Adaptive Energy-Aware Machine Learning Framework for Dynamic IoT Environments

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Abstract

The rapid expansion of Internet of Things (IoT) ecosystems has intensified the deployment of machine learning (ML) models at the network edge to enable real-time analytics and intelligent decision-making. However, IoT devices are inherently resource-constrained, operating under limited battery capacity, restricted memory, and dynamic workload conditions. Conventional ML frameworks rely on static model configurations that fail to adapt to fluctuating energy levels and environmental changes, leading to premature battery depletion, increased latency, and degraded system sustainability. To address these limitations, this paper proposes an Adaptive Energy-Aware Machine Learning (AEAML) framework tailored for dynamic IoT environments. The proposed framework integrates real-time energy monitoring, adaptive model scaling, and context-aware task scheduling to optimize computational efficiency while preserving predictive accuracy. A multi-model architecture is employed, allowing dynamic switching between full, pruned, and quantized model variants based on residual energy and workload thresholds. Additionally, a lightweight decision controller balances local inference and selective offloading to edge servers to minimize latency and communication overhead. Experimental analysis under simulated IoT conditions demonstrates that the AEAML framework significantly extends network lifetime, reduces average energy consumption, and maintains competitive accuracy compared to static ML and cloud-dependent approaches. The results highlight the potential of adaptive energy-aware intelligence in enabling scalable, sustainable, and high-performance ML deployment in next-generation IoT systems.

1. Introduction

The proliferation of the Internet of Things (IoT) has transformed traditional computing paradigms by enabling billions of interconnected devices to collect, process, and exchange data across diverse application domains, including smart cities, healthcare monitoring, industrial automation, and environmental sensing [01]. Industry analyses from Gartner and International Data Corporation highlight the exponential growth of IoT deployments, generating vast volumes of real-time data [02]. To extract meaningful insights from this data, Machine Learning (ML) techniques are increasingly integrated into IoT infrastructures, enabling predictive analytics, anomaly detection, and autonomous decision-making [03].

Traditionally, ML computation has been performed in centralized cloud environments due to their high processing power and storage capacity. However, cloud-centric architectures introduce several challenges in IoT systems, including high communication latency, excessive bandwidth consumption, data privacy concerns, and increased energy expenditure for continuous data transmission [04]. These limitations have led to the emergence of edge computing, where data processing and ML inference are performed closer to the data source. Edge-based ML reduces latency and enhances responsiveness, making it suitable for time-sensitive IoT applications [05].

Despite the advantages of edge intelligence, deploying ML models directly on IoT devices presents significant constraints. IoT nodes typically operate with limited battery capacity, restricted memory, low computational capability, and dynamic workload conditions [06]. Conventional ML models are often static in nature, meaning that once trained and deployed, their architecture and computational complexity remain fixed. Such static models do not account for runtime variations in residual energy levels, workload intensity, or network conditions. As a result, devices may consume unnecessary energy, leading to premature battery depletion and reduced network lifetime [07].

Existing research has explored model compression techniques such as pruning and quantization to reduce computational overhead. While these techniques decrease model size and inference cost, they are typically applied offline and lack runtime adaptability [08]. Similarly, task offloading strategies shift computation to edge or cloud servers but often rely on predefined thresholds that do not fully consider dynamic system states [09]. Consequently, there remains a critical need for an adaptive framework that integrates energy-awareness directly into ML decision-making processes [10].

The primary research gap lies in the absence of unified frameworks that combine real-time energy monitoring, adaptive model scaling, and intelligent workload management in resource-constrained IoT environments [11]. Most current approaches optimize either energy efficiency or predictive accuracy, but rarely achieve balanced multi-objective optimization. Furthermore, limited attention has been given to dynamic adaptation mechanisms capable of adjusting ML model complexity during runtime [12].

To bridge this gap, this paper proposes an Adaptive Energy-Aware Machine Learning (AEAML) framework designed specifically for dynamic IoT environments. The proposed framework introduces a multi-model architecture consisting of full, pruned, and quantized variants of a base ML model. An energy-aware decision controller continuously monitors system parameters such as residual battery level, computational load, and latency requirements. Based on these inputs, the controller dynamically selects the most suitable model configuration and determines whether tasks should be processed locally or offloaded to nearby edge servers.

