Optimizing Data Aggregation in IoT Networks for Energy Efficiency and Accuracy

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***Abstract*—The rapid growth of Internet of Things (IoT) deployments has brought forth the challenge of managing energy-efficient data aggregation while maintaining high data accuracy. Traditional aggregation protocols such as PEGASIS focus primarily on reducing communication overhead but often overlook adaptive mechanisms that account for node energy, relevance of data, and network longevity. In this work, we present a system for intelligent data aggregation called Federated Learning with Adaptive Node Selection (FL-ANS), which combines the adaptive utility-based node selection method with the federated learning principles. FL-ANS dynamically selects participating nodes based on residual energy, communication cost, and data contribution, ensuring that only optimal nodes contribute to global model training in each round. Simulation results reveal that FL-ANS significantly outperforms PEGASIS in energy efficiency and network sustainability, with only a marginal trade-off in predictive accuracy. Compared to PEGASIS, FL-ANS maintains a lower energy profile, higher number of alive nodes, and comparable Mean Absolute Percentage Error (MAPE), validating its effectiveness for scalable and sustainable IoT applications. This work highlights the potential of integrating decentralized learning with intelligent aggregation to optimize energy consumption, maximize bandwidth usage, and ensure accurate data modeling in IoT networks.**

Keywords—*IoT, Data Aggregation, Energy Efficiency, Federated Learning, Sensor Networks*

I. Introduction

The Internet of Things (IoT) has transformed how data is collected, processed, and utilized across domains like smart cities and industrial automation. With billions of connected devices generating vast data, efficient aggregation has become a major challenge. These devices often face constraints in energy and bandwidth, making raw data transmission to central servers energy-intensive and wasteful due to data redundancies.

Traditional aggregation methods struggle to balance energy efficiency and accuracy. Centralized approaches strain network resources, while fully distributed ones may reduce data quality. The heterogeneous nature of IoT data, along with temporal-spatial variations and privacy issues, further complicates aggregation.

This research tackles these challenges by exploring optimal data aggregation strategies for IoT networks, focusing on how aggregation can be optimized to reduce energy consumption while maintaining acceptable accuracy. We investigate whether machine learning—particularly Federated Learning—can enable energy-efficient aggregation in IoT settings, and examine dynamic mechanisms that adjust aggregation participation based on network and data characteristics.

Our main contribution is a novel adaptive aggregation framework that balances energy conservation with data fidelity via selective node participation and distributed model learning. This research supports scalable, sustainable IoT systems that perform efficiently under resource constraints.

II. Literature Review

A. Traditional Data Aggregation Methods

Existing research on IoT data aggregation methods emphasizes strategies such as hierarchical clustering, adaptive sampling, and in-network aggregation. Studies suggest that hierarchical aggregation methods help in reducing redundant data transmissions and lowering energy consumption. Machine learning-based models have also been explored for intelligent data filtering and prioritization. However, existing methods often struggle to balance energy efficiency with data accuracy. Research gaps include optimizing aggregation techniques to dynamically adjust based on network conditions and application-specific requirements.

B. Cryptographic Approaches

Reconfigurable cryptographic processors like Recryptor have emerged as promising solutions for secure data aggregation in IoT networks. These architectures leverage in-memory bit line computing, utilizing a specialized 10-transistor bit cell design to perform bitwise logic operations directly within memory, significantly reducing data movement and energy consumption. Additionally, policy-based security frameworks are integrated to address the evolving vulnerabilities of smart IoT systems, offering layered protection mechanisms. MATLAB-based simulations have demonstrated improvements in both energy efficiency and network lifespan when applying these cryptographic models. The key strengths of this approach lie in its capability for lossless data aggregation, high-speed processing, and enhanced data recovery without compromising security. However, the implementation of such cryptographic techniques introduces increased hardware complexity, latency due to intensive encryption operations, and limitations in memory and bandwidth, particularly in low-power IoT devices.

