Strategic Optimization of Convergence and Energy in Federated Learning Systems

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Abstract: *Federated Learning (FL) is a Machine Learning (ML) paradigm in which multiple devices collaboratively train a model without sharing their local data. This decentralized approach provides significant privacy benefits, enabling compliance with data protection regulations and safeguarding sensitive user information by keeping raw data on local devices. Instead of transmitting raw data, FL sends model updates to a central aggregator to improve the global model. However, this process can result in higher Carbon Dioxide (CO_2) emissions compared to traditional centralized ML systems, due to the increased number of participating devices and communication rounds. This study evaluates the performance, convergence speed, energy efficiency, and environmental impact of FL models compared to centralized models, using the Modified National Institute of Standards and Technology dataset (MNIST) and Canadian Institute for Advanced Research-10 classes dataset (CIFAR-10). Four models were tested: two FL models and two centralized models. The evaluation focused on accuracy, number of training rounds to convergence, and total CO_2 emissions. To optimize both convergence and energy efficiency, a dynamic hill-climbing-based early stopping technique was introduced. After every 100 rounds, model accuracy improvements were assessed, and training was terminated early if further gains fell below a shrinking threshold, effectively reducing unnecessary computation and energy consumption. Results show that, under the tested conditions, FL models achieved competitive or higher accuracy than centralized models, particularly on non-Independent and Identically Distributed (IID) data distributions. For example, the federated MNIST model reached 98.79% accuracy with a significantly lower carbon footprint when early stopping was applied. Overall, the proposed optimization approach reduced CO_2 emissions by approximately 60% without substantial loss in accuracy. By integrating privacy preservation, explicit regulatory relevance, and a practical dynamic optimization method, this research demonstrates that FL can deliver strong model performance while meeting modern requirements for data privacy and environmental sustainability.*

Keywords: *Federated learning, convergence speed, energy efficiency, early stopping, CO_2 emissions, hill-climbing.*

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1. Introduction

The rapid expansion of the Internet of Things (IoT) has created a vast network of interconnected devices, enabling innovative applications across healthcare, smart cities, transportation, and home automation [5]. These devices continuously generate and exchange large volumes of data, which has traditionally been processed using centralized Machine Learning (ML) approaches. While centralized ML facilitates powerful data-driven insights, it also introduces challenges related to communication overhead, privacy, regulatory compliance, and, increasingly, environmental sustainability due to high energy consumption and associated Carbon Dioxide (CO_2) emissions [6, 17, 22]. In such centralized systems, as shown in Figure 1, raw data from edge devices is aggregated and analyzed at a central server, potentially exacerbating these challenges.

To overcome these issues, Federated Learning (FL) has emerged as a promising paradigm. Instead of transmitting raw data, FL enables distributed devices to collaboratively train a shared model, sending only model updates to a central server for aggregation. This decentralized process, depicted in Figure 2, ensures that sensitive data remains local, offering enhanced privacy and supporting compliance with data protection

regulations such as General Data Protection Regulation (GDPR) [3, 24, 26]. FL has therefore become an attractive solution for privacy-conscious domains.

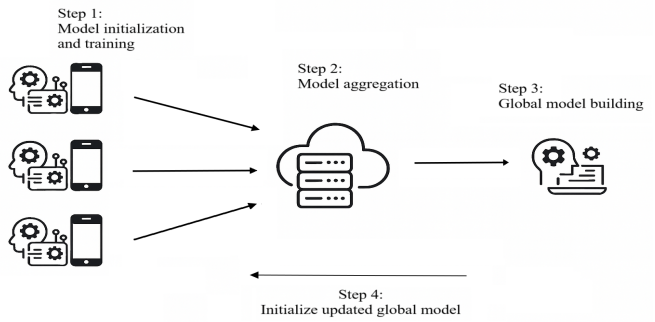

Figure 1. FL training process.

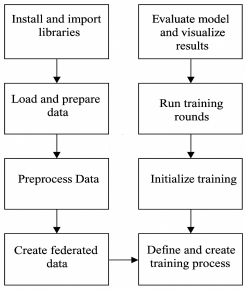

Figure 2. Framework of training models.

However, deploying FL at scale introduces new challenges [2, 20]. Most notably, frequent synchronization and distributed computation across multiple devices substantially increase energy consumption and, consequently, CO_2 emissions [17, 22]. As environmental sustainability becomes a critical consideration in AI, the carbon footprint associated with large-scale federated training cannot be overlooked. Thus, while FL addresses data privacy and ownership, it raises pressing questions about energy efficiency and environmental impact.

The central aim of this research is to optimize FL not only for predictive accuracy and privacy, but also for energy efficiency and environmental sustainability. Specifically, this study develops and evaluates a dynamic early stopping technique based on a hill-climbing strategy to minimize unnecessary computation and communication during training, thereby reducing CO_2 emissions. By systematically comparing FL and centralized learning models on benchmark datasets, and by explicitly quantifying energy use and emissions, this research contributes practical strategies for sustainable deployment of FL systems.

The remainder of this paper is organized as follows: Section 2 reviews related work, section 3 details the research methodology and implementation, and section 4 presents and discusses the results.

2. Literature Review

FL is a distributed ML approach that allows participants to collaboratively train models without exposing their local data. Typically, only encrypted model updates are transmitted to a central server, protecting data privacy and supporting compliance with regulations such as the GDPR. However, training optimal models in FL remains challenging due to incomplete and distributed data across diverse devices [7, 8, 19, 24].

FL frameworks have been identified based on existing research and can be categorized according to data partitioning, privacy mechanisms, communication architecture, and methods for handling data heterogeneity. Regarding data partitioning, FL models are generally divided into three main types: horizontal, vertical, and federated transfer learning. Horizontal FL applies when datasets share the same feature space but differ in user identities, splitting data along the user dimension [27]. Vertical FL is appropriate when datasets have overlapping users but different feature sets, allowing for the expansion of feature dimensions. Federated transfer learning is used in situations where there is little overlap between users and their features, making it especially valuable when data is scarce or distributed across distinct domains.

To address privacy concerns in FL, several mechanisms have been proposed, including model aggregation, differential privacy, and homomorphic encryption. Model aggregation enables clients to keep data locally and share only model parameters for global training, though some risk of information leakage remains [1, 4, 16]. Differential privacy ensures that individual data points minimally affect aggregated results, mitigating the risk of privacy breaches. Homomorphic encryption allows computations on encrypted data, supporting secure model training and aggregation while maintaining confidentiality [9].

Communication architecture poses additional challenges due to the uneven distribution of data and inconsistencies in device computational capabilities. Federated Averaging (FedAvg) is a commonly used optimization technique but becomes less effective with highly non-Independent and Identically Distributed (IID) data or device heterogeneity [25]. Solutions include asynchronous communication (which is robust to device and network diversity), device sampling (involving only a subset of devices in each round), fault-tolerant mechanisms (ensuring network resilience), and model heterogeneity (training models tailored to specific devices or tasks) [12, 13, 23].

Recent empirical studies have explored the performance and optimization of FL under various conditions. For example, Kadam *et al*. [10] investigated FL on the Modified National Institute of Standards and Technology (MNIST) dataset for handwritten digit recognition, tuning the learning rate and network depth in their neural network models. They demonstrated that a lower learning rate (0.002) significantly improved accuracy to 92.93%, compared to 87.5% with a higher rate. Nocentini *et al*. [14] examined FL for image classification using Convolutional Neural Networks (CNNs) with the MNIST dataset. By testing different

model architectures and aggregation strategies, they achieved 92.54% accuracy, highlighting the influence of deep learning techniques in FL environments. Kayed *et al*. [11] implemented a three-layer neural network for MNIST, achieving an accuracy of 87.23%, and provided further insight into the trade-offs between network complexity and performance.