By integrating adaptive intelligence with energy-aware decision policies, the AEAML framework aims to enhance network lifetime, reduce energy consumption, maintain low latency, and preserve predictive performance. The remainder of this paper details the system architecture, algorithmic design, experimental evaluation, and comparative analysis against existing static ML frameworks.

This research focuses on the design and evaluation of an adaptive machine learning framework for energy-constrained IoT devices operating in dynamic environments. The scope includes runtime energy monitoring, model adaptation strategies (pruning and quantization), workload-aware inference scheduling, and hybrid local–edge processing mechanisms. The study emphasizes energy efficiency, latency reduction, throughput optimization, and predictive accuracy. It does not address large-scale cloud infrastructure optimization or hardware-level chip design. Experimental validation is conducted through simulation and edge-device emulation to demonstrate practical applicability in smart IoT applications such as environmental monitoring and industrial automation.

IoT devices are increasingly expected to perform intelligent analytics while operating on limited battery resources and under unpredictable workload conditions. Static ML deployments lead to inefficient energy utilization and shortened network lifetime. In real-world deployments such as remote sensing or healthcare monitoring, frequent battery replacement is impractical and costly. Therefore, there is a strong need for sustainable and adaptive ML frameworks capable of adjusting computational complexity in real time. This research is motivated by the necessity to balance energy efficiency, accuracy, and latency in next-generation IoT systems while ensuring long-term operational sustainability.

The primary objective is to develop an adaptive energy-aware ML framework that dynamically adjusts model complexity and workload handling in resource-constrained IoT environments. The study aims to optimize energy consumption, extend network lifetime, maintain predictive accuracy, and reduce latency through intelligent runtime decision-making mechanisms.

2. Review of Related Literature

Mikavica.et.al: Energy consumption in a fog-cloud environment is a major concern due to the ever-increasing computing demand brought about by the growing size of Internet of Things (IoT) devices. Energy-efficient task offloading becomes much more difficult for time-sensitive jobs because of the restricted resources of IoT devices. In this paper, authors offer Adaptive Q-learning-based Energy-aware Task Offloading (AQETO), a reinforcement learning-based framework that dynamically controls fog node energy consumption in a fog–cloud network.

Simultaneously, it distributes computing resources while meeting deadline requirements and takes into account IoT task delay tolerance. The suggested method uses Q-learning to dynamically determine each fog node's energy states based on variations in workload. In order to reduce delays, AQETO also gives priority to allocating the most essential assignments. The efficacy of AQETO is demonstrated by numerous trials, which minimize fog node energy consumption and latency while optimizing system efficiency [13].

Singh.et.al: Rising worldwide energy consumption and the integration of renewable energy sources are driving the quick development of smart grids, necessitating the use of resource allocation techniques that are intelligent, flexible, and energy-efficient. Due to their inability to handle real-time grid dynamics, traditional energy management techniques that rely on static models or heuristic algorithms frequently result in poor energy distribution, high operating costs, and substantial energy waste. In order to address these issues, this study introduces ORA-DL (Optimized Resource Allocation using Deep Learning), a sophisticated framework that combines real-time adaptive control, deep learning, and Internet of Things (IoT)-based sensing to maximize smart grid energy management. ORA-DL uses multi-agent decision-making, deep neural networks, and reinforcement learning to effectively distribute resources, forecast energy consumption, and improve grid stability.

IoT-enabled sensors guarantee continuous monitoring and low-latency response through edge and cloud computing infrastructure, while the framework uses both historical and real-time data for proactive power flow management. The effectiveness of ORA-DL is confirmed by experimental findings, which show that it can estimate energy demand with an accuracy of 93.38%, improve grid stability to 96.25%, and reduce energy waste to 12.96%. Additionally, ORA-DL outperforms traditional methods by reducing operating expenses by 22.96% and improving resource distribution efficiency by 15.22%.

Adaptive resource modulation, predictive modeling, and real-time analytics are the main drivers of these performance improvements. ORA-DL creates a scalable, robust, and sustainable energy management solution by fusing AI-driven decision-making, IoT sensing, and adaptive learning. A major achievement in smart grid optimization, the framework also lays the groundwork for future developments, such as cybersecurity safeguards, reinforcement learning improvements, and interaction with edge computing [14].