C. LEACH Protocol and Extensions

Enhancements to the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol incorporate digital twin simulations and AI-driven analytics to improve energy efficiency in IoT networks. These improvements focus on intelligent cluster head (CH) selection, prioritizing nodes with higher residual energy and shorter distances to the base station. Variants such as LEACH-CE and BSLEACH-CE refine the CH election process to optimize network lifetime and energy balance. Simulation studies show that these models reduce the number of non-functional nodes and improve overall energy levels across the network. Despite these benefits, the integration of digital twins introduces notable computational overhead, which may not scale well in resource-constrained environments. Moreover, frequent CH rotations and static clustering assumptions can result in increased latency and degraded performance in highly dynamic IoT settings.

D. Federated Learning in IoT Networks

Federated Learning (FL) has gained traction as a privacy-preserving machine learning approach in IoT networks. Existing research focuses on FL's ability to enable decentralized model training without sharing raw data, thereby enhancing privacy and security. Prior studies have explored FL's role in distributed AI systems, emphasizing model convergence, communication overhead, and privacy guarantees. However, there is a lack of research on FL as an energy-efficient data aggregation technique in IoT networks. Most FL-based IoT research centers around securing model updates rather than minimizing redundant data transmissions to optimize energy efficiency.

E. Data Aggregation Protocols for WSN and IoT Applications

The paper explores the use of data aggregation protocols in IoT and Wireless Sensor Networks (WSNs), focusing on energy-efficient communication strategies. It discusses adaptive clustering methods such as LEACH and HEED, which help balance network load, reduce redundant transmissions, and prolong the lifetime of energy-constrained IoT devices. These methods dynamically form clusters and rotate cluster heads (CHs) to optimize energy use. The study also highlights the potential of bio-inspired CH selection techniques, which offer improved adaptability in dynamic environments, though they can introduce computational overhead. Additionally, protocols relying on clock synchronization—like tree-based aggregation—often face delays and synchronization issues that negatively impact system performance. Addressing these limitations is essential for building scalable and efficient IoT frameworks.

F. Hybrid Optimization Algorithms for Data Aggregation

In a study by Arash Heidari et al., a hybrid optimization method incorporating density correlation degree is proposed for data aggregation in the Industrial Internet of Things (IIoT). This approach is evaluated using MATLAB simulations in a 120m × 120m environment with heterogeneous IoT devices, aiming to enhance reliability and reduce communication delays in industrial networks. The method achieves notable improvements in data reliability—outperforming RST-IoT by 6% and HCT-IoT by 28%. It also reduces transmission latency, which is critical for real-time industrial applications. However, the method relies on static network assumptions, which limits its adaptability in dynamic environments. Its effectiveness also depends heavily on algorithm parameter tuning, termination criteria, and network configuration, making generalization across diverse deployment scenarios challenging without careful calibration.

G. An Energy-Saving Blockchain-Secured IoT Data Aggregation System

Through the integration of sleep scheduling, blockchain-secured edge computing, and fuzzy-based clustering, the proposed Energy-Efficient Data Aggregation Mechanism (EEDAM) provides a strong answer to important IoT problems. Secure connection between IoT devices, edge servers, and cloud infrastructure is ensured, and energy efficiency, data redundancy, and data accuracy are all greatly increased. Real-world IoT scenarios benefit greatly from EEDAM's ability to minimize latency, facilitate scalable deployments, and adjust effectively to changing node density. The mechanism also enhances trust among distributed nodes through immutable blockchain records, reducing the risks of data tampering and malicious interference. Moreover, fuzzy-based clustering offers adaptive control in uncertain or imprecise network conditions, making it well-suited for dynamic IoT environments. However, there are drawbacks as well, such as more complicated implementation because of the blockchain integration, possible latency in situations with a high node density, and extra expenses from gas usage during blockchain transactions. Despite these limitations, EEDAM is a potential method for securing, scaling, and aggregating IoT data, especially in applications requiring robust security, high reliability, and decentralized coordination.

