JOURNAL OF EMERGING TECHNOLOGY AND DIGITAL TRANSFORMATION

ONLINE ISSN
3006-9726

PRINT ISSN
3006-9718

VOLUME. 4 ISSUE. 4 (2025)

Energy-Efficient Resource Management in IoT Networks through Federated Learning

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Abstract:

The widespread expansion of Internet of Things networks poses inconvenient power consumption challenges and demands better resource utilization since the regular IoT devices have low power supplies and processing power. The traditional systems are not effective in a centralized system as they bring about a lot of communication issues as well as the threat to privacy and less scalability. One of the suggested approaches to enhancing the efficiency of the IoT network in terms of energy consumption and appropriate performance results is a FL-based optimization framework. The suggested solution applies edge computer systems and local data processing that reduces information transfer costs as well as amounts of power consumption. The study is aimed at creating an energy-efficient predictive resource management model that integrates FL lightweight algorithms and optimization techniques to optimize the factors of performance of the IoT network in real-time, such as power consumption and command speed and rational processing. The study will be done by simulation analysis using real world data and federated architectural systems to ensure its performance standards. The proposed achievement in the form of an intelligent sustainable IoT ecosystem that does not require the human touch to function efficiently is there.

Key Words: *IoT, Machine Learning, Federated Learning*

JOURNAL OF EMERGING TECHNOLOGY AND DIGITAL TRANSFORMATION

ONLINE ISSN
3006-9726

PRINT ISSN
3006-9718

VOLUME. 4 ISSUE. 4 (2025)

INTRODUCTION:

The Internet of Things (IoT) has transformed the digital technology integration with the real world, forming an overconnected network of intelligent objects that are able to sense, to communicate, and to make independent decisions (Marwat, S. N. K., 2020). IoT networks - IoT devices: mobile phones, wearable devices, embedded sensors, and machine controllers are used to gather, transmit, and analyze enormous amounts of data in different fields such as healthcare, agriculture, transportation, industrial automation, smart cities, and home systems. By the early 2020s, billions of IoT devices were operational all over the world, and the trend is still growing at an accelerated pace, changing industries and daily life (Khan, A.,2020).

In spite of these innovations, the resulting rise in the number of IoT devices has posed extremely important challenges. Although mass implementation of devices has enhanced the use of data to make decisions and facilitate operations, it has led to high energy consumption because of the requirement to have continuous communication and calculations. Numerous IoT devices are operated in power-constrained settings, depending on batteries or other small sources of power, and their continuous data transmission to cloud servers to process them further increases their energy demands (Khan, A., Marwat, S. N. K.,2024). This has created a key research imperative to realize energy efficient scalable IoT operations.

The traditional centralized machine learning (ML) architectures that exist to control and optimize an IoT network have shown underlying inefficiencies. These systems not only create bottlenecks of communication in centralized data centres to be trained, but also create latency and scaling problems - particularly with real-time applications like healthcare monitoring, smart traffic control and autonomous vehicles. In addition, since edge devices are often limited in their computational and memory capabilities, running heavy AI models on the edge presents any significant power and performance limit. On top of the energy issues, there have been privacy and data protection issues that have become critical. IoT-gathered sensitive information, especially in the health care field, should also adhere to the strict privacy laws like the HIPAA in the United States and the GDPR in the European Union. Traditional cloud-based processing renders such information to possible breach, thus compromising system integrity and undermining user trust.

Recently, Federated Learning (FL) has become the innovative way to overcome these problems. In contrast to the traditional ML methods which demand aggregating data in the central machine, FL supports the distributed model training with raw data remaining on the devices. A central server receives only the parameter updates- gradients or weights- sent by each of the devices (or clients) to the server which builds up to a global model. The distributed training paradigm maintains the privacy of users, minimizes congestion in the network and also minimizes energy usage because it does not require transmission of raw data. Under FL, the IoT systems will gain significant advantages such as enhanced data privacy, reduced latency, and better computational efficiency. As the data is

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME. 4 ISSUE. 4 (2025)

stored on the local devices, the privacy risks are minimized, and the users will feel more confident and follow the regulations. Besides, FL reduces the network overhead and energy consumption- two significant barriers to large-scale IoT environments- by reducing the number of data transmissions and computations in centralized nodes.