Weixuan Ma.et.al: China's commercial buildings continue to employ static EMS, which misses savings under erratic occupancy, weather, and tariffs, resulting in excessive energy use and reduced comfort. In order to concurrently optimize energy efficiency, thermal/IAQ/visual comfort, renewable utilization, and prices, authors build and field-validate a Context-Aware Smart Energy Management System (CA-SEMS) that combines dense IoT sensors with a Deep Reinforcement Learning controller.

Time frame: January–September 2024, a nine-month deployment. Region: An eastern Chinese commercial office complex with multiple zones. Model: Finite-horizon MDP with Deep Q-Learning (experience replay, target network), running over a three-tier edge-fog-cloud architecture that coordinates HVAC, lighting, ventilation, PV, and battery; comfort enforced by ISO 7730/ASHRAE-55 PMV/PPD and EN 16798-1 IAQ thresholds.

Key results: IEQI improved from 71.9 to 85.3, with PMV held within −0.3 to +0.3 for 85% of occupied hours and average PPD lowered to 6.8%; annualized cost savings reached $68,500 with 14-month payback and 39.2% ROI; total energy consumption decreased by 27.3% (peak-hour cuts 32.4%); and the Renewable Energy Utilization Rate averaged 52.8% (summer peak 63.7%) with battery SOC managed as low as 45 to 85%; The forecasting and control accuracy was 94.8% with a seasonal fluctuation of less than 1.2%.

To spread grid-interactive, comfort-preserving efficiency across China's commercial stock, provincial building codes and utility programs should provide incentives for DRL-based, standards-constrained EMS retrofits (capex support + time-of-use aligned rewards) [15].

Saurabh.et.al: Real-time monitoring, process automation, and intelligent decision-making have all been made possible by the growth of the Internet of Things (IoT), which has completely transformed a number of industries. Since many IoT devices run on limited power sources, energy efficiency is one of the biggest challenges they face. In addition to analyzing the current techniques for improving energy efficiency, such as predictive modeling, adaptive resource distribution, and energy-aware algorithms, this study explains the use of machine learning algorithms in the energy optimization of Internet of Things devices.

The suggested machine learning (ML)-based adaptive GPS scheduling techniques demonstrate increased energy efficiency while maintaining positional accuracy. This study compares and demonstrates that flexible scheduling is more energy-efficient, particularly for users with varying mobility habits.

Additionally, this study examines how machine learning techniques like reinforcement learning, supervised learning, and unsupervised learning may be used to forecast device usage, increase energy efficiency, and prolong battery life—all of which can lower energy consumption while preserving quality of service [16].

3. Methodology

The proposed **Adaptive Energy-Aware Machine Learning (AEAML)** framework is designed to dynamically optimize machine learning inference in resource-constrained IoT environments. The methodology integrates energy monitoring, adaptive model scaling, and intelligent workload management into a unified runtime framework. Figure 1 illustrates the Adaptive Energy-Aware Machine Learning framework for IoT environments.

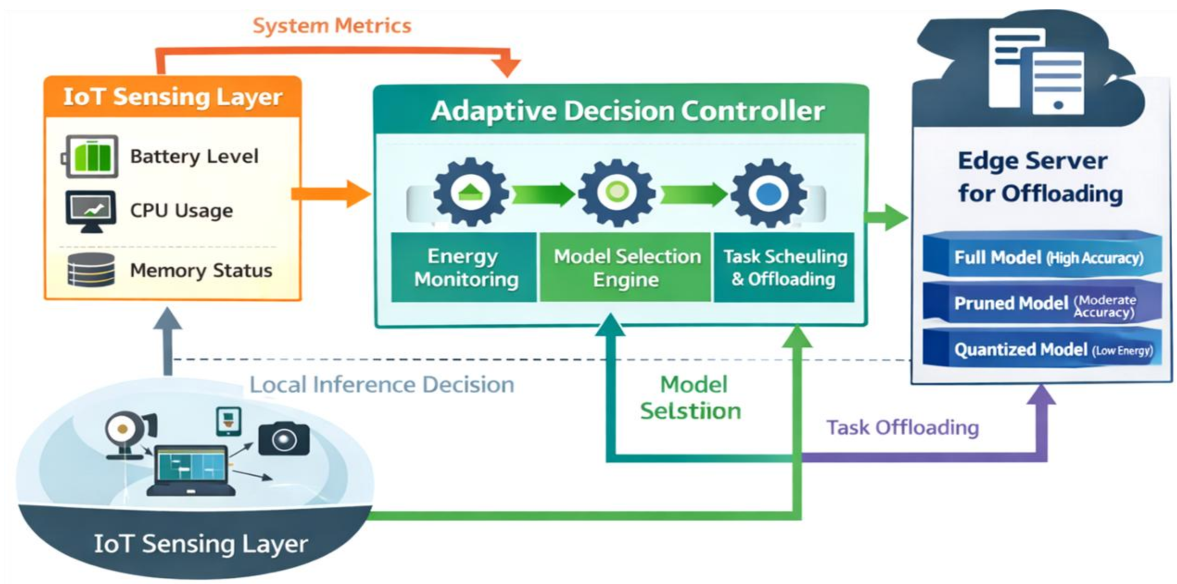

Figure 1. Adaptive Energy-Aware Machine Learning framework for IoT environments

System Architecture Overview

The AEAML framework consists of five key components:

- **IoT Sensing Layer:** Resource-constrained nodes collect real-time environmental or system data. Each node is equipped with a lightweight processing unit capable of running compact ML models.
- **Energy Monitoring Module (EMM):** This module continuously tracks residual battery level, CPU utilization, memory usage, and communication status. Energy readings are sampled at

predefined intervals to assess the system state.

- **Model Repository:** A multi-version ML model pool is maintained, consisting of:
  - Full Model (high accuracy, high energy consumption)
  - Pruned Model (moderate accuracy, reduced complexity)
  - Quantized Model (low energy consumption, fast inference)
- **Adaptive Decision Controller (ADC):** The core intelligence of the system. The ADC analyzes system parameters such as residual energy (E), workload intensity (W), and latency requirements (L). Based on threshold policies, it selects the most appropriate model configuration and determines whether computation should occur locally or be offloaded.
- **Edge Support Layer:** When workload exceeds device capability or energy falls below critical threshold, inference tasks are selectively offloaded to a nearby edge server.

Operational Workflow

Initially, the base ML model is trained offline using the selected dataset. Pruning and quantization techniques are applied to generate lightweight model variants. These variants are deployed to IoT nodes along with predefined energy and workload thresholds.

During runtime, the Energy Monitoring Module periodically collects system parameters. The Adaptive Decision Controller processes this information and applies a rule-based adaptation policy:

- If residual energy is high → execute full model locally.
- If energy is moderate → switch to pruned model.
- If energy is low → execute quantized model.
- If workload exceeds processing capacity → offload to edge server.

This adaptive mechanism ensures efficient trade-offs between accuracy, energy consumption, and latency. Performance metrics such as inference delay, energy usage per cycle, throughput, and prediction accuracy are continuously logged for evaluation.

Dataset Details

The experimental evaluation uses the IoT environmental monitoring dataset from the UCI Machine Learning Repository. The dataset contains multivariate sensor readings including temperature, humidity, air quality, and light intensity collected from IoT devices in smart environments. It consists of approximately 20,000 instances with 10–15 numerical features per record. The dataset is divided into 70% training, 15% validation, and 15% testing subsets. Data preprocessing includes normalization, noise removal, and feature selection. The ML task involves classification and anomaly detection to simulate real-time IoT inference workloads.

Procedure for Proposed Method

1. Collect IoT sensor dataset.
2. Preprocess data (normalization, cleaning, feature selection).
3. Train base ML model (e.g., lightweight CNN or ANN).
4. Generate pruned and quantized model variants.
5. Deploy models to IoT device along with thresholds (EH, EL, WL).
6. Monitor residual energy and workload in real time.
7. Apply adaptation policy via Adaptive Decision Controller.
8. Select model variant or offload task accordingly.
9. