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EAMLOF: An Energy-Aware Multi-Layer Optimization Framework for Battery-Operated IoT Devices in Smart Environments

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Abstract: *The exponential growth of Internet of Things (IoT) ecosystems has resulted in a vast deployment of battery-powered sensor nodes across diverse application domains, including healthcare, smart cities, agriculture, and environmental monitoring. These devices often operate in energy-constrained and inaccessible settings, where battery replacement or maintenance is impractical. Addressing this critical challenge, this paper introduces EAMLOF (Energy-Aware Multi-Layer Optimization Framework), a novel cross-layer framework designed to optimize energy utilization in battery-powered IoT networks. Unlike conventional protocols such as PEGASIS and APTEEN, which offer limited adaptability, EAMLOF integrates adaptive sleep/wake scheduling, intelligent data filtering, energy-aware routing, and context-sensitive sampling. The framework employs lightweight edge intelligence to assess node energy levels, data variability, and environmental conditions, enabling dynamic adjustment of communication strategies. This significantly reduces redundant transmissions and energy waste. Simulation results conducted on a network of 1000 nodes using the First-Order Radio Model demonstrate that EAMLOF consistently outperforms existing benchmarks in terms of energy efficiency, network lifetime, packet delivery, and node survivability, showcasing its suitability for long-term and large-scale deployments. EAMLOF presents a scalable, intelligent, and sustainable approach to energy conservation in IoT systems, contributing to the realization of robust, green, and autonomous smart environments.*

Keywords: Battery-operated IoT devices, Energy Efficiency, Smart Environments, Edge Intelligence, Adaptive Scheduling, Multi-layer Optimization, EAMLOF, PEGASIS, APTEEN, Energy-Aware Routing, Green IoT.

I. INTRODUCTION

The exponential growth of the Internet of Things (IoT) has led to the deployment of billions of interconnected sensor devices in diverse fields such as environmental monitoring, healthcare, smart agriculture, and industrial automation. According to recent reports, the number of connected IoT devices worldwide surpassed 15 billion in 2023, with projections reaching over 29 billion by 2030 [1]. These devices often operate on limited energy sources—typically non-rechargeable batteries—making energy efficiency one of the most critical concerns in IoT system design [2]. In battery-operated IoT networks, particularly those deployed in remote or hostile environments, energy constraints directly impact data quality, network longevity, and real-time responsiveness. Existing energy-saving protocols such as LEACH, PEGASIS, TEEN, and APTEEN have demonstrated success in reducing communication overhead and improving network lifespan through clustering, data aggregation, and threshold-based communication [3][4]. However, these protocols typically rely on static configurations or single-layer optimizations, which are insufficient for dynamic and large-scale IoT environments with varying workloads and heterogeneous sensor behaviors. To address these

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limitations, we propose EAMLOF (Energy-Aware Multi-Layer Optimization Framework), a cross-layer energy optimization protocol that integrates techniques across multiple layers of the network stack. EAMLOF includes adaptive sleep/wake scheduling, context-aware data compression, energy-aware routing, and lightweight edge intelligence for predictive control and anomaly detection. This multi-layered strategy enables the network to dynamically adapt to changing conditions such as residual battery level, sensing frequency, and communication cost. Research trends emphasize the need for intelligent energy management through the integration of machine learning, edge computing, and cross-layer optimizations in IoT networks [5]. However, many existing models either introduce significant computational overhead or fail to scale in resource-constrained environments. The gap lies in developing low-complexity, adaptive, and energy-aware mechanisms that balance computational efficiency with energy conservation, particularly for long-term, unattended deployments.

