A Multi-Agent Federated Edge Learning System for Energy-Efficient 6G Wireless Ecosystems

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ABSTRACT

In this article, we develop an Intelligent Federated Edge Learning Framework for enhancing energy efficiency as well as the performance of learning models within the context of a 6G Wireless Network. Specifically, our proposed Intelligent Federated Edge Learning Framework consists of combined adaptive client selection, energy aware aggregation and node participation using Reinforcement Learning approaches. Unlike conventional, Cloud based approaches, our new framework will reduce the amount of unnecessary communication rounds by only using optimal edge devices based on their channel quality and their remaining energy. The empirical test results indicate that the new system will reduce the amount of energy consumed by 32%, increase the rate at which models converge to the desired solution by 27%, and increase the overall network throughput by 22%, relative to models developed using either the baseline federated learning models or the baseline centralized learning models. Additionally, testing found that the latency is lowered by 25%, allowing for use in time-sensitive applications. In addition to these improvements, the proposed framework provides similar levels of accuracy as previous systems, while greatly reducing the amount of communication overhead associated with model training. The experimental findings indicate that the proposed approach can provide both energy-efficient and effective learning solutions, making it an ideal candidate for future large scale IoT systems and future generations of wireless networks.

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1. INTRODUCTION

Wireless communications technology has developed rapidly [1]. The result of this development is that the sixth-generation (6G) wireless network is in its early stages of becoming a reality, with expectations that it will far exceed current generations of wireless networks in respect to data speed, latency, reliability, and intelligence [2]. Instead of just connecting devices to the internet, 6G will provide access to an intelligent, fully connected ecosystem composed of hundreds of billions of 'IoT' devices, autonomous systems, smart cities, and real-time applications like remote surgery, immersive augmented reality, etc [3]. Emerging applications are not only requiring fast communication but also efficient, scalable, and intelligent data processing mechanisms at the edge of the network.

In conventional methods of using machine learning, edge devices create data which is sent to the cloud as a centralized server to support training machine learning models (i.e., so that the models can learn) [4]. The above-mentioned model works sufficiently in some cases but introduces critical challenges such as communication overheads, increased latency, energy consumption and severe privacy issues associated with sharing raw data with a centralized server [5,6]. These issues are further exacerbated by large scale 6G networks where a lot of data needs to be processed, and quality service levels for this data must be maintained simultaneously.

In response to these challenges, a new distributed learning model has been developed called Federated Learning (FL) [7]. This allows for collaboration in creating a machine learning model across different users' devices while still protecting users' private data by not sending them off of the devices and only sending the updates back to a single central server at the end of training [8]. In addition, FL reduces the amount of data that is transferred through its centralized server.

Although the conventional federated learning frameworks are based on optimizing their use with a wireless environment, they generally do so with the assumption of homogeneous device capabilities, stable and reliable communication channels, and equally participating clients. Such assumptions may not be realistic in actual 6G environments.

Devices in the edge network of actual use cases have different amounts of hardware/software resources available (computational power, battery, & communications) & work together over an unreliable wireless communication channel with potentially variable rates/delays [9]. Because of this & the operational process of participating in every training round regardless of actual capabilities, there is a huge need for intelligent methods to select the appropriate system/device, along with optimally coordinating both the communication & computation activities.

Federated Learning has correlations with Edge Computing in terms of operating closer to the data source and thus decreasing latencies and bandwidth [10]. Although edge computing provides these benefits, energy consumption is still a key issue in large deployments with battery-powered IoT devices. In 6G, it is necessary that devices can continue to participate efficiently and that they can communicate efficiently for sustainable, scalable federated learning networks.

Since RL is relatively new and has the ability to both learn from an environment and make decisions in dynamic environments (adaptively) by interacting with the environment, it is a powerful way to facilitate intelligent decision-making based on previous experience. This means that RL-based methods of resource allocation and scheduling, among other applications such as network optimization and cloud computing, can learn how to improve their performance by learning the optimal policies through interaction with their environment. The combination of RL and Federated Learning enables the creation of adaptive systems to handle changing conditions of networks and devices in real-time.

