this approach helps protect privacy and reduces problems related to data transfer and storage. As a result, FL can be used in many areas such as medical image analysis, personalized recommendation systems, and the Internet of Things (IoT).

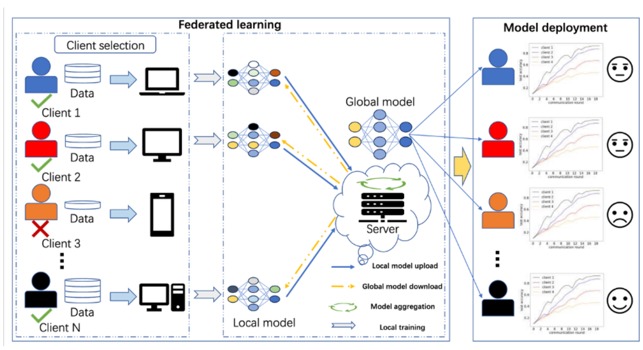

Figure 1: (Left): Example of horizontal FL. (Right): Performance fairness of FL

However, federated learning is not a perfect solution as several challenges have emerged in recent years. In [1], the author has focused on the issue of fairness in FL, which is one of the key factors limiting its practical adoption. As illustrated in 1, since the global model is trained on the local datasets of clients, which are often unknown to the central server, there can be discrepancies between the data and the models of the clients. This leads to variability in the performance of the global model between different clients, resulting in unfair outcomes such as unequal accuracy levels, as shown on the right side of 1. Although the global model may perform well on average, this unfairness becomes apparent in certain clients, who are called vulnerable clients, who receive lower accuracy due to biased client selection.

Exitsing several fair FL methods, like AFL[2] and q-FedAvg[3] aim to improve fairness by adjusting the weights of different clients during training. AFL[2] uses a minimax optimization approach to improve the performance of the worst-performing client, while q-FedAvg[3] introduces a parameter q to reweight the loss contributions from different clients. However, these methods often overlook the importance of client selection in achieving fairness. Current client selection strategies are often either random or based on local data size. These limited selection methods can result in the global model performing poorly on the local data of clients. A significant challenge is to design a fair federated learning system that effectively manages client selection without negatively impacting client-side performance.

L. Wang et al. [1] proposed a novel federated learning approach named FCFL (Fairness Compensation–based Federated Learning) to address unfairness in federated learning. It keeps a small **fairness queue value** for each client. The value goes up when a client's accuracy is worse than the global model, and it goes down when the client is selected and contributes. This queue is then used in two lightweight rules:

- **Client Selection :** Most training slots go to clients with larger queue values with a small random fraction r kept for diversity.
- **Aggregation :** When any queue value is non-zero, the client updates are weighted by their queue values. If all queue-values are zero, the method falls back to standard FedAvg.

With only two knobs— α (how fast the queue value grows) and r (how many(%) random clients to include)— FCFL narrows accuracy gaps across clients while keeping the average accuracy almost unchanged, and it adds only a tiny overhead (each client sends one extra accuracy number per round).

However, FCFL still uses fixed settings chosen by hand and does not directly address the "chance to join" issues. The values of α and r are fixed before the execution. So here in this project, we have -

(1) Rebuilded FCFL using Vanilla FL with fixed α and r and reproduced the results.
(2) Added adaptive rules to change α and r dynamically during training time.
(3) Added another rule so every client gets roughly the same chance to take part in training

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(4) Run experiments on our initially written FCFL and Adaptive FCFL and compared their outcomes.

2 MOTIVATION

Fairness in FL is wider than just closing the accuracy gap. A practical system should work well for every client, give each device a fair chance to take part, and avoid pushing all the workload onto one group of machines. Our project has focused on the following reasons for the extra steps we propose:

(1) **Adaptive Settings :** Training dynamics change over time because the data seen by the model evolves, and the pool of active devices is never the same from one round to the next. Letting the algorithm tune α (queue growth) and r (random share) on its own removes manual grid search, shortens deployment time, and makes the method self-correcting if conditions drift after launch. Also, manually searching the grid to find values of r is time-consuming.
(2) **Selection Fairness :** The second queue that rewards long-waiting clients balances participation, spreads communication cost, and keeps the training data stream rich in diversity, which can also improve overall accuracy in the long run.