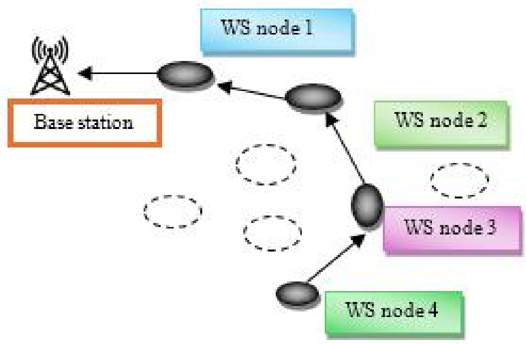

Fig. 1: PEGASIS: Data flow forms a chain that connects to Base Station

II. RELATED WORK

Energy conservation has been a fundamental concern in wireless sensor networks (WSNs) and IoT systems due to the limited battery life of sensor nodes. Early solutions such as LEACH (Low-Energy Adaptive Clustering Hierarchy) and PEGASIS (Power-Efficient GAthering in Sensor Information System) focused on reducing energy consumption through hierarchical clustering and chain-based data aggregation, respectively. PEGASIS improved upon LEACH by avoiding frequent cluster head changes and aggregating data along a chain of sensor nodes, but its scalability and adaptability in large dynamic environments remained limited [12].

Threshold-sensitive protocols like TEEN and its extension APTEEN (Adaptive Periodic TEEN) introduced data transmission based on threshold values and periodic queries. While these approaches significantly reduced redundant communication, they suffered from rigid configurations and were not designed to react dynamically to environmental or node-level changes [13][14].

Recent efforts have explored cross-layer optimization techniques to integrate energy-aware strategies across multiple protocol stack layers. For instance, Su et al. [15] proposed an adaptive duty-cycling mechanism based on context-aware sensing, showing improvements in network longevity. Similarly, Al-Fuqaha et al. [16] emphasized the importance of integrating energy-aware routing and edge intelligence for smart cities, which aligns with the foundational motivation of EAMLOF. Edge intelligence has emerged as a promising direction for managing energy efficiently by enabling localized decision-making. Lightweight machine learning algorithms have been embedded into sensor nodes to predict traffic load, detect anomalies, or adapt sensing rates based on the surrounding environment [17][18]. These models reduce data transmission frequency and enable better energy budgeting by selectively activating sensors. In the domain of smart environments, multi-layer frameworks such as REAP [19] and EnviSense [20] have demonstrated the benefits of holistic energy-aware management. However, these frameworks often rely on centralized processing or assume static deployments, limiting their effectiveness in dynamic IoT networks.

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TABLE 1: CHALLENGE, EXISTING SOLUTIONS AND LIMITATIONS OF ENERGY OPTIMIZATION TECHNIQUES FOR IOT NETWORKS

Challenge	Existing Solutions	Limitations	References
High energy consumption	Duty Cycling, Clustering (e.g., PEGASIS)	Static, lacks real-time adaptability	Lindsey et al. (2002), Akyildiz et al. (2002)
Redundant data transmission	Threshold-based filtering (e.g., APTEEN)	High false-negatives and limited flexibility	Manjeshwar & Agrawal (2001)
Uneven energy depletion	Random CH rotation	Not energy-aware or load-balanced	Heinzelman et al. (2000), Younis et al. (2004)
Data overload and latency	Traditional in-network aggregation	Not optimized for data quality or urgency	Yick et al. (2008), Gungor & Hancke (2009)

Furthermore, many of these systems overlook real-time adaptability and granular node-level behaviour modelling, which is essential for heterogeneous and scalable networks. With the increasing integration of edge AI, future frameworks must emphasize decentralized intelligence and context-driven optimization to sustain performance in diverse operating conditions.