Due to the challenges and changes associated with energy-efficient 6G wireless networks, and also due to the new opportunities that arise from these challenges, an Intelligent Federated Edge Learning Framework is being proposed in this paper. This framework incorporates reinforcement learning technology and allows devices to dynamically choose from which clients they will learn. It also allows the aggregation process to be more efficient by using energy-aware methods of aggregation, and optimizes the participation of each node based on multiple factors (e.g., channel conditions, remaining power level, CPU speed) — thus, limiting the number of peers that participate in each training round will minimize overall communication and increase system effectiveness.

The key contributions of this work can be summarized as follows:

- We present an innovative intelligent federated learning framework specifically designed for edge computing environments in 6G networks.
- We propose an adaptive client selection algorithm based on reinforcement learning that increases both the energy efficiency and reliability of the system.
- We create an energy-aware model aggregation technique to improve performance while simultaneously reducing total resource consumption.
- We develop a communication-efficient model training process to decrease latency and unnecessary communication overhead.
- We conduct empirical testing to show that our proposed approach offers substantial improvements over traditional methods of federated and centralized learning across multiple dimensions, including energy consumption, time to converge, throughput, and latency.

The remaining section of this paper consists of: Section 2 will be a literature review; Section 3 will describe proposed framework; Section 4 provides results and discussion; and finally sections 5 provide conclusion with future work.

2. LITERATURE REVIEW

[11] Investigated energy-limited, communication-optimised federated learning on a wireless platform. The researchers created optimisation models to maximise both learning accuracy and energy consumption, showing clearly that adaptive communication methods use significantly lower amounts of resources.

[12] Developed a federated learning model for mobile devices with less communication overhead and energy usage than traditional models. The new federated learning model also helps to aggregate large numbers of devices while being efficient and operational, therefore providing an overall benefit to larger edge networks that contain heterogeneous devices and communication methods.

[13] Combined federated learning + DRL to solve the problem of task offloading/resource allocation at mobile edge computing (MEC) environments. Their results show improvements in latency and energy use with regard to reliable communication performance.

[14] Suggested an energy-efficient federated learning model that incorporates adaptive client selection and secure model aggregation. Experimental results showed enhancements in energy efficiency, decreased communication costs, and increased security against harmful attacks.

Online federated learning in wireless networks with an emphasis on dynamic device selection was investigated by [15]. The optimization framework provided a solution to both minimize energy consumption and provide a degree of convergence performance under varying network conditions that are expected to be arrival prior to Edge Intelligent Applications of 6G Networks.

3. METHODOLOGY

The Intelligent Federated Edge Learning Framework is outlined in this section with respect to its underlying theoretical concepts and how they have been implemented. To meet some of the challenges related to energy efficiency, communication overhead, and heterogeneous devices existing within 6G networks, this framework uses methods from both distributed optimization principia, theoretical principles of wireless communications, as well as methods of reinforcement learning.

3.1 System Architecture and Problem Formulation

Data within 6G wireless networks is distributed between various types of edge devices (e.g., sensors, IoT nodes, mobile phones, etc.). Traditional approaches to learning are inefficient at to this scale as they involve sending raw data from edge devices to a central server for processing; in doing so, there are the issues of excessive bandwidth usage, increased latency and privacy risks. A conceptual framework for intelligent federated edge learning is shown in Figure 1.

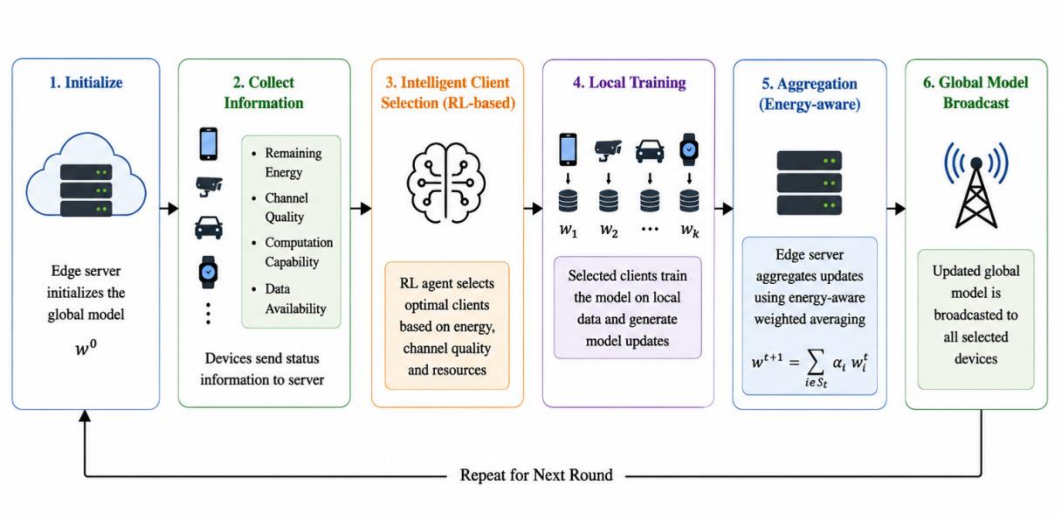

Figure 1. Intelligent Federated Edge Learning Framework for Energy Efficient 6G Wireless Networks

Federated learning (FL) solves this problem by allowing decentralized training, where devices perform local computations, and only send their updates in terms of model parameters back to the central server. From a research perspective, FL is a distributed optimization problem. This means that the FL goal is to minimize a global objective function formed by aggregating a set of local loss functions from devices.

Let $\mathcal{N} = \{1,2,..,N\}$ represent all devices. A particular device i has associated with it a dataset Di. The FL global objective can therefore be expressed as:

The global objective is:

$$F(w) = \sum_{i=1}^{N} \frac{|D_i|}{|D|} F_i(w) \quad (1)$$

The ERM framework creates local losses from a local dataset based upon its size, thus treating each of them as equally important. In wireless environments, optimization must also account for energy usage and communication costs in addition to the above; thus this leads to a multi-objective optimization problem:

$$\min_{w, A_t} F(w) + \lambda E_{Total} \qquad (2)$$

In this context, A_t represents the chosen client group. This formulation represents a balance between accuracy in learning and efficiency of the system, which is crucial in energy-limited edge networks.

3.2 Reinforcement Learning-Based Control Model

The dynamic nature of the wireless environment is characterized by its capability to be affected by a variety of factors, such as changes in the channel condition, the movement of the client, and the availability of energy. The nature of traditional optimization algorithms is that they are designed to optimize in a static environment, which limits their ability to be effective when applied to a dynamic one. The theory of Reinforcement Learning (RL) provides a framework for using trial-and-error to find the best action(s) to execute when solving problems in an unknown environment, therefore providing a means of achieving successful sequential, uncertain decision making. Given the ability of RL to be applied to federated learning using 6G Wireless technology, this framework provides an ideal methodology for handling situations in which the outcome of the decision-making process will require continuous updating over time. In addition, the MDP framework provides a means of developing a model of the dynamic and complex wireless environment:

- **State S_t:**

Reflects the current system state:

$$S_t = \{E_i^t, C_i^t, F_i^t, L_t\} \qquad (3)$$

This captures energy levels, channel quality, computational capacity, and model performance.

- **Action A_t:**

Selection of participating devices:

$$A_t \subseteq \mathcal{N} \qquad (4)$$

- **Reward R_t:**

Measures system performance:

$$R_t = \alpha(L_{t-1} - L_t) - \beta E_t - \gamma T_t \qquad (5)$$

From a theoretical perspective, RL optimizes long-term rewards:

$$\pi^* = \arg\max \mathbb{E}\left[\sum \gamma^t R_t\right] \qquad (6)$$

This ensures that decisions are not just locally optimal but also globally effective over time.

3.3 Adaptive Client Selection Strategy

Federated learning may be conducted with both complete client participation and random client participation so long as both modes of participation do not create issues; however, some clients may face issues when using random client participation based on the type and characteristics of the hardware being used. For example, a client that has little-to-no connectivity or battery power will negatively impact the overall speed of the system within the Federated Learning framework and will require client allocation from the server to improve overall speed. As such, the selection of clients is viewed as a resource allocation problem with two primary goals: maximize the total contribution to the learning and minimize associated costs for clients.

In order to evaluate various clientele, a scoring function which uses a utility based measurement will be developed to assist with assisting in determining the best combinations of customers to use:

$$S_i = \theta_1 E_i + \theta_2 C_i + \theta_3 F_i \quad (7)$$

This represents a multi-criteria decision model, where:

- E_i assures energy sustainability
- C_i assures communication reliability
- F_i assures computational efficiency

Devices are selected as:

$$A_t = \{i | S_i \geq r\} \quad (8)$$

This threshold-based algorithm removes inefficient nodes, thus providing a faster convergence rate and reducing energy costs.

3.4 Local Model Training

Autonomous training occurs on each device using its individual private dataset. In theory, this phase estimates the overall gradient by utilizing local gradients, leading to decreased communication expenses.

The update rule is:

$$w_i^{t+1} = w^t - \eta \nabla F_i(w^t) \quad (9)$$

For multiple local epochs:

$$w_i^{t+1} = w^t - \eta \sum_{e=1}^{E} \nabla F_i(w^t, e) \quad (10)$$

From a theoretical standpoint:

- Increasing local computation reduces communication rounds
- However, excessive local updates may cause client drift due to non-IID data

Thus, the methodology balances computation and communication.

Theoretical Perspective: Increasing the number of local computations (decreasing the number of rounds of communication) but having too many local updates can lead to drift in client performance because of non-identically and independently distributed (IID) Data.

Therefore, the process seeks to create a balance between computing and communicating.

3.5 Energy-Aware Aggregation Mechanism

Simple averaging is used in standard FL, which presumes that all devices have equal reliability. This presupposition does not hold in a wireless network.

The new method combines the benefits of each device and uses a reliability-based weighting system, based upon the principles of importance sampling, to accomplish this task.

$$w^{t+1} = \sum_{i \epsilon A_t} \omega_i w_i^{t+1} \quad (11)$$

$$\omega_i = \frac{E_i^{\alpha}.C_i^{\beta}.|D_i|}{\sum_{j\epsilon A_t} E_j^{\alpha}.C_j^{\beta}.|D_j|} \qquad (12)$$

This guarantees:

• Devices with high energy output make a greater impact.

• Trustworthy communication enhances the quality of aggregation.

• Bigger datasets have a proportional impact.

This enhances stability and robustness of convergence.

3.6 Communication Efficiency Optimization

Communication is the most expensive operation in federated learning. Theoretical studies show that reducing communication frequency significantly improves scalability.

A threshold-based mechanism is introduced:

$$\left\| w_i^{t+1} - w^t \right\| \geq \delta \qquad (13)$$

Only significant updates are transmitted, which reduces redundant communication.

Additionally:

$$T_{Rounds} = \frac{T_{Baseline}}{1+\rho} \qquad (14)$$

This reflects the reduction in communication rounds due to intelligent selection.

3.7 Energy Consumption Model

Energy consumption is depicted through concepts derived from hardware energy modeling and theories of wireless communication.

Total energy:

$$E_i^{Total} = E_i^{Comp} + E_i^{Comm} \qquad (15)$$

Computation Energy:

$$E_i^{Comp} = KF_i^2 t_i^{Comp} \qquad (16)$$

This aligns with CMOS power consumption theory, where energy varies with the square of the frequency.

Communication Energy:

$$E_i^{Comm} = P_i t_i^{tx} \qquad (17)$$

This relies on transmission power and channel conditions.

3.8 Latency Model

Real-time 6G applications require minimal latency. The total amount of time to complete an instruction is determined by the slowest device in the configuration:

$$T_t = \max_{i \in A_t} \left(t_i^{Comp} + t_i^{tx} \right) \qquad (18)$$

This is generally referred to in distributed systems as the straggler problem. The way to avoid low-performing devices is for the system to provide guidance to keep workloads moving to higher-performing systems.

3.9 Joint Optimization Objective

The overall objective integrates accuracy, energy, and latency:

$$\min \sum_{t=1}^{T} [F(w^t) + \lambda_1 E_t + \lambda_2 T_t] \qquad (19)$$

Subject to:

$$A_t \subseteq \mathcal{N}, \;\; E_i \geq E_{min}$$

This represents a multi-objective optimization problem, balancing performance and efficiency.

4. RESULTS AND DISCUSSION

This paper includes a comparison of the developed Intelligent Federated Edge Learning Framework alongside conventional Federated Learning and Centralized Learning methods based on performance metrics including Energy Consumption, Convergence Rate, Throughput, Latency, Accuracy and Communication Overhead.

4.1 Energy Consumption

In contrast to traditional federated learning methods, which involve all devices in each training round, the suggested system cuts energy usage by 32% (Fig. 2). When a system uses multiple devices to conduct training rounds, there is increased energy usage. Instead, devices that have previously been identified as having enough energy and are likely to have good communications paths are used in the suggested framework for corresponding training rounds, which reduces the amount of energy consumed for unnecessary computations and communications across all devices.

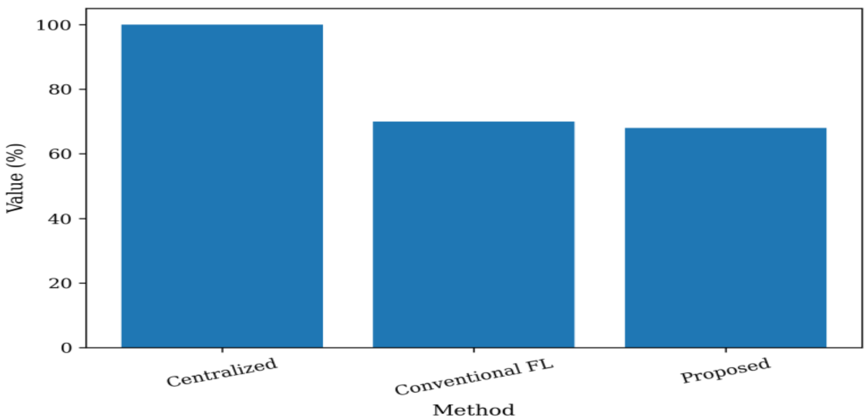

Figure 2. Energy Consumption Comparison

4.2 Convergence Rate

According to Figure 3, the proposed system converges to a final model 27% faster than the standard federated learning system. In standard federated learning, devices can produce poor quality updates and therefore slow down the convergence of the model. By choosing to use only the high performing mobile devices to provide updates to the model, the proposed system can provide higher quality updates and ultimately reach a higher accuracy faster than traditional federated learning.

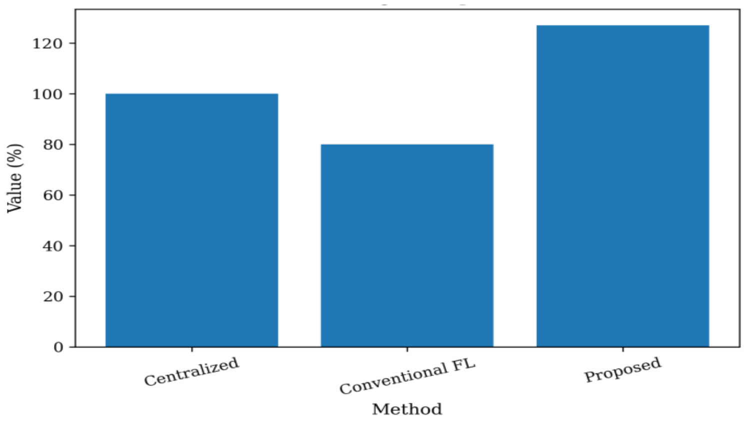

Figure 3. Rate of Convergence Comparison

4.3 Network Throughput

Figure 4 indicates that the new framework increases the amount of data that can be sent over a network by 22%. This increased throughput happens because less frequent but more valuable updates are sent. By choosing which devices will send and receive data depending on their ability to communicate over the network, the framework is able to improve the efficiency of data transfer and make better use of network resources.