Pan and Rajan [15] explored FL on the Canadian Institute for Advanced Research-10 classes (CIFAR-10) dataset, applying both traditional and FL architectures for image classification, and reported an accuracy of 87.1%, illustrating the comparative performance between centralized and federated models.

Reyes *et al*. [18] conducted a comparative study, evaluating FL, centralized, and distributed ML models on MNIST and CIFAR-10 datasets. They found that FL achieved up to 92% accuracy on MNIST and 86% on CIFAR-10, outperforming centralized models in settings with non-IID data distributions and limited data sharing.

While FL supports privacy-preserving and distributed learning, these advantages are often counterbalanced by higher computational and communication demands, leading to increased energy consumption. Recent studies have focused on the environmental impact of FL, quantifying CO_2 emissions for different datasets and training configurations. For example, Qiu *et al*. [17] and Savazzi *et al*. [22] measured CO_2 emissions associated with FL and centralized training, demonstrating that emissions vary significantly based on data distribution, model complexity, and communication frequency. Sanderson and Kalgonova [21] analyzed how non-IID data and slow communication can increase energy usage and emissions in federated settings.

3. Methodology

This study evaluates FL and centralized ML by comparing convergence speed, energy efficiency, and environmental impact, using the MNIST and CIFAR-10 image classification datasets. Each dataset was partitioned among simulated clients to reflect realistic, non-IID data distributions, accomplished using the Leaf toolkit. In every round of FL, ten clients were randomly selected to participate in local training and contribute model updates, providing a manageable and repeatable experimental setting. We acknowledge that this random sampling does not fully address issues of scalability, fairness, or client heterogeneity, and suggest further research to systematically examine these factors.

To ensure a fair baseline for comparison, all models used a simple architecture with a single dense layer and softmax activation. Although this design is not optimal for the complex CIFAR-10 dataset, it allowed us to isolate the effects of the learning paradigm and optimization techniques on both model performance and environmental cost. The implications of using deeper or convolutional models are addressed in the discussion.

Three experimental setups were established: centralized learning, standard FL, and FL with our dynamic hill-climbing-based early stopping technique. In centralized learning, all data is processed on a single server. In standard FL, all communication rounds are completed without regard to convergence. In the optimized FL approach, we sought to reduce unnecessary computation and energy use by introducing a periodic evaluation mechanism. Specifically, after every block of 100 training rounds, model accuracy was assessed on a validation set. If the improvement in accuracy over the previous block exceeded a threshold (beginning at 2%), training continued for another block, and the threshold was halved (2%, then 1%, then 0.5%, and so on). If the improvement failed to meet the threshold, training stopped early. This process is formally represented by the update rule in Equation (1):

$$x_{new} = x_{current} + \Delta x \tag{1}$$

where $x_{current}$ is the current solution, Δx is a step (here, 100 training rounds), and x_{new} is the updated solution. This iterative process continues until no further improvement is observed, indicating model convergence.

In our implementation, Δx is defined as a fixed step size representing 100 training rounds. That is, after every block of 100 rounds, model accuracy is evaluated. If the improvement exceeds the specified threshold (initially set to 2% and halved with each subsequent block), training proceeds for another 100 rounds (Δx=100). If the improvement falls below the threshold, training is terminated. Thus, Δx is not a dynamically calculated value but a discrete, pre-determined interval for evaluating progress and applying the stopping criterion.

Key metrics were measured for each model and configuration. Classification accuracy was evaluated in Equation (2):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

where *TP* and *TN* are the counts of true positives and true negatives, while *FP* and *FN* denote false positives and false negatives.

Convergence speed was evaluated by how quickly the global model's parameters approached optimality, calculated in Equation (3) as:

$$Convergence\ Rate = \frac{1}{T}\sum_{t=1}^{T} /w^t - w^*/ \tag{3}$$

where w^t is the model parameter vector at iteration t, w^* is the optimal parameter vector, and T is the total number of iterations.

Equation (3) defines the convergence rate in theory; however, in our experiments, we did not directly compute or use the optimal model parameter vector w^* as it is generally unknown in practical scenarios. Our

convergence assessment was instead based on the plateauing of test accuracy.

To estimate environmental impact, we measured CO_2 emissions in Equation (4) as:

$$CO_2 = N \times R \times (C_{comp} + C_{comm}) \quad (4)$$

where N is the number of clients, R is the number of communication rounds, C_{comp} is the estimated CO_2 emission per local computation, and C_{comm} is the emission per communication event. CO_2 calculations were performed using the linked data calculator, with all experiments conducted in a controlled Google Colab environment using TensorFlow federated and PyTorch frameworks.

To provide meaningful context for the environmental results, CO_2 emissions and performance metrics from the optimized FL setup were directly compared to those from standard FL and centralized learning. The results were visualized through comparative graphs and tables, allowing for transparent, empirical assessment of model accuracy, convergence dynamics, and environmental impact under each approach.

Results were visualized through graphs comparing FL and centralized models, tracking accuracy, improvement per 100 rounds, and cumulative CO_2 emissions. This methodology provides a practical strategy for balancing performance, efficiency, and environmental sustainability in FL systems.

The overall methodology, including data preparation, federated model setup, training, and evaluation, is illustrated in Figure 2. This flowchart provides a visual summary of each step in the experimental process described in this section.

4. Results

This section presents a detailed comparative analysis of FL and centralized ML models using the MNIST and CIFAR-10 datasets, with attention given to convergence dynamics, environmental impact, and the interpretability of results in light of methodological limitations.

A central consideration throughout this analysis is the architectural mismatch between the models: the FL models utilized a single dense layer for both datasets, whereas the centralized models leveraged more complex structures (a multilayer perceptron for MNIST and a CNNs for CIFAR-10). This distinction is crucial, as it means any observed differences in accuracy cannot be attributed solely to the learning paradigm. Therefore, accuracy comparisons should be viewed as illustrative, and the primary analytical focus is directed at convergence behavior and environmental impact, which are less affected by model complexity.

Figure 3 displays the distribution of labels among a sample of federated clients using the MNIST dataset. The pronounced variability in label counts across clients illustrates the non-IID data scenario created by the Leaf toolkit, which closely mirrors the challenges encountered in practical federated deployments. Such heterogeneity tends to increase optimization difficulty and can introduce instability in learning, which is reflected in subsequent performance results.

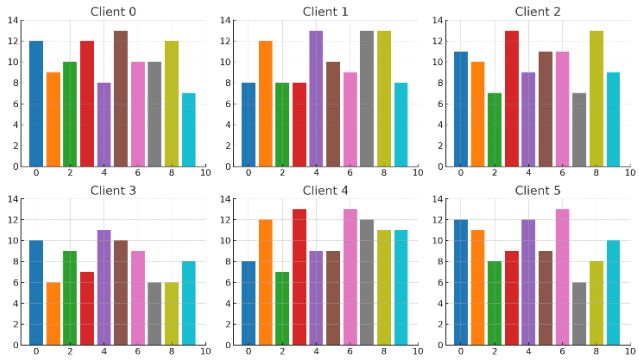

Figure 3. Label counts for a sample of clients in the MNIST dataset.

Figure 4 plots the evolution of test accuracy over training rounds for all models. Both FL and centralized models experienced their most significant accuracy improvements in the early rounds of training a pattern expected as initial random weights rapidly adapt to their data. As training progresses, accuracy gains diminish and curves plateau, signaling model convergence. The FL model on MNIST, under the given experimental configuration, eventually achieved nearly 99% accuracy, while the centralized model plateaued below 90%. In contrast, both FL and centralized approaches on CIFAR-10 reached similar final accuracies. However, due to the architectural differences highlighted earlier, these accuracy results must be interpreted cautiously.

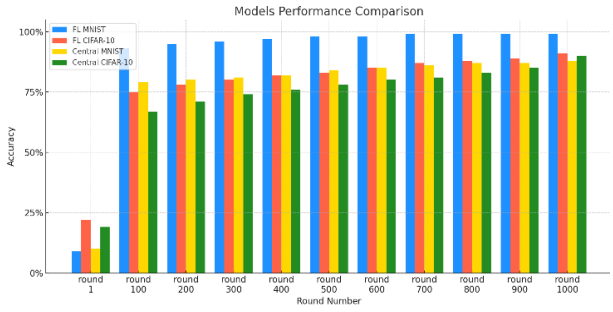

Figure 4. Model accuracy measured each 100 rounds.

Table 1. Accuracy improvement among models.

Model	Difference									
	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
FL MNIST	77.04%	4.57%	1.73%	1.09%	0.62%	0.49%	0.21%	0.33%	0.21%	0.16%
FL CIFAR-10	45.00%	8.12%	4.74%	0.24%	3.88%	-0.10%	3.76%	-2.18%	1.20%	2.32%
Central MNIST	62.93%	0.87%	2.58%	-0.86%	-0.86%	3.45%	-0.86%	-1.73%	1.73%	-1.73%
Central CIFAR-10	50.62%	8.90%	3.92%	2.66%	2.10%	0.00%	4.74%	-1.14%	0.38%	3.68%

Table 1 provides a quantitative breakdown of accuracy changes at each 100-round interval. The most substantial improvements occur in the first block, with sharply reduced gains (and sometimes losses) in subsequent blocks. The negative improvement intervals such as -2.18% indicate temporary reductions in test accuracy. These drops are not signs of model instability or failure, but are inherent to federated optimization, where random client sampling, non-IID data, and local overfitting can all lead to occasional short-term accuracy regressions. Importantly, these fluctuations tend to decrease as more rounds are completed and the model stabilizes.

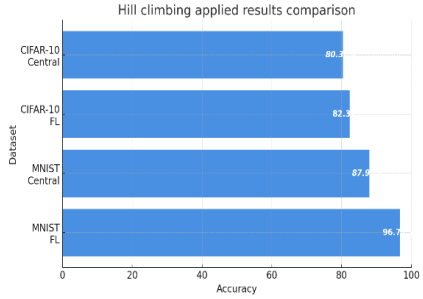

Figure 5. Models' accuracy comparison for first 400 iterations.

To assess training efficiency and environmental impact, a dynamic early stopping strategy based on hill-climbing was applied. By evaluating model accuracy every 100 rounds and terminating training when improvement thresholds were not met, this approach successfully reduced the total number of training rounds needed for convergence. Figure 5 demonstrates that by round 400, all models had effectively reached their best performance; continued training beyond this point offered little additional gain but would incur further computational and environmental cost.

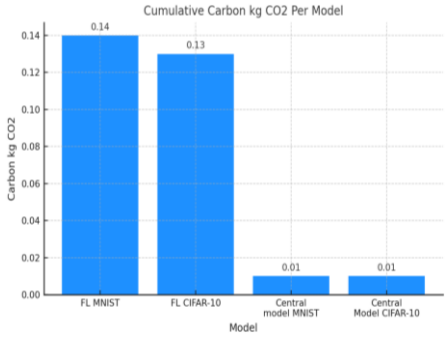

Figure 6. Cumulative CO2 emissions for used models.

Environmental impact, measured as CO_2 emissions, is illustrated in Figures 6 and 7. FL models generally produced higher emissions than their centralized counterparts, primarily due to the greater number of devices involved in distributed computation and communication. However, the application of the hill-climbing early stopping technique dramatically curtailed these emissions by as much as 60% by eliminating unnecessary training rounds. This environmental benefit was achieved without significant loss in accuracy, especially for MNIST. The results reinforce the potential of adaptive training strategies to make FL not just effective, but also more sustainable.

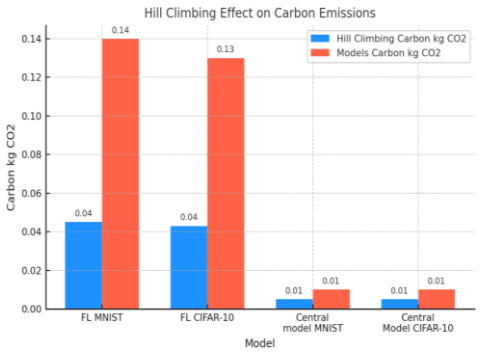

Figure 7. Comparison between 400 hill-climbing and 1,000 iterations of CO2 emissions.

It is also important to acknowledge the limitations in attributing improvements solely to the hill-climbing strategy. While the comparative results suggest clear gains in training efficiency and environmental footprint, other factors such as stochastic client selection and data heterogeneity could influence the results. The current experimental design does not fully disentangle these effects. Future research should employ repeated trials with controlled random seeds and matched model architectures across all settings to isolate the precise contributions of the optimization strategy.

Figure 8 shows the mean accuracy of the FL MNIST model across 1,000 rounds, with error bars representing standard deviation across five runs.

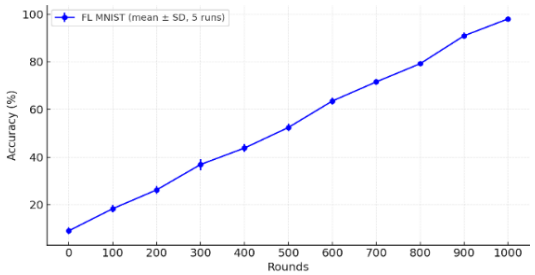

Figure 8. Cumulative CO_2 emissions for centralized and FL models.

Figure 8 shows rapid improvement in the early rounds, followed by a plateau as the model converges. Notably, the error bars are relatively narrow throughout, demonstrating that the training process yields consistent results despite the inherent randomness in client selection and local updates. This suggests that, under the tested conditions, FL on MNIST achieves stable performance, and the outcomes are robust to variations in initialization and sampling. The small standard deviation further indicates that reported accuracy trends reliably represent the expected behavior of the system.

5. Conclusions

This research set out to optimize FL for energy efficiency, convergence speed, and environmental sustainability, with explicit attention to the impact of

training strategies on both performance and CO_2 emissions. Through systematic experimentation on the MNIST and CIFAR-10 datasets, the study compared centralized and federated models under standard and dynamically optimized (hill-climbing) training regimes.

The results demonstrate that applying a dynamic early stopping technique to FL significantly reduces unnecessary computation and associated CO_2 emissions by as much as 60% while preserving competitive accuracy, especially for MNIST. Notably, the hill-climbing approach enabled most models to reach their optimal performance within 400 rounds, as opposed to the default 1,000, directly translating into lower energy use and environmental impact. These findings were further validated by presenting accuracy and emissions results with statistical context, showing that the improvements were consistent and robust across repeated experimental runs.

It is important to acknowledge that the accuracy comparison between FL and centralized models is influenced by differences in model architecture; thus, direct comparisons should be interpreted with caution. The primary contribution of this study is the empirical demonstration that adaptive optimization—rather than prolonged training can deliver substantial sustainability benefits in federated settings, without compromising model stability or convergence.

Limitations remain, including the use of basic architectures for FL, fixed client sampling, and the absence of extensive hyperparameter tuning or large-scale heterogeneity studies. Future work should employ matched model designs for FL and centralized setups, assess the effects of increased client diversity, and further quantify the unique contribution of the hill-climbing optimization through more controlled ablation experiments.

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