3 RELATED WORKS

Fairness in Federated Learning (FL) can be divided into different categories based on fairness goals:

- **Collaborative Fairness :** Collaborative fairness aims to reward clients in proportion to their contributions
- **Group Fairness :** Group fairness seeks to minimize performance disparities between different demographic groups, such as those defined by gender or race.
- **Selection Fairness :** Selection fairness in federated learning guarantees that every client has an equal and fair opportunity to be chosen for training.
- **Performance Fairness :** Performance fairness aims to ensure that the final global model performs equally well for all clients, regardless of their individual data. It's not enough for the model to have high average accuracy; performance fairness focuses on reducing the variance of that accuracy across the client.

In FCFL[1], the authors focus primarily on performance fairness.

3.1 Performance Fairness in FL

The vanilla FedAvg algorithm aggregates local client models by calculating the weighted average based on the amount of training data, which causes significant discrepancies in model accuracy due to the heterogeneity of the data of different clients. To counter this issue, the first proposed approach was AFL[2], which utilized minimax optimization. The intuition was to maximize the performance of the worst-performing device, but the outcome of this method in large-scale settings was not guaranteed. To enhance the scalability of AFL, researchers introduced the q-FedAvg[3] method, which incorporates a parameter q to reweight clients and ensure improved fairness. Since the development of q-FedAvg, ensuring performance fairness has become a central challenge in federated learning, leading to the proposal of numerous approaches such as designing new objective functions, reweighting strategies, eliminating gradient conflicts, and multi-objective optimization techniques.

Table 1: Related work on Performance Fairness of FL

References	Method
AFL (2019) [2]	Minimax optimization
q-FedAvg (2019) [3]	Reweighting
FedGini (2023) [4]	Objective function
DRFL (2022) [5]	Reweighting
Ada-FFL (2023) [6]	Reweighting
FedFa (2022) [7]	Reweighting
PG-FFL (2022) [8]	Reweighting
FedFV (2022) [9]	Gradient projection
GIFAIR (2023) [10]	Reweighting; Objective function
FedMGDA (2022) [11]	Multi-objective optimization
FedMDFG (2022) [12]	Multi-objective optimization
FairWire+ (2024) [13]	Multi-objective optimization

3.2 Client Selection

Although the methods mentioned above can help mitigate unfairness using different strategies, they often overlook the influence of client selection on the overall fairness of federated learning. Client selection itself is a crucial area of research. In FCFL[1], the authors first addressed the issue of client selection in FL performance fairness.

4 AFCFL OVERVIEW

In this section, we provide an overview of the AFCFL method, including its problem formulation, proposed algorithms, and analytical insights.

4.1 Problem Setting

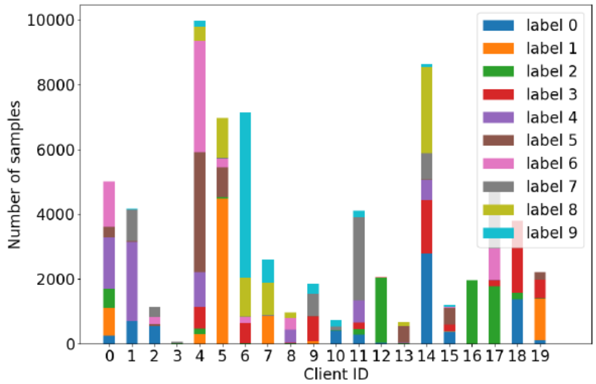
As shown in Figure 1, a general FL has the following three main steps:

(1) Client Selection
(2) Local Training of the models
(3) Weighted Aggregation of the local trained models

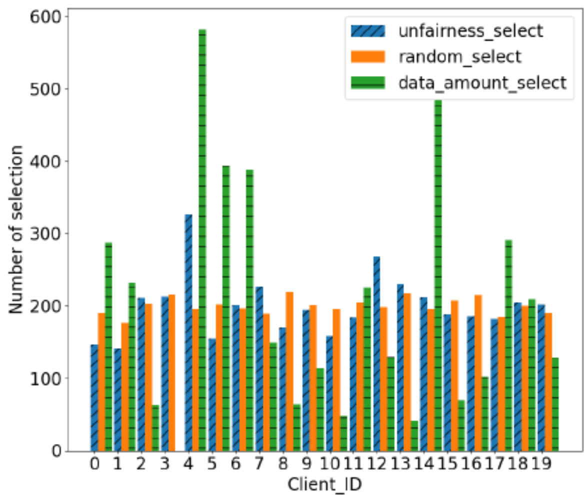
Because local datasets are distributed differently, the global model's performance tends to vary significantly across clients. This variation is known as performance fairness. Specifically, the fairness of the global model can be defined as follows.

Definition 4.1. (Fairness of performance distribution[3]). A model θ_1 is said to be fairer than θ_2 if the accuracy of θ_1 on the N clients $a_1, a_2, ..., a_N$ is more uniform than that of θ_2 on the N clients.

In FCFL[1], the authors propose using the variance in accuracy across all clients as a fairness metric, aiming to minimize this variance while keeping the global model's average accuracy consistent. Client selection is essential to achieving this objective but is often neglected in existing studies. Typically, Federated Learning (FL) selects clients based on the quantity of their local data [14], [10], which can introduce bias towards clients with larger datasets. This issue is illustrated using the MNIST dataset and a CNN model



(a) Data distribution of each client



(b) The numbers of being selected

Figure 2: The impact of data distribution on client selection methods.

in Figure 2. Figure 2a demonstrates how the distribution of local data varies significantly between clients, with some (e.g., clients 3, 10, and 13) having substantially fewer or distinct classes of data. This setup reflects real-world data distribution. When client selection is based on data quantity, it results in vulnerable clients being selected less frequently during training, as seen in the green bins of 2b. On the other hand, random selection treats each client equally but harms the performance of the global model for the vulnerable clients. The unfairness-based client selection approach focuses on prioritizing vulnerable clients, thus achieving fairness in performance. For example, client 3, which has limited local data and is rarely selected with data amount-based selection, is chosen more often with the unfairness-based method, which adjusts client selection based on fairness considerations in each round.

4.2 Overview of the AFCFL Workflow

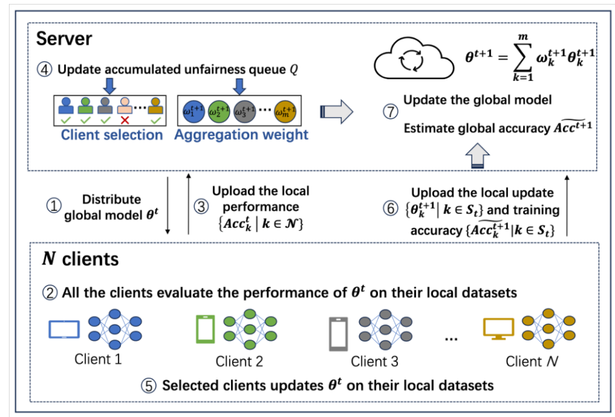


Figure 3: AFCFL Workflow

Figure 3 shows the AFCFL workflow at a high level.

Intuition. Each client keeps a small *unfairness queue value*. The queue value goes up when the client's local accuracy is worse than the global average, and it goes down when the client is selected and its update is used. This single number drives both whether a client will be selected in the next round and how much its weight will be.

The proposed system leverages Federated Learning (FL) with adaptive fairness control through an adaptive α and adaptive r mechanism and an accumulated unfairness queue (Q). The process involves multiple rounds of client updates and model aggregation while considering fairness across clients. This architecture can be divided into the following key steps:

(1) **Distribute global model to clients :** The global model, θ^t, is distributed to all participating clients at the start of each round.
(2) **Evaluate All Clients Performance :** Each client evaluates the global model θ^t on their local dataset and computes their accuracy, $\{Acc_k^t | k \in N\}$. These local performance results are uploaded to the server.
(3) **Calculate Adaptive α and r:** Before updating the unfairness queue, the server computes the adaptive α^t using equation 3, and adaptive r_t using equation **??**.
(4) **Update Accumulated Unfairness Queue (Q) :** The accumulated unfairness queue Q is updated using adaptive α and client selection in the previous round.
(5) **Evaluate Selected Clients :** Based on the updated Q, m clients are selected for training. The selected clients update θ^t by training it on their local datasets.
(6) **Upload Local Update and Training Accuracy :** The selected clients upload their local update $\{\theta_k^{t+1} | k \in S_t\}$ and training accuracy $\{Acc_k^{t+1} | k \in S_t\}$ to the server
(7) **Update Global Model and Estimate Global Accuracy:** The server aggregates the weights of the selected clients using weighted averaging of the received selected client updates:

$$\theta^{t+1} = \sum_{k=1}^{m} \omega_k^{t+1} \theta_k^{t+1} \tag{1}$$

The server estimates the global model's accuracy, Acc^{t+1}, using the performance of the selected clients. This estimate helps in computing the fairness signal for the next round.

4.3 Adaptive α

The parameter α_t controls how much priority is given to clients with lower accuracy. First, a raw value is computed by mapping the unfairness signal g_t into the range $[\alpha_{\min}, \alpha_{\max}]$:

$$\alpha_t^{\text{raw}} = \alpha_{\min} + (\alpha_{\max} - \alpha_{\min}) \cdot g_t. \tag{2}$$

During the warm-up phase, α_t is set directly to α_t^{raw}. After warm-up, α_t is updated using an exponential moving average to avoid abrupt changes:

$$\alpha_t = (1 - \beta)\, \alpha_{t-1} + \beta\, \alpha_t^{\text{raw}}, \tag{3}$$

where $\beta \in (0, 1]$ is the smoothing factor. A larger β lets α_t react quickly to changes in unfairness, while a smaller β provides stability. When unfairness is high, α_t rises towards $\alpha_{\max}$, giving more weight to vulnerable clients so they are prioritized in training.

4.4 Adaptive Selection Ratio r

The ratio r_t controls how many clients are chosen from the top of the queue. When adaptive r is enabled, a target value is computed from the unfairness signal g_t within $[r_{\min}, r_{\max}]$:

$$r_t^{\text{target}} = r_{\min} + (r_{\max} - r_{\min}) \cdot g_t. \tag{4}$$

To avoid sudden jumps, r_t is updated using an exponential moving average:

$$r_t = (1 - \rho)\, r_{t-1} + \rho\, r_t^{\text{target}}, \tag{5}$$

where $\rho \in (0, 1]$ is the smoothing factor. When unfairness is low, r_t remains close to $r_{\min}$ to maintain diversity; as unfairness increases, r_t grows towards $r_{\max}$ so that more vulnerable clients are deterministically selected.

4.5 Accumulated Unfairness Queue and Client Selection

In Federated Learning, client unfairness is measured by the difference between the estimated global model accuracy and the evaluated local accuracy as in equation 6, since the actual global model is not available during training. To track the cumulative unfairness of each participant, providing a basis for subsequent client selection and weight allocation, a queue $Q_i(t)$ is used. The value of $Q_i(t)$ is calculated using the equation 7.

$$uf_i^t = \begin{cases} \widetilde{Acc}^t - Acc_i^t, & \text{if } \widetilde{Acc}^t > Acc_i^t \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

$$Q_i(t) = \max\left\{Q_i(t-1) + \alpha_t uf_i^t - \omega_i^t \cdot \mathbf{1}_{[x_i(t-1)=1]}, 0\right\} \tag{7}$$

$$\omega_i^{t+1} = \begin{cases} \frac{n_i}{\sum_{i=1}^m n_i}, & \text{if } Q_1(t) = \cdots = Q_m(t) = 0 \\ \frac{Q_i(t)}{\sum_{i=1}^m Q_i(t)}, & \text{otherwise} \end{cases} \tag{8}$$

The cumulative unfairness queue $Q_i(t)$ is designed to favor vulnerable clients with low accuracy, those not selected, or those with small weights, resulting in a higher $Q_i(t)$ value that the AFCFL algorithm uses to compensate them through client selection and aggregation re-weighting using equation 8. After updating the unfairness queue for all clients, the server selects the top-m clients with the highest unfairness scores to participate in the next training round. This process ensures that vulnerable clients are prioritized and then assigned more weight during aggregation to increase their contribution.

4.6 Algorithm

Algorithm 1 AFCFL ALgorithm

Input: clients N, rounds T, local epochs E, step size η
Output: global model θ^{T+1}
Initialize global model θ^0; queues $Q_i \leftarrow 0$; selection ratio r; weights $\omega_i \leftarrow 0$; indicators $x_i^{\text{prev}} \leftarrow 0$
for $t = 0$ to T **do**
    Broadcast θ^t to all clients
    Clients evaluate locally and send acc $\{Acc_i^t\}$
    Compute unfairness g_t (e.g., accuracy gap)
    Calculate α_t (adaptive mapping)
    Compute r_t to adapt current selection ratio
    Update accumulated unfairness queues:

$$Q_i \leftarrow \max\big(Q_i + \alpha_t\, (\widehat{Acc}^{\,t} - Acc_i^t)_+ - \omega_i\, x_i^{\text{prev}},\ 0\big)$$

    Select m clients: top $\lfloor r_t m \rfloor$ by Q
    Select rest of the clients randomly
    Set aggregation weights for $i \in S_t$:

$$\omega_i \leftarrow \begin{cases} \dfrac{n_i}{\sum_{j \in S_t} n_j}, & \text{if } Q_j = 0\ \forall j \in S_t \\ \dfrac{Q_i}{\sum_{j \in S_t} Q_j}, & \text{otherwise} \end{cases}$$

    Set $x_i^{\text{prev}} \leftarrow \mathbf{1}[i \in S_t]$ for all i
    for each $i \in S_t$ **do**
        $(\theta_i^{t+1}, Acc_i^{t+1}) \leftarrow$ ClientUpdate(i, θ^t)
    end for
    Aggregate and estimate performance:

$$\theta^{t+1} \leftarrow \sum_{i \in S_t} \omega_i\, \theta_i^{t+1} \qquad \widehat{Acc}^{\,t+1} \leftarrow \sum_{i \in S_t} \omega_i\, Acc_i^{t+1}$$

end for
function ClientUpdate(i, θ) ▷ runs on client i
    Train θ for E epochs with step size η on client i's data
    Evaluate to get local accuracy Acc_i
    return $(\theta_{\text{updated}}, Acc_i)$
end function

4.7 Communication and Computation Overhead

The primary bottleneck of Federated Learning (FL) is the communication cost between the server and edge devices, as well as the limited local computation power. The proposed AFCFL scheme introduces minimal communication overhead, requiring clients to upload their local accuracy (Acc_i^{t+1}) which costs only 8 more bits per round. On the computation side, the AFCFL scheme reduces the local computational cost by allowing clients to use mini-batch samples to estimate accuracy instead of evaluating it on their entire local dataset. The server, which has high computational power, then handles the calculations for unfairness, aggregated weights, and global performance estimation using simple arithmetic operations, thus not impacting the efficiency of the AFCFL scheme.

5 EXPERIMENTS AND RESULTS

The performance of the AFCFL algorithm is evaluated on MNIST Dataset using both IID and Non-IID data distribution to simulate real-world conditions. The experiments utilize MLP and compare AFCFL against the vanilla FedAvg algorithm and basic FCFL algorithm.

5.1 Accuracy Comparison

The results 4a show that on IID data, all algorithms improve with more training, and FEDAVG gives the best accuracy overall. The FCFL methods also perform well and stay close to each other, but a little below FEDAVG.

On Non-IID data 4b, the difference is clearer. FEDAVG starts with good accuracy but later goes down, while the adaptive methods (FCFLA and FCFLAR) improve steadily and finish with the best results. This means that FEDAVG works best on balanced data, but adaptive FCFL methods are more reliable when the data is not balanced.

5.2 Accuracy Variance Comparison

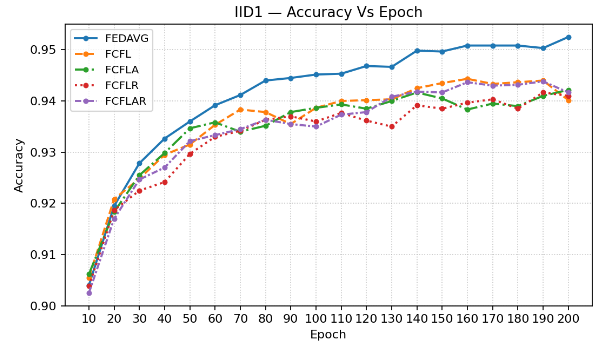
The variance results show that on IID data 5b, all algorithms gradually reduce their accuracy variance and become stable after enough epochs. The differences among the methods are small, and all reach a low variance level.

On Non-IID data 5b, the variance starts much higher but decreases over time. FEDAVG shows some instability at later epochs, while the FCFL methods, especially FCFLA and FCFLAR, keep the variance lower and more stable. This means adaptive methods can handle unequal data better and give more consistent results.

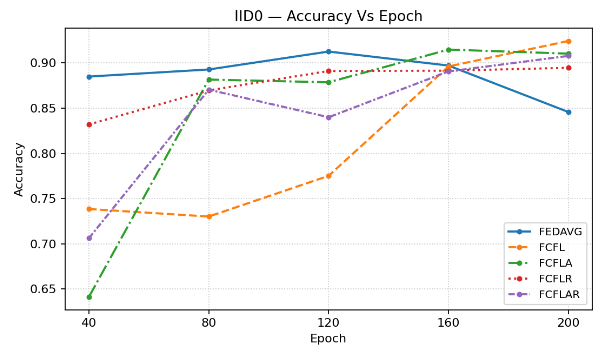
5.3 Unfairness Comparison

The unfairness results show that on IID data 6a, all algorithms gradually reduce the unfairness gap as training goes on, with FCFL reaching the lowest level. The differences among the other methods are small, but FEDAVG remains slightly higher.

On Non-IID data 6b, the unfairness gap is much larger and more unstable. FEDAVG shows the highest unfairness, while the adaptive FCFL methods (especially FCFLA and FCFLAR) reduce the gap more effectively and stay more stable. This shows that fairness-aware methods are better at handling unequal client distributions.