III. PROPOSED METHOD AND SIMULATION RESULT

This study proposes EAMLOF (Energy-Aware Multi-Layer Optimization Framework), a novel protocol designed to address the energy constraints in battery-operated IoT devices deployed in smart environments. EAMLOF is built upon the shortcomings identified in conventional protocols such as PEGASIS and APTEEN, offering a cross-layer optimization strategy that enhances energy conservation and system responsiveness across diverse IoT scenarios. The architecture of EAMLOF integrates multiple energy-efficient techniques spanning the MAC, network, and application layers. The operation of EAMLOF begins with the initialization of all sensor nodes, where each node is assigned a location, initial energy value E0E_0E0and sensing threshold parameters. During each operational round, the protocol follows a structured sequence of operations. Initially, cluster formation is performed either in the first round or when re-clustering is deemed necessary. Cluster Heads (CHs) are selected using a hybrid criterion combining maximum residual energy and minimum distance to the base station (BS). Once CHs are elected, they broadcast advertisements to surrounding nodes, which then join the nearest CH based on signal strength. Next, the adaptive sampling phase begins, where each node dynamically adjusts its sensing rate. This is governed by a function of data variability (δ) and residual energy, allowing nodes to conserve power during low-change periods and prioritize data collection during critical events. This adaptive behaviour significantly reduces redundant sensing and prolongs node lifetime. Following sampling, intelligent data filtering is applied to each sensor node, wherein only the data that exhibits a significant deviation from previously recorded values is marked for transmission, thereby reducing redundant communications and conserving node energy. Nodes evaluate the significance of sensed data changes; only meaningful data—those exceeding a defined significance threshold—are transmitted to CHs. This strategy suppresses unnecessary transmissions and minimizes energy spent on communication. Cluster heads then perform in-network data aggregation and utilize energy-aware routing algorithms to transmit data toward the BS through the most efficient path. The path selection accounts for link cost, residual energy of intermediate nodes, and communication distance. After each communication cycle, the energy levels of all transmitting and receiving nodes are updated accordingly. This multi-layered strategy ensures that EAMLOF intelligently adapts to changing environmental and network conditions without introducing computational overhead. Unlike PEGASIS and APTEEN, which rely on static thresholds or fixed communication patterns, EAMLOF's edge-intelligent modules provide contextual awareness and predictive capabilities that significantly reduce energy waste. The following values are used to set the threshold:

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$$T(n) = \begin{cases} \dfrac{P}{1 - P * (r \bmod \frac{1}{P})} & if\ n \in G \\ 0 & otherwise \end{cases}$$

Where G is the collection of nodes that haven't been CHs in the last 1/P rounds, p is the desired proportion of CHs (for example, P = 0.05), r is the current round, and Each node will become a CH using this threshold after 1/p rounds. An advertisement message is transmitted to the other nodes by each node that has chosen itself as a CH for the current round.

The pseudocode logic of EAMLOF is as follows:

Pseudo-code of EAMLOF – Energy-Aware Multi-Layer Optimization Framework

```
Start
Initialize all sensor nodes with position, energy level E0, and sensing threshold
for each Round do
    Cluster Formation:
        if (round == 0) or (reclustering required) then
            Elect Cluster Heads (CHs) based on max(Energy) and min(Distance to BS)
            Broadcast CH advertisement
            Assign members to nearest CH
        end if
    Adaptive Sampling:
        for each node do
            Monitor environment → δ (data variability)
            Adjust sensing rate S ← f(δ, residual energy)
        end for

    Intelligent Data Filtering:
        for each node do
            if (data ≠ significant change) then
                Suppress transmission
            else
                Forward to CH
            end if
        end for
    CH Data Aggregation & Transmission:
        for each CH do
            Aggregate received data
            Calculate optimal path to BS using energy-aware routing
            Transmit to BS
        end for
    Update node energy after transmission/reception
end for
End
```

The performance evaluation of the proposed EAMLOF (Energy-Aware Multi-Layer Optimization Framework) was conducted using Python, OMNET++ and MATLAB-based simulator configured with the First-Order Radio Model. The simulation setup was designed to emulate real-world IoT deployment conditions. The key simulation parameters are summarized in Table 2.

