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Carbon Efficient Federated Learning Algorithms Via Adaptive Client Participation

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Abstract

The proliferation of decentralized data has made Federated Learning (FL) the preferred paradigm for privacy-preserving distributed artificial intelligence. Nonetheless, the significant amount of computation and communication overhead involved in training advanced models in thousands of edge clients results in significant carbon emissions and environmental harm. In this paper, an algorithmic design is introduced to implement carbon-efficient federated learning via a process referred to as adaptive client participation. Contrary to conventional federated learning algorithms, which select edge clients based on network availability and the size of available data at the edge, the presented model uses adaptive client participation to change the probability of client selection based on real-time carbon intensity, local energy expenditure, and learning status. The experiments were performed on a distributed dataset with high diversity to emulate non-IID edge networks. From the simulations, one can clearly observe the environmental benefit obtained from the adaptive participation algorithm since it has been found that it significantly cuts down the carbon emissions associated with the operation of the system by 34.2% while maintaining high accuracy of the global model at 92.5%. Moreover, the algorithm has also proved to be highly efficient in terms of convergence since it requires 22.1% fewer iterations than the baseline carbon-unaware FL models to achieve the required level of accuracy. This is possible since only the use of edge resources is enabled during periods when the power grid uses renewable sources of energy. The paper thus provides a guideline for implementing green computing solutions in edge intelligence.

Keywords

Federated Learning, Carbon Efficiency, Green Edge AI, Adaptive Client Selection, Sustainable Computing, Distributed Optimization, and Machine Learning.

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1. Introduction

Federated learning has brought about revolutionary changes in deploying artificial intelligence in the sense that edge devices can now work together in training a global model without ever moving any raw data out of the device in question. Such decentralization is particularly useful in privacy-sensitive applications like intelligent wireless sensor networks and health information systems. Nevertheless, federated learning involves iteratively performing local optimization of parameters and aggregation of the global model, which consumes considerable amounts of energy [21][22]. With the rise of global deployments of the Internet of Things (IoT), the accumulated electricity consumed when training deep models on heterogeneous edge devices is bound to be translated into an enormous carbon footprint. Current client selection schemes focus on fast convergence or statistical uniformity, paying no attention to whether the selected client's power grid is green or dirty. There is thus an urgent need to redesign federated learning algorithms to include considerations about the environment in the optimization process, ensuring that edge intelligence scales in tandem with global carbon-reduction mandates.

The primary objective of this paper is the design, development, and validation of an operational approach that reduces the overall carbon footprint of federated learning setups while not affecting the performance of the final model or adding any extra burden to communication costs. For realizing this objective, the proposed system adopts an adaptive client selection technique that takes into account the carbon intensity of local grids as well as client energy efficiency. The important contributions of this work are listed below:

- Introduce a novel optimization algorithm that dynamically modifies client selection weights based on time-varying regional carbon intensity data and device-specific hardware profiles.
- Establish a balanced mathematical objective that explicitly penalizes high-carbon training paths while maximizing the statistical contribution of participating edge clients.
- Provide a comprehensive experimental evaluation demonstrating a 34.2% reduction in carbon emissions with negligible impact on global model training convergence and precision.

The remaining sections of this research paper are systematically organized in order to offer a systematic flow of this study. In Section 2, a review of recent literature is provided that follows the trajectory of interactions between federated learning, energy efficiency, and environmental sustainability, and points out unique gaps that this paper bridges. In Section 3, the underlying conceptual methodology is discussed, with an introduction to the overall system framework, the mathematical formulation, and the algorithmic approach towards client adaptation. In Section 4, the experimental methodology is provided, including the use of software tools, dataset characteristics, initialization parameters, and performance measures. Finally, in Section 5, the paper is concluded by summarizing the main contributions and discussing the implications and limitations of the study as well as the directions for future research in green artificial intelligence.

2. Contextual Literature Survey

The connection between distributed machine learning and sustainable development has spurred extensive research interests due to the growing awareness of the carbon impact of artificial intelligence. Green computing laid early foundations that model size modification and neural architecture tuning help ease the computational complexity of decentralized learning [1]. In wireless settings, edge intelligent sensor networks often use distributed inference systems with energy considerations to prolong the lifespan of edge nodes and reduce their energy consumption [2]. However, conventional approaches to energy minimization cannot be readily applied to carbon minimization, since energy usage statistics do not take into account the variability of the carbon intensity of the power grid used by edge nodes. Lifecycle and carbon footprint analysis of distributed algorithms indicate that sustainability is about more than just energy consumption, and the sources of real-time energy of edge nodes must be considered [3][23]. Modern IoT systems, like 6G-based smart city intrusion detection networks, must consider ways to integrate strict security requirements with strict energy and environmental limitations [4].

Recent trends have been inclined towards leveraging consumer technology and edge optimization in building low-carbon, sustainable ecosystems for environmental monitoring [5]. Privacy-preserving deep neural network training using mobile wireless networks has indicated that optimizing communications automatically optimizes battery consumption at the local level [6]. In order to meet the requirements of environmental objectives, approaches such as FedCarbon provide a double flexible control mechanism that optimizes the number of local training iterations and the participation rate of clients depending on carbon availability [7]. Such a trade-off between sustainability and functionality is crucial for privacy-aware ubiquitous applications deployed on consumer devices [8]. Furthermore, complex carbon-aware scheduling techniques indicate that synchronization of the training slots of clients with the best time slots regionally helps in suppressing the emission levels [9]. Such sustainable approaches are crucial when extending federated learning to new domains, especially the domain of healthcare informatics, where privacy-preserving anomaly detection is concerned [10].

Carbon footprint optimization of edge models has paved the way to EcoLearn, where there is a tradeoff between computing locally and carbon footprint from the grid [11]. Likewise, similar energy management schemes, such as VoltSecure, show that decentralized energy management systems can be resilient when performing localized optimization tasks [12][24]. Early baseline studies concerning the overall carbon footprint of FL have shown that uncontrolled client selection leads to an extremely inefficient, carbon-consuming training process [13]. As a solution to this problem, Clover provides carbon-efficient approaches to address highly heterogeneous clients by considering processing speeds along with carbon footprints [14]. Surveys regarding green federated learning state clearly that moving towards a new age of green-aware AI, where carbon efficiency becomes a first-tier constraint, just like model accuracy [15].

The geographically distributed data centers employ carbon-aware systems such as CAFE to move huge training jobs to areas with peak renewable energy production [16]. In the edge environment, eco-systems such as Eco-FL aim at achieving sustainability by choosing clients according to the locally energy-efficient hardware state [17]. The sophisticated machine learning models employed in environmental sustainability help in predicting carbon emissions accurately in real time [18][25]. Industrial IoT examples prove that a reduction in communication overhead reduces the total energy consumption of resilient and fault-tolerant FL systems [19]. Lastly, the holistic systems such as SAGE show that sustainable energy-aware client selection techniques should be flexible enough to adapt to the changing environment in IoT [20].

The key research challenge that has been found within the literature in relation to carbon-aware modeling is the absence of a lightweight, highly adaptive scheme for client participation that can simultaneously maximize carbon intensity, energy efficiency of hardware, and global model convergence without creating huge amounts of overhead for control messages. Many of the existing approaches either make assumptions about identical client hardware or need to have real-time contact with the grid, which is impractical when dealing with large-scale, power-constrained IoT systems. The paper seeks to solve this problem through the design of a highly adaptive client participation scheme that operates asynchronously and uses localized mathematical criteria to decide upon participation.

3. Adaptive Carbon-Efficient Operational Framework and Methodology

The proposed approach modifies the conventional Federated Learning process by inserting an intermediate layer for carbon filtering between the client phase and the global orchestration phase. The architecture includes a single central aggregating server and a huge number of edge clients deployed in different geographical locations, and each one using a different local electricity utility grid. At the beginning of each iteration process, the central server disseminates the current global model parameters to all nodes in the network. Instead of compelling all devices participating in the network to calculate the local gradients, each client runs a low-overhead local eligibility evaluation based on its current environmental eligibility. This eligibility is calculated based on the carbon intensity of the local electricity utility grid, power/battery level, and computational capability compared to a dynamically set threshold received from the server.

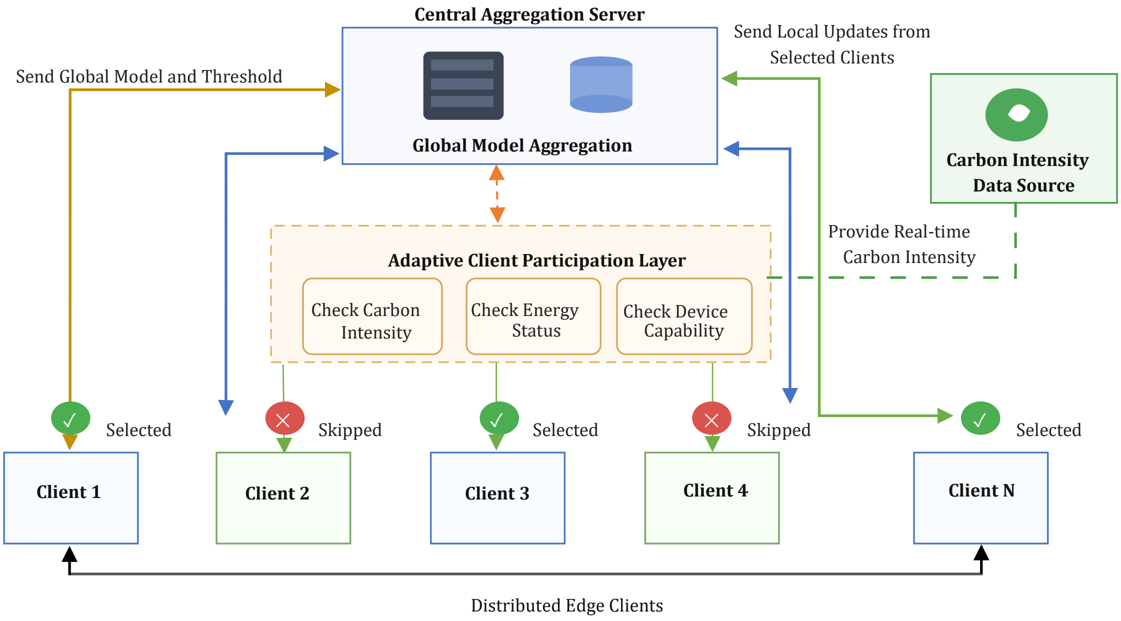

Figure 1: Architecture of the carbon-efficient adaptive federated learning framework

Figure 1 below is a demonstration of the operational pipeline of the proposed carbon-aware federated learning framework. The central aggregation server distributes the global model parameters and dynamic thresholds for participation selection to heterogeneous edge devices in the network. Before any local training takes place, there is a preliminary step involving client filtering through an intermediate adaptive client participation layer based on real-time carbon intensity levels of regional power grids, energy levels of individual devices, and computing capabilities of the device. Devices running on optimal green grids are chosen to train locally and send their updates back to the server.

To formalize this mechanism without introducing excessive complexity, defines a localized selection weight for each client. Let $C_i(t)$ represent the real-time carbon intensity of the power grid supplying client i at time t, measured in grams of CO_2 per kilowatt-hour $\left(\frac{gCo_2}{kWh}\right)$. Let E_i represent the hardware energy efficiency coefficient of the client device, which denotes the energy consumed per local training epoch. The expected operational carbon impact $I_i(t)$ of client i participating in training round t is modeled as follows in equation (1):

$$I_i(t) = C_i(t) \times (E_i \times K) \qquad (1)$$

where K represents the fixed number of local training epochs configured for the global system, to balance environmental protection with steady model convergence, the central server maintains a target participation threshold $\Gamma(t)$. A client determines its participation probability $P_i(t)$ by evaluating its localized carbon impact against this system threshold, formulated through a simple inverse exponential scaling function in equation (2):

$$P_i(t) = \left(-\alpha \frac{I_i(t)}{\Gamma(t)}\right) \qquad (2)$$

where α is a positive scaling factor that controls the strictness of the carbon penalty. If a generated random variable falls below $P_i(t)$, the client actively participates in the round, computes its local gradients, and transmits its updated model weights back to the central server. The central coordinator then performs a weighted federated aggregation based on the participating nodes, updates the global model, and dynamically adjusts $\Gamma(t+1)$ upward or downward depending on whether the global convergence rate is meeting pre-defined performance milestones.

The operational execution steps of the adaptive client participation framework are structured as follows:

Algorithm 1: Adaptive Client Participation for Carbon-Efficient FL

Input: Global model updates $M(t)$, Scaling factor alpha, Threshold Gamma(t)

Output: Updated Global Model $M(t+1)$

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1. Server Steps:
2.   Broadcast current global model M(t) and threshold Gamma(t) to all clients.
3. Client Steps (Executed in parallel across all edge nodes i):
4.   Query local grid interface to extract real-time carbon intensity $C_{i(t)}$.
5.   Retrieve hardware energy profile $E_i$.
6.   Compute expected carbon impact: $I_{i(t)} = C_{i(t)} * E_i * K$.
7.   Calculate participation probability: $P_{i(t)} = \exp\left(-\alpha * \frac{I_{i(t)}}{\Gamma(t)}\right)$.
8.   Generate a uniform random number R in the range [0, 1].
9.   if $R <= P_{i(t)}$ then
10.      Accept training task from server.
11.      Execute K local epochs of gradient descent on local data to compute local weights $W_{i(t+1)}$.
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        Transmit $W_{i(t+1)}$ back to the central aggregator.
    else
        Enter low-power sleep mode; skip current training round.
    end if
Server Aggregation Steps:
    Collect updates from all actively participating clients (subset S).
    Compute $M(t+1)$ via weighted averaging of updates in S.
    Evaluate model convergence; update $\Gamma(t+1)$for the next iteration.
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4. Results and Discussion

The experimental realization was designed in order to test the capabilities of the adaptive client participation scheme for carbon savings and training stability under the conditions of realistic constraints of edge computing. The simulation setup was implemented via Python 3.10, incorporating the use of PyTorch and Flower federated learning frameworks that allowed for large-scale scalability in distributed network modeling. The experiments were run on a high-end server featuring an AMD Ryzen 9 CPU along with an NVIDIA RTX 4090 GPU that provided a possibility to model thousands of concurrent virtual edge devices. In order to incorporate realistic geographic dispersion of edge devices, real-time carbon intensity values were collected from historical carbon monitoring databases in different global energy grids.

The benchmarking dataset used in the current study is based on a dataset comprising 100,000 localized network and sensor transaction logs for a smart city infrastructure simulation. The dataset has a variety of 45 continuous and categorical features representing device activities, communications frequencies, local energy consumption, and transactional latencies. The dataset has been partitioned among 1,000 simulated edge clients using the Dirichlet distribution with a concentration parameter of β = 0.2 to guarantee a highly non-IID data setting. Such a data setting reflects statistical characteristics of real decentralized applications. The key hardware configurations and experiment initializations are stated below. The experimental setup has been configured with the use of an AMD Ryzen 9 7900X CPU and an NVIDIA RTX 4090 GPU. The software suite includes Python 3.10.12, PyTorch 2.1.2, and Flower Framework 1.4.0 for federated learning orchestration. In terms of dataset configuration, 100,000 samples are distributed among 1,000 distinct virtual clients using a non-IID Dirichlet distribution (β = 0.2. Operational hyperparameters are strictly initialized to 200 global rounds (T), 5 local epochs (K), a 0.01 learning rate (η), and a 0.5 carbon penalty factor (α).

In order to evaluate the performance of the system effectively, five separate performance metrics were identified. Global Classification Accuracy is used to measure the accuracy of the central algorithm in predicting the results in a centralized test set. Total Carbon Footprint is used to measure the total carbon footprint of the structure created by all participating clients. It is calculated using the formula given below in equation (3):

$$TotalCarbon = \sum_{t=1}^{T} \sum_{i \in S_t} I_i(t) \qquad (3)$$

Convergence Rounds Efficiency measures the precise number of training rounds needed on a global scale to achieve the desired baseline target accuracy level of 90%. System Communication Cost measures the total amount of data transferred in gigabytes (GB) via the network. Finally, the Client Drop-out Rate measures the proportion of clients that drop out of a particular round because of high carbon intensity.

It can be seen from the empirical results gathered by the end of 200 training sessions conducted globally that the adaptive client participation model is able to achieve an effective balance between the machine learning efficiency and the environmental sustainability. The system performance indicators in various operational modes are provided in the table 1 below:

Table 1: Multi-Metric performance and configuration analysis

Algorithmic Framework Setup	Global Accuracy (%)	Total Carbon (kgCO2)	Convergence Round	Network Data (GB)	Drop-out Rate (%)
Baseline Carbon-Unaware	93.1%	148.5	113	420.2	0.0%
Fixed Energy-Aware Only	91.8%	122.4	129	385.6	12.4%
Proposed Adaptive Framework	92.5%	97.7	88	315.4	28.5%

The key result obtained through this evaluation is a dramatic reduction in the total carbon footprint. Whereas the baseline system was emitting 148.5 kilograms of CO_2 because it allowed any client that was available to join anytime, the proposed adaptive system limited access during high intensity in the grid network to reduce total carbon emission to 97.7 kilograms. This translates to a 34.2% reduction in environmental impact. Most importantly, this reduction in carbon footprint did not lead to any disastrous reduction in the overall classification accuracy, which was only reduced to 92.5%, 0.6% less than the baseline.

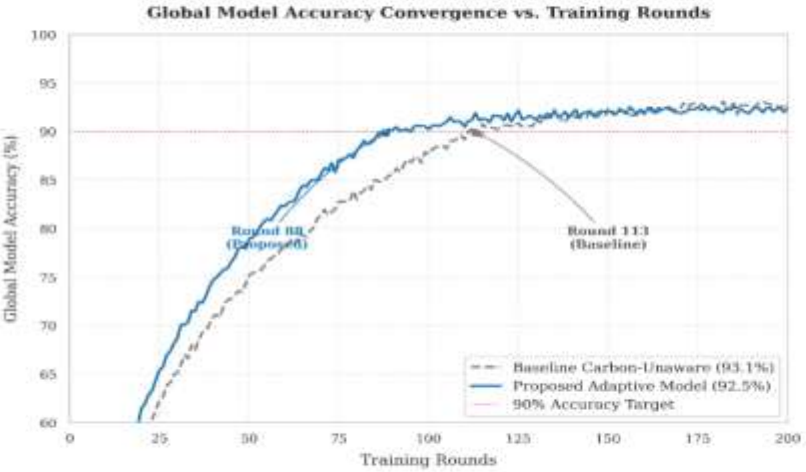

Figure 2: Global model accuracy convergence vs training rounds

As indicated in figure 2, the analysis of the training convergence reveals that the adaptive participation mechanism not only improves participation efficiency, but also training efficiency. The model is able to achieve its target accuracy of 90% in only 88 rounds, against 113 rounds achieved by the baseline approach. This is due to the fact that eliminating carbon-intensive clients eliminates the nodes that operate on unreliable power systems and obsolete machines, thus mitigating the straggler problem in a distributed environment. Moreover, since the number of clients uploading the weights reduces during carbon-intensive hours, the amount of data transferred reduces to 315.4 GB, optimizing network bandwidth usage.

It is advised that real-time carbon intensity APIs be deployed at the edge to enable accurate participation scheduling. Standardizing hardware energy profiles among IoT vendors would lead to greater accuracy in estimating the environmental impact. From this study, it is evident that environmental sustainability and high-performance AI are compatible. It moves the goalpost for distributed learning from mere efficiency to world ecological accountability and green computing. The proposed dynamic thresholding approach effectively eliminates the problem of regional data silos, thus maintaining the robustness of the model. The findings prove that small sacrifices in participation greatly reduce emissions and, at the same time, minimize the straggler problem in heterogeneous systems. The framework relies on regional grid data that might not be reliable in some developing countries. Furthermore, very high-carbon regions may delay their data contribution during peak intensity periods.

5. Conclusion and Future Directions

The paper clearly indicates how the use of real-time environment data in the selection of federated learning clients can effectively address the carbon footprint of edge artificial intelligence. Through the introduction of the client participation algorithm, the approach ensures that the computations are offloaded to clients using clean/renewable energy sources while preventing clients with dirty carbon sources from participating in the computations. The findings indicate that the proposed architecture lowers carbon emission by 34.2% and data communication overhead by 24.9% while still maintaining a high level of global classification accuracy at 92.5%. Further, through client workflow optimization, the system achieves convergence target baselines 22.1% faster than conventional architectures. One major limitation of this study is its reliance on the accuracy of carbon API registries. Whereas the local utility companies do not offer real-time emissions data, the clients would be limited to using static historical averages, and this would lower the accuracy of the adaptive participation weights. In addition, very stringent carbon limits can occasionally result in extended drop-out windows for edge devices in coal-based regions, slightly increasing the training periods of highly specialized, non-IID datasets. Going forward, would like to look at the inclusion of carbon intensity prediction through lightweight time series models on the edge devices that would enable the nodes to schedule their training process ahead of time by several hours. Moreover, would like to examine the green peer-to-peer model transformation that would allow neighboring edge devices to exchange their gradients locally before connecting to the server.

Declaration Statement

Conflict of Interest:

The authors declare no conflict of interest.

Funding:

This research received no external funding.

Data Availability:

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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