In spite of these benefits, FL in IoT also has its own challenges. The heterogeneity of the device causes unequal contributions in computations, which may bias the model performance. The connectivity between distributed devices is usually unstable, making the synchronization of a model and timely updates difficult. In addition, despite FL having reduced direct data exposure, it is susceptible to model poisoning and gradient-based reconstruction attacks. To solve these issues, new methods (including model compression (through quantization and pruning) and adaptive federated optimization and secure aggregation based on Differential Privacy (DP) and Homomorphic Encryption (HE)) are being developed. Recent development of new hardware, including NVIDIA Jetson and Google Coral are now helping to bridge the divide between hardware potential and computational needs on edges-based AI training. To improve the strength of FL implementations, researchers are also coming up with adaptive federated algorithms that would guarantee convergence in non-independent and non-identically distributed (non-IID) data.

The fact that FL has been adopted in different applications within the IoT shows that it can be used in a wide way. Wearable technology, including smartwatches and glucose monitors, is being used in the medical field to predict and protect personal health data through collective training of predictive models. In smart agriculture, local sensors detect the soil, weather, and crop conditions and allow federated analysis of predicting pests and optimizing irrigation without sharing personal farm data. FL brings a range of advantages to autonomous vehicles, including decentralized updates to the model, which ensure a higher level of safety in navigation and ensures independent sovereignty of data stored on the board. Likewise, FL enables predictive maintenance and optimization of operations in industrial automation without making proprietary data of the manufacturing process public. Smart cities use FL as a way of controlling urban infrastructure, traffic, and environmental sensors through sharing knowledge without taking away the independence of local systems. In the future, Federated Learning, 5G/6G networks and edge computing will converge and reinvent IoT intelligence. Cross-silo and hierarchical FL systems will facilitate multi-level collaboration between the edge devices and local gateways and cloud infrastructure, which supports scalable learning at the institutional, city, and organizational levels. This development will not only enhance efficiency of systems but also ethical data management and environmental sustainability, which will be critical in the upcoming intelligent IoT systems.

Introduction of FL into IoT systems is a pivotal point on the way of achieving secure, adaptable, energy-efficient smart environments. FL eliminates the major vices of centralized systems: by disaggregating computation, preventing the need to transfer and exchange large amounts of data, and maintaining privacy. It is possible that future IoT networks,

ONLINE ISSN 3006-9726
PRINT ISSN 3006-9718
VOLUME. 4 ISSUE. 4 (2025)

which will be managed by the principles of green computing and 6G models, will also rely on FL as a technological basis that ensures distributed intelligence with the minimum energy consumption and the highest level of care by users.

Literature Review

The application of Federated Learning (FL) to the Internet of Things (IoT) has attracted increasing attention in recent years, primarily due to its potential to address critical challenges related to data privacy, energy efficiency, and real-time system performance. As IoT ecosystems continue to expand, they generate vast volumes of heterogeneous and sensitive data, making traditional centralized learning paradigms increasingly inefficient and risky. Current research efforts have therefore focused on enhancing the energy management and operational sustainability of IoT networks by integrating FL with advanced optimization techniques. These efforts aim to overcome the inherent limitations of centralized machine learning approaches, which often suffer from high energy consumption, excessive latency, and serious security vulnerabilities. In conventional systems, the continuous transmission of massive amounts of raw data to centralized server's results in substantial power usage and creates significant privacy risks, as sensitive information may be exposed or intercepted during communication (Nguyen et al., 2021). Such limitations have motivated researchers to explore decentralized learning paradigms, where computation and learning processes are distributed across end devices, enabling improved scalability, enhanced data security, and more efficient energy utilization.