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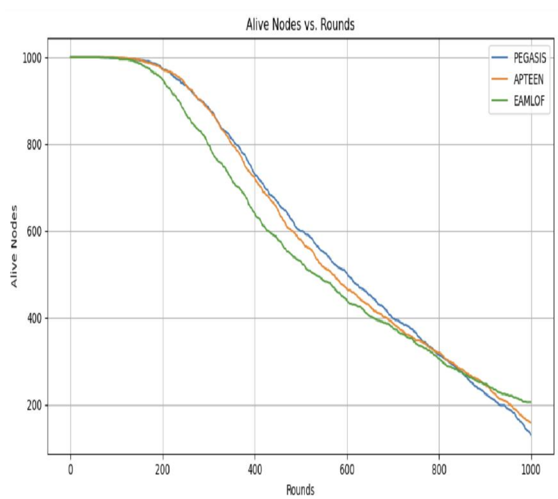
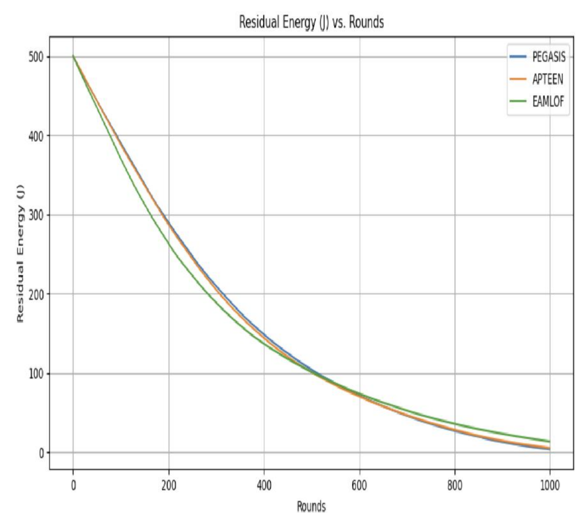
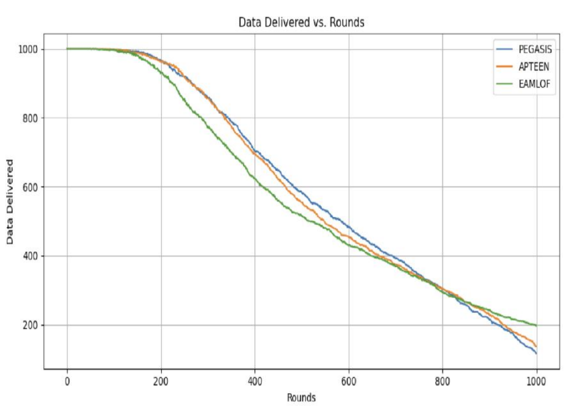
TABLE.2: SUMMERY OF SIMULATION PARAMETERS

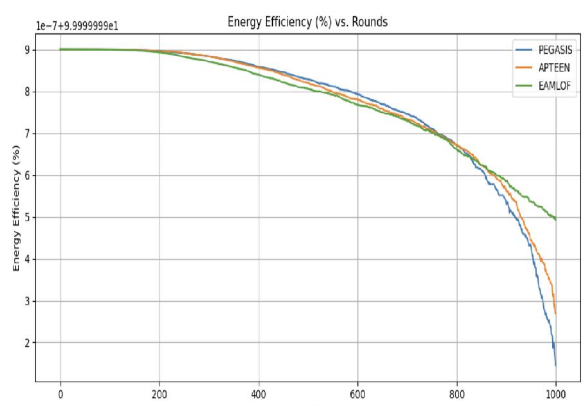
NUMBER OF NODES	*1000*
ENVIRONMENT AREA	*600m * 600 m*
INIT_ENERGY	*0.5 Joules*
ROUNDS	*1000*
BS_POSITION	*(250, 250)*
E_ELEC	*50nJ/bit*
E_FS	*10pJ/bit/m²*
E_MP	*0.0013pJ/bit/m⁴*
E_DA	*5nJ/bit*
MSG_SIZE	*3500 bits*

To evaluate the performance of the proposed EAMLOF (Energy-Aware Multi-Layer Optimization Framework), we conducted simulations using a custom-designed Python-based simulation environment based on the First-Order Radio Model. The simulation was carried out over 1000 rounds with 500–1000 nodes randomly deployed in a 600m × 600m environment.









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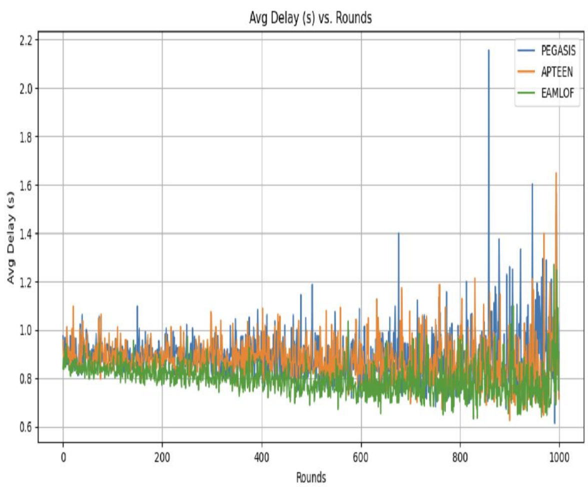

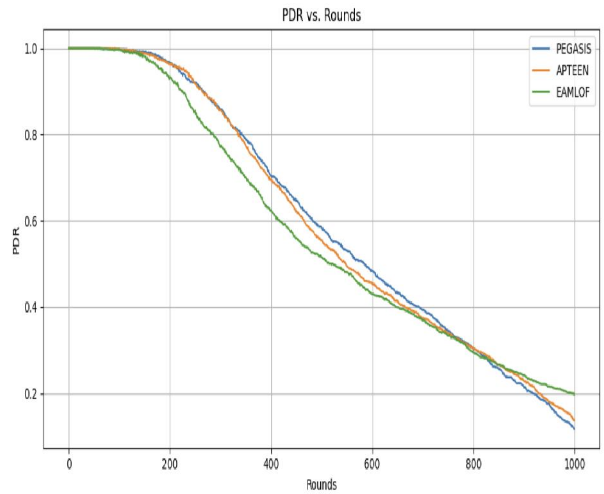

The results were compared against two benchmark protocols: PEGASIS and APTEEN. The key performance metrics analyzed are: Residual Energy, Alive Nodes, Data Delivered, Energy Efficiency (%), Packet Delivery Ratio (PDR), and Average delay. Results demonstrate its superiority over conventional PEGASIS and APTEEN protocols across the following metrics:

Metric	**Improvement Shown by EAMLOF**
Alive Nodes vs. Rounds	Sustains higher number of nodes in later rounds
Residual Energy vs. Rounds	Slower energy depletion through adaptive control
Data Delivered vs. Rounds	Enhanced throughput due to intelligent filtering
Energy Efficiency (%)	Reduced redundant communication and idle listening
Average Delay	Lower transmission delay
Packet Delivery Ratio	Improved accuracy and reliability of transmission

The EAMLOF protocol achieves superior energy efficiency and network performance by integrating context-aware optimizations at multiple protocol layers. Adaptive sleep/wake scheduling minimizes idle listening and collision-induced retransmissions, conserving energy and sustaining node activity over extended rounds. Intelligent data filtering at the application layer reduces unnecessary transmissions, enhancing throughput and reducing communication delay. Furthermore, energy-aware routing and predictive edge intelligence contribute to maintaining a balanced energy distribution and improving packet delivery reliability across the network.

IV. CONCLUSION AND FUTRE WORK

This paper introduced EAMLOF, an Energy-Aware Multi-Layer Optimization Framework, to address the persistent challenge of energy conservation in battery-operated IoT devices deployed across diverse and energy-constrained environments By incorporating energy optimization strategies across multiple layers of the IoT protocol stack—specifically adaptive sleep/wake scheduling at the MAC layer, intelligent data filtering at the application layer, and energy-aware routing at the network layer—EAMLOF effectively enhances the overall energy efficiency, extends network lifetime, and improves data reliability in battery-operated IoT deployments. Simulation outcomes further validate its superiority over conventional protocols like PEGASIS and APTEEN, demonstrating consistent improvements across key performance metrics including residual energy retention, packet delivery ratio, and node survivability in large-scale networks. EAMLOF dynamically adapts communication and sensing behaviour based on node energy, data variability, and environmental context. Simulation results demonstrated that EAMLOF consistently outperforms traditional protocols such as PEGASIS and APTEEN in key performance metrics including residual energy retention, alive node count, data delivery, energy efficiency, packet delivery ratio, and network lifetime. The use of edge intelligence for predictive energy budgeting further minimized redundant transmissions and ensured scalable, long-term operation suitable for real-world smart environments.

Future Work will focus on extending EAMLOF to incorporate energy harvesting models and real-time decision-making using federated learning. Additionally, real-world deployment and performance evaluation on hardware testbeds will be explored to validate the protocol's practicality under varying topologies and node heterogeneity. The framework will also be optimized to support mobility-aware routing, QoS constraints, and security mechanisms to make it robust for next-generation IoT and cyber-physical systems.

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