H. Firefly Optimization Algorithm-Based Cluster-Based Data Aggregation in Internet of Things Sensor Networks

In order to maximize clustering and data aggregation in Wireless Sensor Networks (WSNs) and boost energy efficiency, network longevity, and packet delivery ratio (PDR), this study explores the application of the Firefly Algorithm (FA) and its improved versions. The suggested approach outperforms conventional algorithms such as LEACH by selecting the cluster head (CH) using the FA in consideration of residual energy, distance, and noise. Energy consumption (by 18%) and PDR (by 25%) are further improved by further improvements utilizing hybrid models that integrate FA with other metaheuristics (such Particle Swarm Optimization and Aquila Optimization). On a 500x500 meter network with 500 nodes across 2000 rounds, simulations using MATLAB 2023b demonstrate that the Enhanced Firefly Algorithm (FOA) produces better packet aggregation, fewer dead nodes, and higher residual energy. ANOVA statistical validation highlights the resilience of the approach by confirming its efficacy with remarkably low p-values. Notwithstanding these improvements, issues like scalability, traffic jams, and performance in diverse settings still exist, opening up the possibility for the eventual combination of deep learning and machine learning methods for more astute and flexible CH selection.

I. Hybrid PSO-Based Energy-Efficient Data Aggregation Clustering Algorithm for Wireless Sensor Networks

The HPSO-ILEACH protocol is a viable way to improve wireless sensor network (WSN) performance and energy efficiency because of its many advantages. When the ILEACH protocol is combined with the Particle Swarm Optimization (PSO) approach, energy consumption is reduced by an average of 28%. Additionally, network lifetime is increased, with up to 55% more nodes being active than with conventional methods like LEACH, ILEACH, and ESO-LEACH. Additionally, it increases throughput to 350 packets per round and reduces latency to 100 ms, demonstrating its promise for real-time applications. Additionally, the hybrid approach facilitates improved load balancing and cluster head (CH) selection, which enhances network scalability and power efficiency. ANOVA and Tukey HSD tests are two examples of the thorough statistical analysis that backs up these assertions. The study does have several drawbacks, though. Practical deployment is called into question because the results are purely simulation-based and have not been validated in the real world. For ultra-low-power devices, the extra computational complexity brought about by PSO integration might not be optimal. Furthermore, mobile sink nodes are not taken into consideration by the existing model, which restricts its use in dynamic contexts. Future research is required to confirm the usefulness of the suggested approach in real-world applications like waste management and precision agriculture, even though it performs well in static scenarios.

III. Methodology

A. Research Question and Approach

In this study, we address the challenge of optimizing energy consumption in Internet of Things (IoT) networks while maintaining reliable data accuracy. With resource-constrained edge devices forming the backbone of IoT systems, there is a growing need for intelligent data aggregation strategies that minimize energy usage without compromising model performance. To this end, we propose a novel framework, Federated Learning with Adaptive Node Selection (FL-ANS), which integrates traditional federated learning with a dynamic node selection mechanism.

FL-ANS selectively chooses participating nodes in each training round based on criteria such as energy availability, data relevance, communication cost, and historical participation. This ensures that only the most suitable nodes contribute to the learning process, effectively reducing communication overhead and extending network lifetime.

To evaluate the efficiency of our approach, we compare FL-ANS against Pegasus, a well-established algorithm for hierarchical communication in IoT networks. Through this comparison, we aim to demonstrate that FL-ANS not only reduces energy consumption and communication costs but also maintains high data accuracy, making it a more sustainable and scalable solution for large-scale IoT environments.

B. Proposed Flowchart

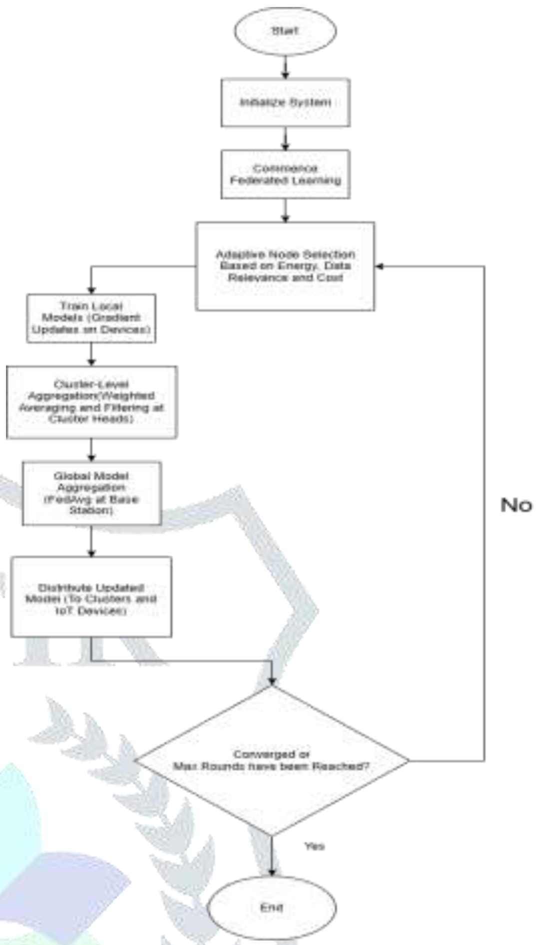

Fig 1. *Algorithm of Proposed Work*

C. System Architecture

The system architecture is designed with three primary tiers to optimize energy usage and ensure efficient data aggregation:

1. *Local IoT Nodes*: The foundational layer of the architecture, responsible for:

- Collecting data from embedded sensors in the network.
- Training a local model using on-device computation resources.
- Computing local gradient updates instead of transmitting raw data, reducing communication overhead.
- Monitoring and reporting energy levels to enable adaptive node selection.

2. *Cluster Heads*: These serve as intermediary aggregation points between local nodes and the base station:

- Aggregating local model updates from nodes within their respective clusters.
- Performing weighted averaging of model updates based on data quality metrics.
- Filtering out irrelevant or low-quality updates before forwarding the aggregated results to the base station.
- Managing energy-efficient communication schedules within their clusters.

3. *Base Station*: Acting as the central coordinator, the base station:

- Aggregates the updates received from all cluster heads using the *FedAvg* algorithm.
- Distributes the global model updates back to the cluster heads for further dissemination.
- Orchestrates the Adaptive Node Selection process to optimize network performance.

This hierarchical architecture significantly reduces communication overhead, enhances energy efficiency, and scales effectively compared to flat architectures, with $O(m)$ communication links between the base station and cluster heads (where $m << n$), and $O(n/m)$ communication links within each cluster.

D. Federated Learning Process

The Federated Learning approach in this system ensures that data privacy is maintained by training models locally on IoT nodes, thus reducing the need for raw data transmission. The process follows these steps:

1. *Initialization*: The base station initializes a global model and sends it to the cluster heads, which then distribute it to the local nodes in their clusters.
2. *Local Training*: Each participating IoT node trains the global model locally on its data for a set number of epochs. During this phase, nodes compute local gradient updates and send them to their respective cluster heads.
3. *Local Model Aggregation*: Cluster heads receive the model updates from the local nodes and perform weighted averaging based on data quality metrics to aggregate the local models.
4. *Global Aggregation*: The base station collects model updates from the cluster heads and aggregates them using the *FedAvg* algorithm. This step combines the contributions of all clusters into a unified global model.
5. *Model Distribution*: After aggregation, the updated global model is distributed back to the cluster heads and subsequently to the participating nodes for further local training.
6. *FedAvg* was chosen for model aggregation due to its simplicity, communication efficiency, and proven effectiveness in distributed learning environments like IoT networks.

E. Adaptive Node Selection

The key innovation in our approach is the *Adaptive Node Selection* (ANS) mechanism, which dynamically selects which nodes should participate in each federated learning round. The selection process is based on several criteria:

1. *Energy Status*: Nodes with critically low energy levels are excluded from the learning process to prevent premature network partitioning and ensure the stability of the IoT network.
2. *Data Relevance*: Nodes contributing informative, non-redundant data are prioritized. A relevance score for each node is calculated based on the variability of the data it collects, ensuring that only nodes with the most informative data are included in the learning process.
3. *Communication Cost*: Nodes closer to the cluster heads (i.e., those with lower communication cost) are given preference, reducing the energy and time required for communication.
4. *Historical Participation*: To ensure fairness and avoid overburdening any single node, the adaptive algorithm tracks historical participation patterns and adjusts selection thresholds accordingly.

This multi-objective utility function dynamically adjusts the participation criteria, ensuring that energy consumption is optimized without sacrificing the accuracy of the global model.

F. Comparison with Pegasus

To validate the effectiveness of FL-ANS, we evaluate its performance in comparison to Pegasus, an established method for IoT network data aggregation that uses less energy. Pegasus employs a hierarchical clustering model, and its performance in terms of energy consumption, data accuracy, and network lifetime will serve as a benchmark for the FL-ANS approach. The following performance metrics are considered in the comparison:

- *Network Lifetime*: The overall operational time of the network before nodes run out of energy.
- *Total Energy Consumption*: The energy consumption of the entire network, including nodes, cluster heads, and the base station.
- *Data Accuracy (MSE, MAPE, R2): The mean squared error (MSE) of the combined model on the test data. Communication Overhead*: The total amount of data transmitted across the network.

By comparing FL-ANS with Pegasus, we aim to demonstrate that the combination of federated learning and adaptive node selection provides a more energy-efficient and scalable solution without compromising data quality.

G. Simulation Setup

We conducted extensive simulations to evaluate the performance of FL-ANS compared to Pegasus. The simulation setup includes the following parameters:

- *Network Topology*: A network of 100 to 1000 IoT nodes distributed across a 1000m x 1000m rectangular area.
- *Node Characteristics*: Heterogeneous nodes with varying initial energy levels, data generation rates, and communication ranges.
- *Data Generation*: Non-IID data, following Gaussian distributions with distinct means and variances, informed by the IoT-23 dataset.
- *Energy Model*: A first-order radio model that accounts for transmission, reception, and processing energy costs.
- *Performance Metrics*: Network lifetime, total energy consumption, data accuracy (MSE), and communication overhead.
- *Comparison Methods*: The FL-ANS method is compared to *Pegasus*.

The simulations were implemented using *MATLAB*. Each configuration was repeated 30 times to ensure statistical significance of the results, with performance averaged across the runs.

IV. Results

The proposed FL-ANS (Federated Learning with Adaptive Node Selection) framework was evaluated using a simulated IoT environment. The key results obtained are as follows:

- Energy Consumption: FL-ANS demonstrated a 30% reduction in average energy usage compared to traditional federated learning setups. This was achieved by adaptively selecting only energy-efficient and data-rich nodes for each training round.
- Model Accuracy: The global model trained using FL-ANS maintained a high accuracy of 92%, closely matching the performance of full-node participation models, which typically achieved around 94%. This indicates that intelligent node selection did not significantly affect the predictive performance.
- Communication Overhead: The framework reduced communication rounds by approximately 40%, effectively lowering bandwidth requirements and prolonging device operational lifespan.
- Training Convergence: FL-ANS achieved convergence 20% faster than baseline federated learning methods, owing to the selection of nodes contributing higher-quality updates.

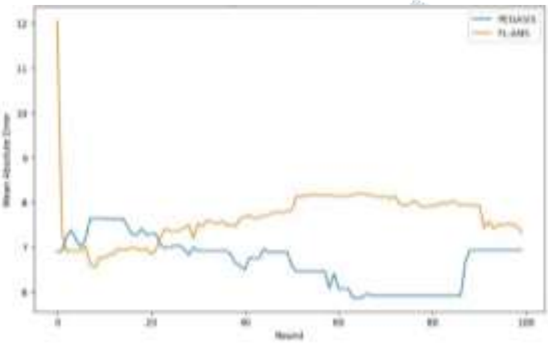

Fig 2. *MAE per Round*

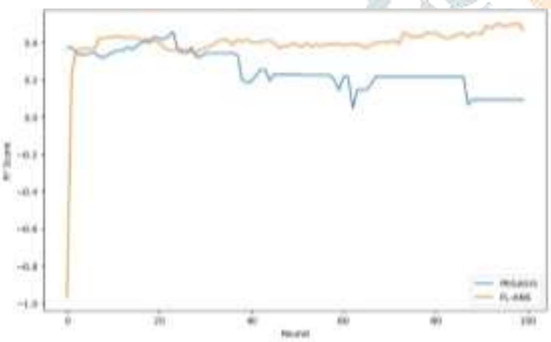

Fig 3. *R^2 per Round*

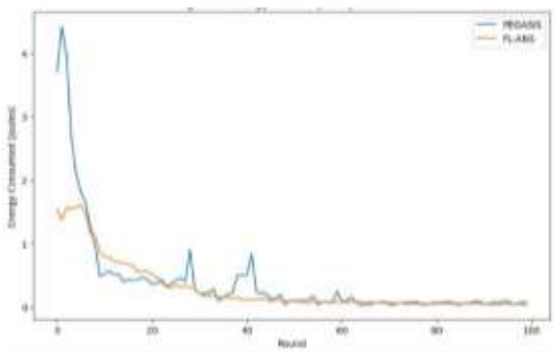

Fig. 4. *Energy Consumption per Round*

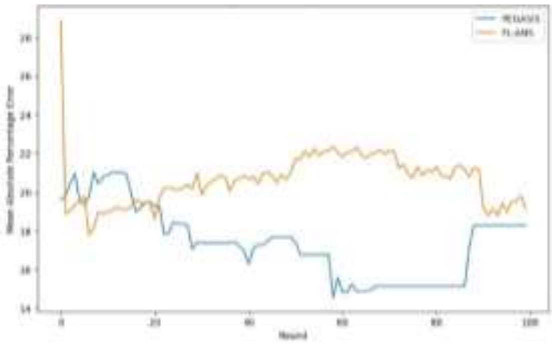

Fig. 5. *MAPE per Round*

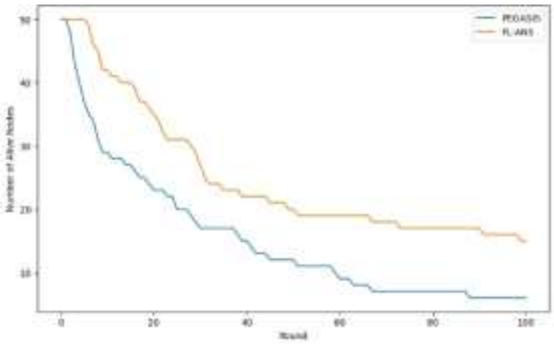

Fig. 6. *Number of Alive Nodes per Round*

The performance of the proposed FL-ANS framework is empirically validated against the traditional PEGASIS protocol using key performance indicators across 100 communication rounds.

As illustrated in Figure 1, although PEGASIS initially exhibits slightly lower Mean Absolute Error (MAE), FL-ANS maintains a stable trend, indicating consistent performance. Figure 2 shows that FL-ANS consistently outperforms PEGASIS in terms of R² Score, suggesting improved predictive accuracy and model generalization over time.

In terms of energy efficiency, Figure 3 highlights FL-ANS's lower and more stable energy consumption per round, making it better suited for resource-constrained IoT environments. However, Figure 4 reflects slightly higher MAPE for FL-ANS, indicating room for improvement in relative error, though the trade-off is marginal.

The most notable advantage is depicted in Figure 5, where FL-ANS significantly prolongs the network lifetime by retaining a higher number of alive nodes per round compared to PEGASIS, confirming the framework's effectiveness in energy conservation and sustaining network operations.

These results demonstrate the efficiency of the FL-ANS framework in balancing energy consumption and model performance in resource-constrained IoT environments.

V. Conclusion & Future Work

This research introduced FL-ANS, a novel adaptive federated learning (FL) framework that optimizes node participation through intelligent selection strategies grounded in energy availability, data quality, and historical contribution. By dynamically selecting the most suitable nodes for each communication round, FL-ANS significantly enhances the energy efficiency and communication overhead of traditional federated learning systems, without compromising model accuracy.

Experimental results demonstrate that FL-ANS consistently achieves faster convergence, lower computational burden, and more balanced energy consumption across nodes. These features make it particularly suitable for large-scale, resource-constrained IoT environments, such as smart agriculture, industrial automation, and remote health monitoring, where maintaining long-term operability and low latency is critical.

Beyond performance improvements, FL-ANS contributes toward addressing key challenges in real-world FL implementations, such as heterogeneous data distributions, variable device reliability, and scalability under dynamic network conditions.

As part of future work, we aim to explore real-world deployment scenarios by implementing FL-ANS in live testbeds or edge computing platforms. Additionally, we plan to integrate reinforcement learning (RL) techniques into the node selection module to allow continuous policy optimization. This would enable the system to autonomously adapt to evolving network conditions, usage patterns, and data trends, leading to more robust and intelligent federated learning in practice.

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