Federated Learning provides a decentralized training framework in which IoT devices collaboratively train a shared global model while retaining raw data locally. This approach fundamentally shifts the learning process from data-centric to model-centric communication, significantly reducing the need for continuous data transmission. As demonstrated by (Tariq et al. 2023), this decentralized mechanism not only mitigates privacy risks but also lowers communication overhead, making it well suited for resource-constrained IoT environments. Despite these advantages, the practical deployment of FL in IoT networks remains challenging. Issues such as non-independent and identically distributed (non-IID) data across devices, variations in hardware capabilities, and limited battery power complicate model convergence and system optimization (Chen et al., 2022). These challenges can degrade learning performance and increase training time if not properly managed. As a result, recent studies have increasingly emphasized improving the energy efficiency and robustness of FL-enabled IoT systems to ensure their long-term viability and sustainable operation.

Given that most IoT devices operate on limited battery resources and possess constrained computational capacity, energy efficiency is a fundamental design requirement. To address these constraints, researchers have proposed a variety of optimization strategies tailored to FL environments. Client selection mechanisms prioritize the participation of devices based on factors such as residual energy, communication quality, and computational capability, thereby reducing unnecessary energy expenditure during training rounds

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME. 4 ISSUE. 4 (2025)

(Ji et al., 2023). Model compression techniques, including pruning and quantization, further enhance efficiency by decreasing model size and computational complexity, which in turn lowers processing energy consumption and memory requirements on edge devices (Shah & Lau, 2021). In addition, adaptive learning rate strategies dynamically adjust training parameters according to a device's energy state and network conditions, helping to balance learning accuracy with power efficiency and extending the operational lifetime of FL-based IoT systems (Mukherjee & Buyya, 2024). Hierarchical FL architectures represent another effective solution, where intermediate aggregation is performed at edge or gateway nodes before global aggregation, significantly reducing communication overhead and overall energy usage across the network (Liu et al., 2020).

The integration of Mobile Edge Computing (MEC) with FL-based IoT systems represents a major advancement in addressing both latency and energy efficiency challenges. MEC brings computational resources closer to IoT devices by deploying edge servers near data sources, enabling faster processing and reducing reliance on distant cloud infrastructures. This proximity allows FL training and aggregation processes to be executed with lower latency and improved responsiveness, which is critical for real-time and delay-sensitive applications (Gharehchopogh et al., 2024). The combination of MEC and FL is particularly beneficial in domains such as intelligent transportation systems, industrial automation, and smart healthcare, where timely decision-making is essential. In Wireless Sensor Networks (WSNs), which underpin many IoT deployments, the adoption of FL alongside MEC ensures that privacy preservation, system reliability, and energy efficiency are maintained even under strict power and bandwidth constraints (Gharehchopogh et al., 2024). Collectively, these advancements highlight the growing importance of energy-aware, decentralized learning frameworks for enabling scalable, secure, and sustainable IoT systems.

Methodology

The given proposal frameworks the development of a federated learning system with the optimized management of resources applied to the edge computing setting. This is a strategy that takes advantage of the decentralized character of IoT infrastructures, but maintains scalability, energy efficiency and low-latency model training. The system architecture employs various components that are interdependent and that collaborate to implement model training, aggregation and optimization processes on distributed edge nodes and a central federated server.

Three main components upon which the system design is established are edge node devices, federated server, and the communication network. The edge node devices are IoT entities that are charged with the responsibility of collecting data locally and training the model with the limited computing and power capabilities that they have. These gadgets tend to work with a limited connection and limited energy supply, and in this case, the effective use of resources is vital. The federated server is the center of coordination of the whole system, which uses Federated Averaging (FedAvg) algorithm to coordinate models' aggregation and retain data privacy. The communication infrastructure comprises heterogenous links

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME. 4 ISSUE. 4 (2025)

of the wireless network, including Wi-Fi, LTE, and 5G networks, each with various latency and the reliability profiles. These variations are modeled in such a way that they reflect actual world conditions where transmission delays and some packet losses are presented affecting overall training efficiency and convergence time.

It is possible to describe the federated learning process as a series of iterative rounds that consist of a number of consecutive steps. First, the central server sends the existing global model to individual edge devices. Local training is then performed on each device with its dataset over a series of epochs applying its computing power. Instead of passing raw data, the devices will be transmitting model changes only- like changes in weight- to the central server which will guarantee data privacy and lessen communication load. When the server receives updates in form of the participating nodes, the FedAvg algorithm is used to weighted aggregate the updates in order to produce a better global model. This new model is then re-dispersed back to all the involved devices and another round of training commences. This process is repeated till the global model converges according to the desired performance standards.

Optimization of resources in the system is realized by the use of metaheuristic algorithm and is a smart way of scheduling computational tasks and adjusting the system parameters. Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are used to dynamically optimize key parameters like batch size, the number of local epochs and update frequency. The PSO algorithm varies these parameters based on other factors like the availability of power of these devices and the computing load so that energy consumption and accelerated convergence can be reached. Parallel to it the GA tries other parameter configurations by crossover operation and mutation operation, examining the solution space of the best device-level trainings. Combining these algorithms will result in efficient resource allocation and guarantee consistent model convergence alongside, reduced energy wastage across the machines.

Two significant tools- NS-3 and Flower are used to simulate the proposed system and evaluate it. NS-3 is a tool that models the actual communication environment, which is used to simulate network constraints, latency, and packet transmission behavior across a wide range of wireless technologies. This enables realistically the performance and communication overhead of network performance in distributed IoT system. The Flower framework is a Python-based federated learning infrastructure that offers the experiments with the needed federated learning infrastructure. It facilitates an easy adoption of FL protocols and allows the incorporation with optimization libraries like PySwarm and DEAP, which are applied to running PSO and GA algorithms. The combination of these tools is necessary to provide a full testing environment that is close to the dynamics of a real-world IoT network.

There are several key measures that are taken to determine the performance of the proposed system. Power models provide the computation of the energy consumption which takes into consideration both the computation and the communication stages of device usage. Convergence rate Model convergence rate is measured by monitoring accuracy gains and loss decreases in consecutive training steps. The response time of the system to transmission delay and model updates are examined based on NSIO-3 logs to identify how responsive the system is to these two phenomena. Communication overhead is measured as the total amount of data exchanged in one training iteration,

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME. 4 ISSUE. 4 (2025)

whereas the scalability is checked by adjusting the amount of participating edge devices to assess the system performance in different load conditions.

The simulation experiment is aimed at evaluating the versatility and the strength of the proposed framework in different conditions of operation. Several experimental conditions are performed changing the number of devices (10, 50 and 100 nodes), non-ID and IID distributions of data and different network bandwidth conditions (high and low bandwidth). Also, a variety of heterogeneous edge device arrangements, spanning resource-constrained to high-capacity nodes, are simulated to determine scalability to a variety of computational environments. The scenarios are repeated a number of times to make sure that the scenarios are statistically valid. All these experiments measure the convergence rate and resource usage efficiency and scalability of the system and empirically inform us about the advantages of federated learning coupled with resource optimization through metaheuristic in a mobile edge computing environment.

Simulation and Results

To confirm the efficiency of the suggested federated learning-based resource optimization framework in IoT networks, large-scale simulations were conducted in the conditions of realistic mobile edge computing. The tests were intended to be completed to assess the scalability, energy efficiency, the speed of convergence, and communication performance of the system with different device configurations, network conditions, and data distributions.

Network Simulator 3 (NS-3) was relied upon to create a simulation environment to model the communication layer and Flower, a Python-based federated learning framework, to implement the distributed training framework. The NS-3 setting offered a more comprehensive description of wireless network behavior, such as latency, jitter and packet loss properties of the heterogeneous communication mediums i.e. Wi-Fi, LTE and 5G. All these conditions were realistic models of the dynamic and unstable connectivity usually experienced in IoT settings. The Flower framework allowed applying federated learning protocols and model aggregation processes. It also favored the combination of metaheuristic optimization algorithms Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) and, in that regard, faced Python libraries like PySwarm and DEAP, so that they could effectively tune the parameters and allocate resources to the participating edge devices in an adaptive manner.