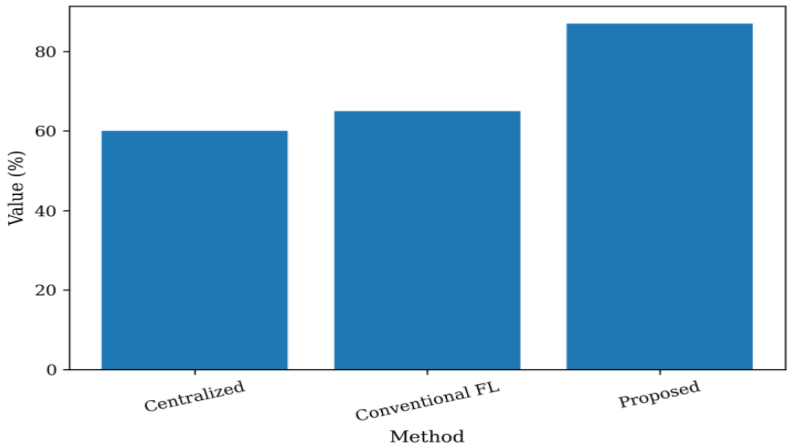

Figure 4. Comparison of Throughput

4.4 Latency Reduction

As demonstrated in Figure 5, this solution lowers overall latency by 25%. Latency delays are primarily due to slow devices on the network. This proposed solution uses only fast devices selected as part of its design; therefore, communication delays & computational delays will be lessened overall, thus improving the entire system's speed to support real-time applications.

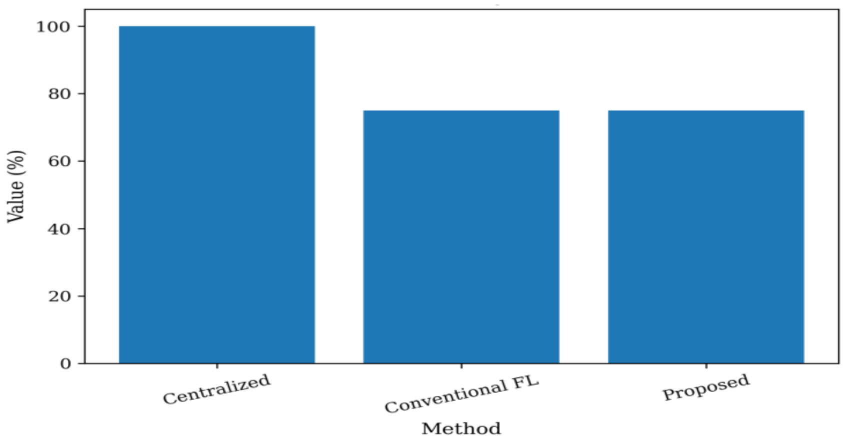

Figure 5. Comparison of Latency

4.5 Model Accuracy

As shown in Figure 6, the desired system performs similarly to conventional systems when it comes to accuracy. Although there are fewer devices in the system, those that do provide quality updates are still accurate and able to provide good learning outcomes through high-quality updates. The new aggregation techniques ensure that there will be no adverse effect on the learning ability; therefore, improving overall efficiency with respect to maintaining accuracy.