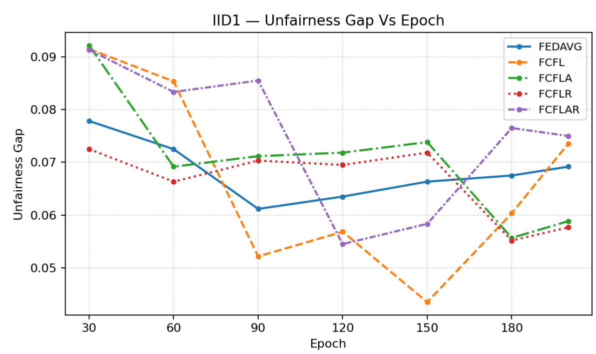


(a) On IID Data

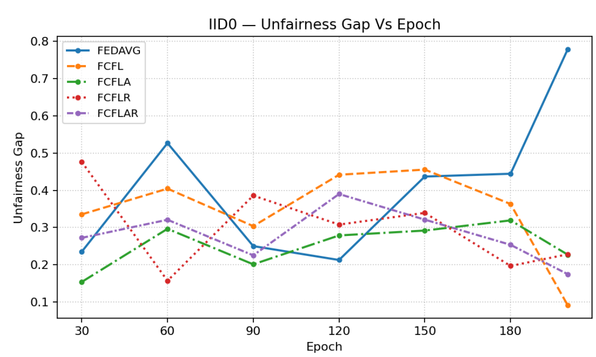


(b) On Non-IID Data

Figure 4: Accuracy Comparison of different algorithms

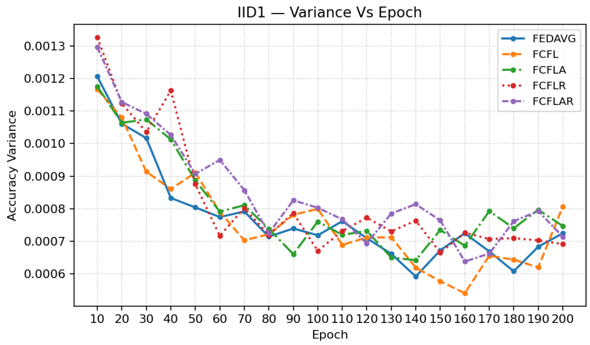


(a) On IID Data

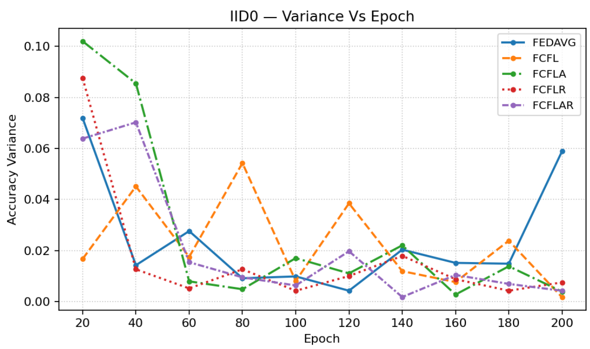


(b) On Non-IID Data

Figure 6: Unfairness of different algorithms

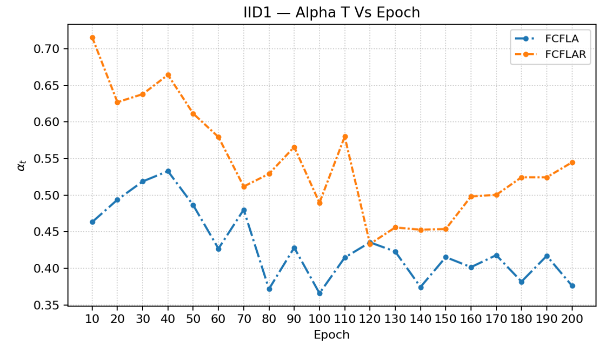


(a) On IID Data

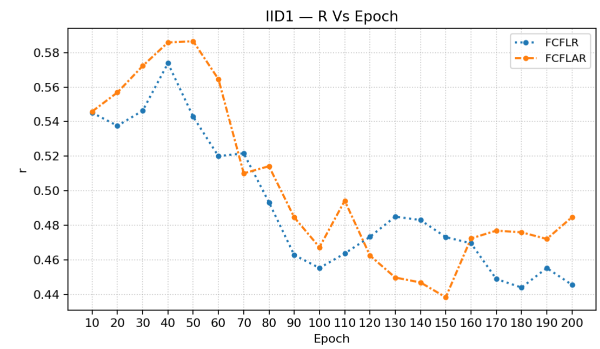


(b) On Non-IID Data

Figure 5: Accuracy Variance Comparison of different algorithms



(a) Adaptive α on IID Data



(b) Adaptive r on IID Data

Figure 7: Change of α and r over runtime

5.4 Adaptive α and R

The adaptive parameters show how α and r change over training. For α 7a, FCFLA and FCFLAR both fluctuate but remain within a stable range, with FCFLAR keeping slightly higher values than FCFLA. This helps the method adjust fairness more actively.

For r 7b, both FCFLR and FCFLAR gradually decrease over epochs, showing the system adapts towards a more balanced client selection. FCFLAR follows a similar trend to FCFLR but with smoother changes, which indicates better stability during training.

6 CONCLUSION

The results show that FEDAVG achieves the best accuracy on IID data but fails to remain stable and fair on Non-IID data. The adaptive FCFL methods, especially FCFLA and FCFLAR, perform more consistently, giving high accuracy while also reducing variance and unfairness across clients. The adaptive control of α and r further helps to balance training, making these methods more reliable in practical federated learning scenarios.

7 LIMITATIONS AND FUTURE WORKS

This study is tested on a limited number of datasets and models, so the results may not fully generalize to more complex real-world applications. The experiments also focused mainly on accuracy and fairness, while other factors like communication cost, privacy, and scalability were not deeply analyzed.

In future, the framework can be extended to larger and more diverse datasets, and tested with different model architectures. Further research should also study the trade-offs between fairness, accuracy, and efficiency. Exploring the combination of adaptive fairness control with privacy-preserving techniques such as differential privacy or secure aggregation could make the approach more suitable for real-world deployment.

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