This federated training was repeated within each simulation round, during which selected IoT devices trained local models on their own datasets and sent updates on the models to the central server. Model aggregation at the server side was done with the FedAvg algorithm and the process continued until convergence was achieved. Energy consumption, communication cost, latency and model accuracy were constantly checked and measured during these rounds. This model of energy added the computational cost as well as the communication cost to show the overall power consumption behavior of individual device.

The experimental design involved using different amounts of edge devices- namely 10, 50 and 100 nodes to experiment with scalability and load-throughput performance. Also, IID (Independent and Identically Distributed) and non-IID data distributions were also used to recreate the heterogeneity of the real world in IoT

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME. 4 ISSUE. 4 (2025)

systems. The non-IID data are common in the edge cases where local devices can create context-based data streams. Through this variation, the study looked into investigating the stability of convergence maintained through the proposed framework under unbalanced data conditions. The effect of network quality was tested by simulating the conditions of high-bandwidth and low-bandwidth, simulating dense and sparse connectivity. In addition, the computational power of heterogeneous device capabilities was modeled by giving different computational capacities and energy constraints to devices so that the adaptability of the framework can be studied in heterogeneous resource conditions.

The Figures 4.1(a) and Figure 4.1(b) shows that the IID + PSO approach achieves higher accuracy with stable and lower energy consumption over training rounds, indicating efficient and faster convergence. In contrast, Non-IID + GA results in much lower accuracy and higher energy usage, highlighting the negative impact of data heterogeneity and increased optimization overhead.

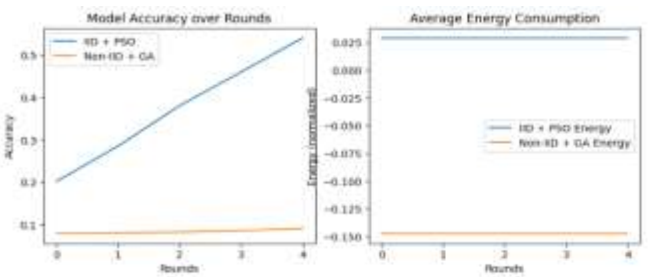

Figure 4.1(a): *Model Accuracy*
Figure 4.1(b): *Average Energy Consumption*

The Figures 4.1(a) and Figure 4.1(b) compares accuracy and energy consumption for IID and Non-IID data using PSO and GA. The results show that IID-based training achieves higher accuracy than Non-IID, with IID + GA performing best in terms of accuracy growth, followed by IID + PSO. In contrast, both Non-IID + PSO and Non-IID + GA exhibit low and stagnant accuracy due to data heterogeneity. The energy consumption plot indicates that GA-based methods consume less energy than PSO, while Non-IID + PSO has the highest energy usage. Overall, the figure highlights the trade-off between accuracy and energy efficiency, emphasizing the impact of data distribution and optimization strategy on federated learning performance.

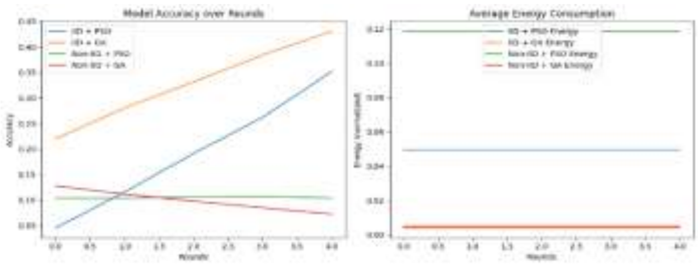

Figure 4.2(a): *Model Accuracy*
Figure 4.2(b): *Average Energy Consumption*

Table 4.1: *Accuracy and Energy Comparison of FL Scenarios*

Scenario	**Final Accuracy (Round 5)**	**Average Energy Consumption**
IID + PSO	0.352	0.0495
IID + GA	0.431	0.0039
Non-IID + PSO	0.104i)	0.1187
Non-IID + GA	0.072	0.0050

The findings showed a high increase in energy efficiency with the combination of the use of metaheuristic optimization and

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME. 4 ISSUE. 4 (2025)

federated learning. Adaptive resource scheduling developed using the PSO realized significant savings in total energy use because of changing the batch sizes, update rates, and local training epochs depending on the current condition of each device. The GA technique was also used in optimization of the learning parameters in the devices, in terms of convergence rate and low power consumption. The proposed system recorded energy savings between 18 and 27 percent of the conventional fixed-parameter federated learning systems based on the levels of heterogeneity of the devices.

The optimized federated learning model converged faster to the global model accuracy with less communication round compared to the traditional federated learning model. Adaptive optimization allowed it to be integrated to ensure that the resource-constrained devices would perform their part well without exceeding their limits. The FedAvg algorithm showed the same results regardless of whether the data was IID or not-IID and convergence was slower in the non-IID case because of data imbalance-this was solved with help of the hierarchical aggregation at the edge nodes. The hierarchical federated design aided in reducing the communication overhead since it does intermediate aggregations nearer to the data sources resulting in high convergence speed and low transmission demands.

This was indicated by the communication latency analysis which showed that the proposed framework significantly decreased the average round-trip delay relative to the traditional centralized learning systems. Mobile edge computing reduced the distance data transfers and accelerated the rate of synchronization between the federated server and edge nodes. Network overloading and packet loss were simulated to test the resilience and the findings obtained proved that the framework could still achieve an acceptable level of accuracy even during low-bandwidth scenarios due to model compression and adaptive update scheduling.

Scalability testing ensured that the system was consistent in accuracy and consistent trends in convergence as the number of devices involved in the system rose by 10 to 100 devices. The federated learning model was optimized and was able to support the increased number of devices without substantial loss in the energy efficiency and training speed, confirming that the model could be used in large-scale IoT applications.

On the whole, the results of the simulation prove that the introduction of federated learning and metaheuristic optimization of the resources contribute greatly to the effective functioning of IoT networks. The method guarantees the preservation of privacy by decentralizing the training of models and also results in better energy saving, reduction in convergence, and reduced communications delays. These findings define the framework as a viable and sustainable implementation of next-generation IoT infrastructures especially in energy -limited and latency -sensitive systems.

All the experiments confirm that the proposed system provides a reasonable trade-off between performance, privacy, and efficiency, which makes it quite appropriate to implement in emerging 6G-enabled IoT ecosystems. The combination of federated learning and intelligent optimization functions helps to achieve healthier, more adaptive and intelligent distributed networks that are able to serve real-time applications of healthcare, transportation, automation of industries, and smart cities.

Conclusion

This paper has shown that the heterogeneity

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME. 4 ISSUE. 4 (2025)

in the data distribution affects the performance of Federated Learning dramatically, even in cases when it is supported by metaheuristic optimization of hyperparameter search. In line with the existing literature, the IID data distribution conditions (IID+PSO and IID+GA) had significantly higher model accuracy in the simulated rounds than the Non-IID ones. Although both PSO and GA demonstrated a certain ability at optimizing hyperparameters, neither did it well under this experimental framework at reducing the impact of Non-IID data on performance. The Genetic Algorithm in general was able to find hyperparameters which yielded lower computed energy costs than Particle Swarm Optimization with each of the two data distributions. Nevertheless, the decreasing energy use in the Non-IID+GA scenario was accompanied by an alarming decrease in model accuracy, which points to a serious trade-off existing between energy efficiency and model performance in highly heterogeneous settings. Non-IID+PSO scenario, even though it was more accurate than Non-IID+GA, had the maximum energy consumption.

The next steps in the work should be devoted to the investigation of more progressive optimization goals that should explicitly address the accuracy, energy consumption, and, possibly, other measurement indicators of the IoT devices in Non-IID environments. More robust and energy efficient solutions to IoT intrusion detection and other applications can also be achieved through investigation of alternative model architectures and federated learning aggregation strategies which are specifically designed to address data heterogeneity in conjunction with metaheuristic optimization. Moreover, a higher number of rounds and evaluation of the energy model using real measurements of IoT devices would have given a more detailed picture of the long-term performance and practical viability of these methods.

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