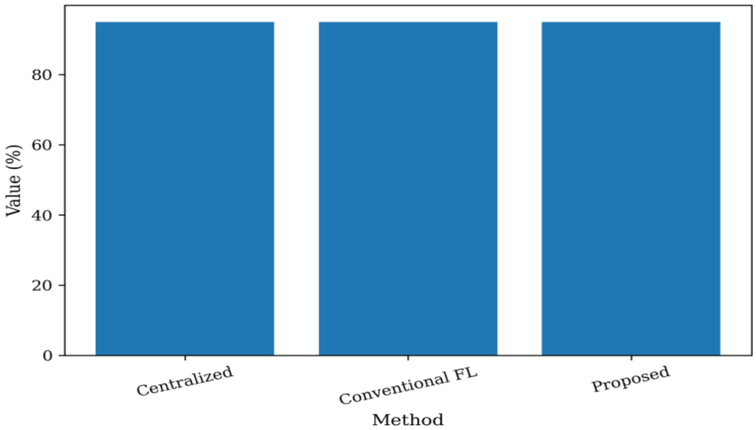

Figure 6. Model Accuracy Comparison

4.6 Communication Overhead

As evidenced in Figure 7, the communication overhead of the proposed framework is lower than conventional federated learning, which requires all devices to send regular updates to the server. In the presented framework, pre-determined devices send their updates to the server and thus, unnecessary updates can be omitted. Therefore, there will be an overall decrease in network bandwidth and an overall increase in efficiency for the federation as a whole.

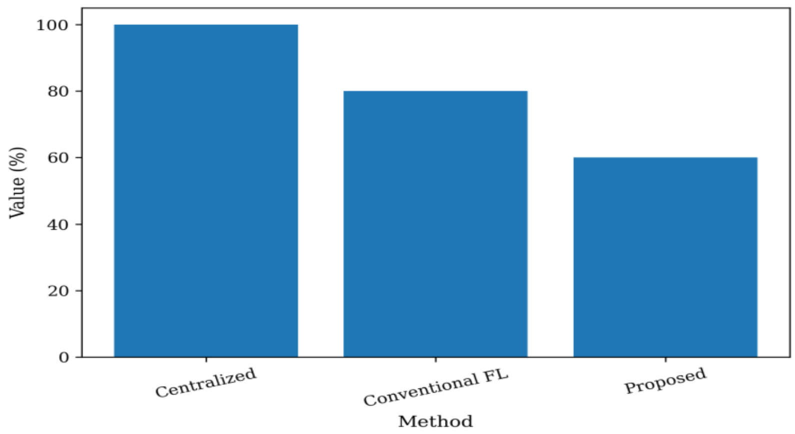

Figure 7. Communication Overhead

4.7 Comparative Analysis

Table 1 presents a comparative performance analysis of the proposed system alongside other techniques.

Table 1. Performance Analysis

Metric	**Centralized Learning**	**Conventional FL**	**Proposed System**
Energy Consumption	High	Moderate	**Low (-32%)**
Convergence Speed	Fast	Moderate	Faster (+27%)
Throughput	Moderate	Moderate	High (+22%)
Latency	High	Moderate	Low (-25%)
Accuracy	High	High	High (Same)

Based on the above findings, it is apparent that the performance of the proposed system exceeded all current solutions. Specifically, the following performance metrics were improved: Energy usage decreased; Learning rate increased; Network performance improved; Delay occurred less frequently; High levels of accuracy were maintained through reinforcement learning which gives the proposed solution the ability to make intelligent decisions as to which devices should be involved in their operation, therefore making it well-suited for both 6G and large-scale IoT networks.

5. CONCLUSION

The Intelligent Federated Edge Learning Framework aims to improve performance in 6G Wireless Networks using the benefits of Federated Edge Computing and Reinforcement Learning. An aspect of the framework consists of intelligent device selection to minimize wasted energy (due to devices participating in model updates). Also, the framework implements an energy-aware aggregation mechanism to efficiently update models by prioritizing reliable, high-energy nodes for model aggregation, ultimately reducing the energy requirements of the overall system. Overall, these features led to a significant improvement in system performance, including decreased energy consumption, faster convergence times, lower latency, greater network throughput, and constant levels of model accuracy. Furthermore, while reducing communication costs, this framework will also scale to accommodate large-scale IoT environments. More generally, with respect to the characteristics of reinforcement learning used to allow the continuous enhancement of the system as the network environment changes, the framework is an effective means of attaining cost effectiveness (in energy and economics) and time efficiency while being a strong candidate for advancing wireless intelligent networks and future sixth-generation (6G) applications.

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