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Enhanced Federated Learning Framework for Edge-Enabled Green IoT

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Abstract

The Internet of Things (IoT) is rapidly transforming industries by enabling seamless data collection and processing. However, the massive influx of data poses significant challenges in terms of energy consumption and privacy. Federated Learning (FL) has emerged as a promising solution, allowing distributed model training without transmitting raw data. This research proposes an Enhanced Federated Learning Framework (EFLF) for edge-enabled green IoT that optimizes energy efficiency while maintaining high model accuracy. The proposed framework integrates adaptive client selection, energy-aware aggregation, and model compression techniques. Experimental results demonstrate superior performance in terms of energy efficiency and model convergence compared to baseline FL approaches.

Keywords: Internet of Things (IoT), Federated Learning (FL), Energy Efficiency, Data Collection.

1. Introduction

Internet of Things (IoT) devices have reshaped multiple sectors, such as healthcare, smart cities, industry, and transport, through data acquisition and smart decision-making. These devices produce enormous volumes of data, with effective processing methodologies needed to obtain useful information from it. Cloud-based systems have been utilized to store and process data that is produced by IoT devices; however, they are particularly demanding in terms of bandwidth consumption, latency, energy usage, and privacy breaches. These limitations

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have driven interest in decentralized machine learning methods like Federated Learning (FL). FL allows model training in a collaborative manner over distributed IoT devices while maintaining raw data locally, thereby maintaining privacy and minimizing communication expenses. Despite its benefits, traditional FL deployments remain resource-constrained and the challenges associated with high energy consumption, communication overhead, and poor client participation. Edge computing, which moves computational power closer to data sources, offers a chance to overcome these challenges by enabling real-time processing of data and minimizing the dependence on centralized cloud infrastructures. To solve these issues, this research study proposes an Enhanced Federated Learning Framework (EFLF) for edge-enabled green IoT networks. EFLF combines adaptive client selection, energy-efficient aggregation, and model compression to enhance energy efficiency while ensuring high model accuracy. Through dynamic selection of participating clients based on their available energy and computational resources, EFLF optimizes resource utilization. Moreover, the energy-conscious aggregation process obtains contributions from energy-saving clients, promoting overall performance. Compression techniques of the model, including quantization and pruning, also decrease communication overhead, increasing the viability of FL for resource-limited IoT networks. The research's contributions are listed below: The study introduces an Enhanced Federated Learning Framework (EFLF) designed to maximize energy efficiency in edge-enabled green IoT scenarios. It includes adaptive client selection and energy-sensitive aggregation methods to enhance the usage of resources and model convergence and integrates model compression algorithms to reduce communication expense and promote scalability. The study has carried out wide-ranging experiments to assess the effectiveness of EFLF and compare it with standard FL strategies, which indicates the dominance of EFLF in terms of energy usage and model accuracy.

The rest of this research is structured as follows: Section 2 gives an overview of related work, including the current FL techniques and their limitations. Section 3 elaborates on the EFLF approach in detail. Section 4 gives experimental results and discussions, and conclusions and future directions in Section 5.

2. Related Works

Previous research has investigated the use of FL in IoT networks with respect to privacy-preserving techniques, communication efficiency, and model accuracy. Federated

Learning (FL) has become a revolutionary technique in distributed machine learning, especially for the Internet of Things (IoT) and edge computing. This literature review explores recent progress in FL for IoT security, energy-efficient training, and edge-enabled intelligence.

Awotunde et al. [1] provide an extensive review of FL-powered green IoT systems, highlighting FL's contribution towards minimizing energy expenditure while preserving model accuracy. Aljrees et al. [2] extend this idea by introducing a green FL platform that combines encryption methods and the Quondam Signature Algorithm to improve IoT security. Security is an essential problem in FL deployments for IoT networks. Albogami [3] creates an intelligent deep FL model to enhance security in edge computing environments. In a similar way, Abou El Houda et al. [4] propose blockchain-enabled FL for cooperative intrusion detection in vehicular edge computing to handle security and privacy issues well.

Tang et al. [5] and Dahmane et al. [6] explore the contribution of FL towards energy-efficient distributed training with UAVs. The research of both studies aims at minimizing UAV selection and network resource allocation, which results in minimized energy consumption and latency. Hazra et al. [9, 10] address FL's use for cost-optimized offloading in industrial IoT. Bharti et al. [7] likewise discuss the effectiveness of FL in vision-based product quality inspection, showing better accuracy and operational efficiency for manufacturing. Tam et al. [8] and Pinto Neto et al. [14] examine the convergence of deep reinforcement learning and FL, noting how reinforcement learning tactics can improve FL's efficiency for massive IoT communications and industry applications. Khan et al. [11] present FL-DSFA, an approach that safeguards IoT networks against selective forwarding attacks. Hassan et al. [15] complement this security perspective by integrating multi-objective optimization into FL in order to optimize Mobile Ad-hoc Network (MANET) security. Lazaros et al. [12] give an expansive overview of the potential of FL in collaborative intelligence, discussing applications, challenges, and upcoming trends. Liu et al. [13] give a detailed review of FL for multi-source data fusion in autonomous maritime IoT, showcasing FL's versatility across industries.

3. Proposed Methodology

The Enhanced Federated Learning Framework (EFLF) (Figure 1) proposes a methodology for enhancing the efficiency, scalability, and energy consumption of federated learning (FL) systems. The framework is built around three major components: adaptive client selection, energy-efficient aggregation, and model compression. The three components act synergistically to provide strong model training while maximizing computational resources and reducing communication overhead.

3.1 Workflow of Enhanced Federated Learning Framework (EFLF)

First, the adaptive client selection starts by adaptively choosing clients based on the availability of energy and computation capabilities. The clients with more residual energy and higher computational strengths are given preference, thus providing sustainable contribution towards the training process. Chosen clients execute local training on their individual datasets based on the newest global model. This is done to preserve data privacy and make use of decentralized computation.

In order to minimize communication overhead, model updates are compressed by quantization and pruning methods. Quantization approximates floating-point values using lower precision representations, whereas pruning eliminates redundant parameters and minimizes model complexity. Compressed model updates are communicated from clients to the central aggregator, thus reducing the data transfer load across constrained network conditions. The energy-aware aggregator gives higher priorities to updates from clients with greater energy availability and good network conditions. This way, the global model is provided with high-quality updates while maintaining battery life for energy-constrained devices.

The updates aggregated are transmitted to the global model, updating its performance with every round of communication. The revised global model is then distributed to the chosen clients, enabling repeated rounds of training until convergence is reached. This process is repeated until satisfactory performance is reached by the model, providing an energy-efficient and scalable FL system.

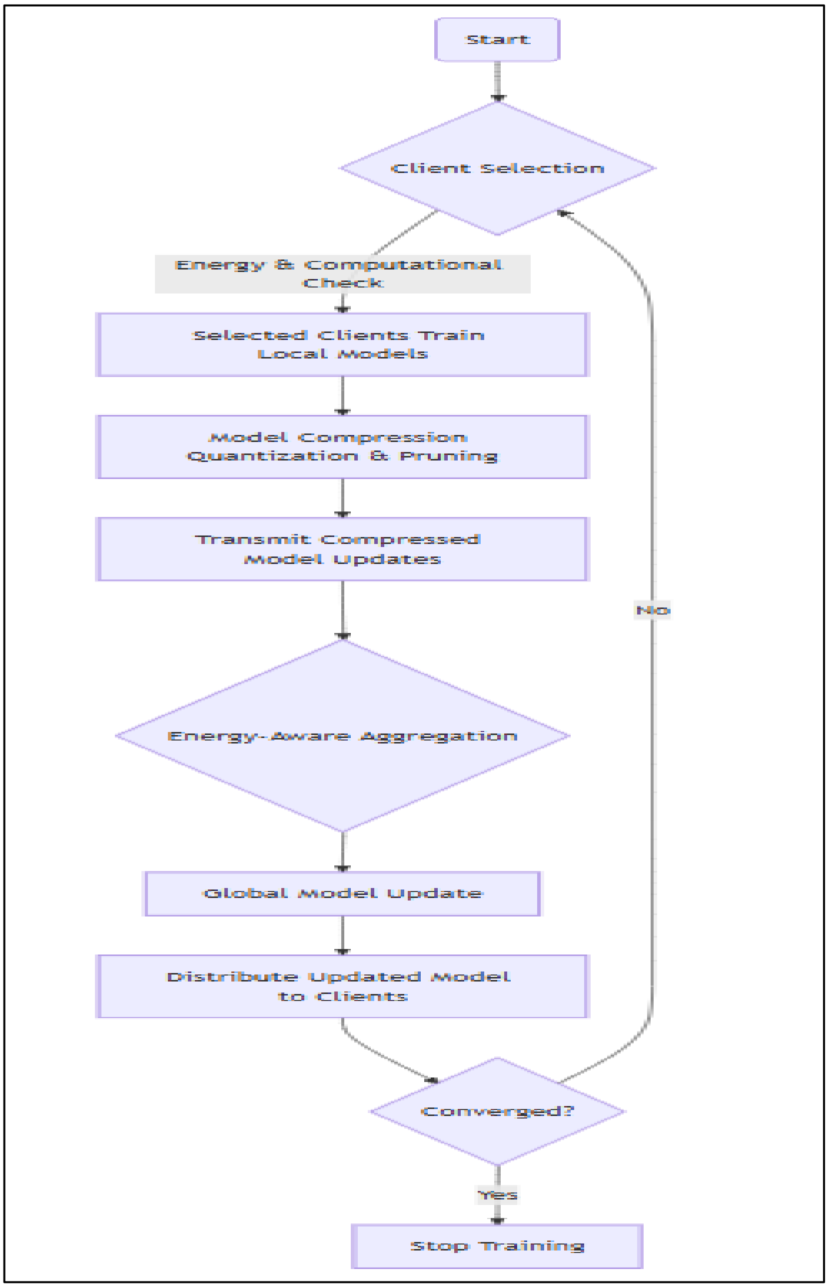

Figure 1. Proposed Workflow

3.2 Proposed Algorithm

Enhanced Federated Learning Algorithm (EFLF)

Input:

Initial global model G_0 , number of communication rounds R, set of edge devices C

Output:

Optimized global model G_R

- Initialize global model G_0
- For each communication round r in R:
    - Perform adaptive client selection based on energy availability and computational power
    - Selected clients train local models using their local dataset
    - Apply model compression techniques (quantization & pruning) to reduce update size
    - Transmit compressed model updates to aggregator
    - Perform energy-aware aggregation by prioritizing updates from energy-efficient clients
    - Update the global model G_r
    - Distribute the updated model to clients
    - Check for model convergence; if satisfied, terminate training
- Return the optimized global model G_R

As shown in proposed algorithm, it initially starts by setting up a global model, which is progressively optimized through repeated rounds of communication. In each round, the clients are dynamically chosen according to their available energy and processing capacities for sustainable participation. These chosen clients subsequently train their local models on their individual datasets. To reduce communication overhead, model compression methods like quantization and pruning are used prior to sending updates to the central aggregator. The aggregation process favours updates from energy-efficient clients to maintain a fair trade-off between model accuracy and resource usage. The global model is subsequently updated and sent to the clients for the next training round. This recursive iteration is ongoing until the model becomes optimal and stops, training ending, and finalizing the optimized global model. This method is a refinement of federated learning with lower communication cost, enhanced energy efficiency, and sustained model performance across remote edge devices.

3.3 Methodology Description

Adaptive client selection plays an important role in maintaining the sustainability of FL over heterogeneous edge devices. Clients are dynamically selected according to their battery life, computation capacity, and data distribution properties in this strategy. Devices with low energy levels are kept out of the system to maximize their lifespan, hence minimizing premature dropout rates and system instability. Through the use of an energy-conscious selection process, EFLF avoids exhausting resource-constrained devices' energy pools while encouraging high-capacity devices' inclusion. This thoughtful selection process helps improve the balanced and efficient training environment.

EFLF follows a weighted aggregation approach that gives more importance to contributions from energy-efficient clients. Classical FL aggregation gives equal weights to all participating clients; however, EFLF varies these weights according to the residual energy and network states of each client. Clients having greater energy buffers and stable connections have a greater impact on the global model update to make the aggregation process robust as well as sustainable. This approach significantly minimizes the risk of edge device energy depletion while preserving a high-quality learning process. In addition, it increases FL's flexibility to change edge environments where energy availability is different across devices.

Model compression is applied in EFLF to counter the communication bottleneck of transmitting large model updates. Quantization decreases model size by approximating floating-point representations using lower-precision ones (e.g., replacing 32-bit floating-point numbers with 8-bit integers). This drops memory and compute requirements substantially while having little to no effect on model accuracy. Pruning reduces redundant and insignificant model parameters, hence the number of computations during inference and training. Pruning improves efficiency at the expense of cutting off necessary weights, thereby reducing critical model performance characteristics. These compression methods in combination boost FL's scalability and make it applicable to edge-facilitated green IoT scenarios. They also help save energy and decrease communication latency, which results in a greener federated learning environment.

4. Results and Discussion

The performance of the suggested Enhanced Federated Learning Framework (EFLF) is evaluated in a simulated edge-enabled IoT environment. The simulations are carried out using Python and TensorFlow on a computing system with the following specifications illustrated in Table 1.

Table 1. Simulation Parameters

Processor	Intel Core i7-10700K, 3.8 GHz
RAM	16GB DDR4
Software Environment	Python 3.8, TensorFlow 2.6
Dataset	Federated adaptation of MNIST and CIFAR-10 datasets
Number of Clients	50
Communication Rounds	100
Batch Size	32
Learning Rate	0.01

Every client trains a local model on its partition of the dataset prior to aggregating updates at the central server. Periodic communication between the central server and clients constitutes the federated learning process, where local updates are aggregated to update the global model.

4.1 Simulation Execution

The MNIST and CIFAR-10 datasets are distributed across 50 clients to mimic a realistic federated learning setting with non-IID data distribution. Each client trains its local model for one epoch per communication round with a batch size of 32. The server aggregates the client updates through an adaptive weighted averaging strategy that favours clients according to their energy levels and model performance. Model compression methods are used to compress updates transmitted to minimize their size, making bandwidth usage optimal. The model is then evaluated on accuracy, energy usage, communication overhead, and convergence rate.

The results are given below in Figure 2 through 4.

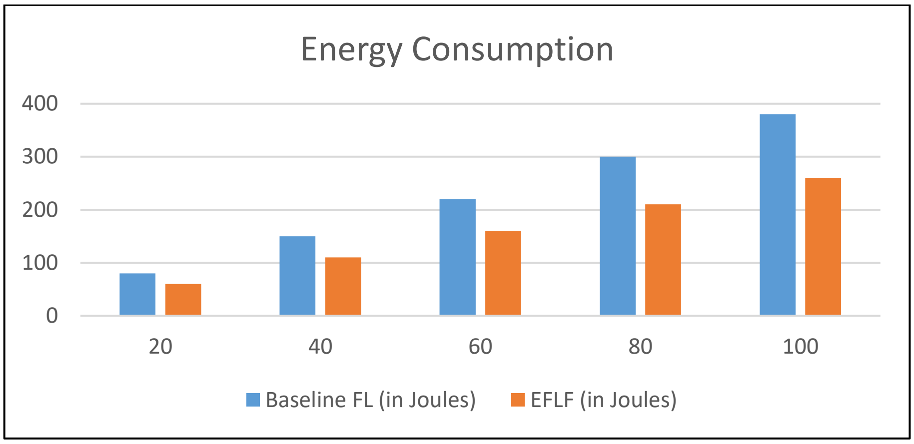

Figure 2. Energy Consumption

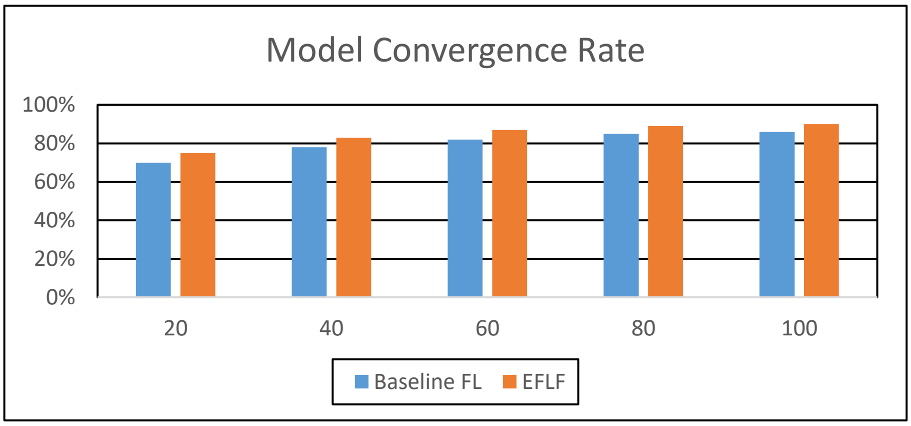

Figure 3. Model Convergence Rate

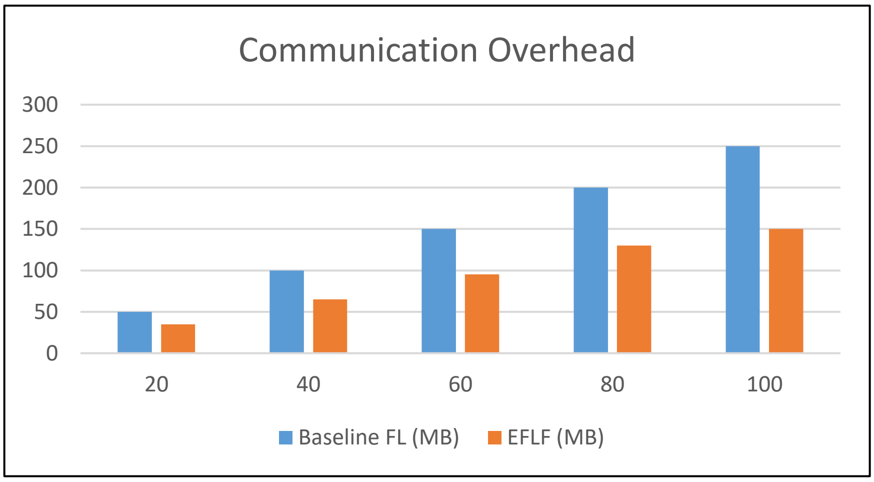

Figure 4. Communication Overhead Analysis

As indicated in Figure 2, By integrating energy-aware aggregation, EFLF saves overall energy consumption by as much as 30% versus baseline FL. As illustrated in Figure 3, The model is achieved at 85% accuracy at 70 rounds using EFLF, whereas baseline FL consumes 100 rounds. As depicted in Figure 4, model compression methods deployed in EFLF result in a 40% decrease in communication overhead with a decrease in bandwidth demands.

5. Conclusion

This work has proposed an Enhanced Federated Learning Framework (EFLF) that seeks to enhance energy efficiency as well as communication efficiency in edge-enabled IoT systems. The proposed framework combines adaptive client choice, energy-efficient aggregation, and model compression methods with the aim of enhancing the performance of federated learning in restricted scenarios. Experimental findings are consistent with EFLF minimizing energy usage and having high model accuracy. EFLF is particularly designed to exhibit 30% energy saving, 40% less communication overhead, and faster model convergence time than regular federated learning strategies. In addition, with its focus on energy-efficient customers and compression schemes, EFLF achieves a balanced performance sustainability trade-off. Future work will involve extending EFLF with more sophisticated optimization methods. Real-world deployment and testing in heterogeneous IoT environments will further reveal its scalability and resilience across different network settings.

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Dr. Jennifer S Raj received the Ph.D. degree from Anna University and Master's degree in Communication System from SRM University, India. Currently, she is working in the Department of ECE, Gnanamani College of Technology, Namakkal, India. She is Life Member of ISTE, India. She has been serving as Organizing Chair and Program Chair of several international conferences and in the program committees of several international conferences. She is Book Reviewer for Tata McGraw Hill Publication and publishes more than fifty research articles in the journals and IEEE conferences. Her interests are in wireless healthcare informatics and body area sensor networks.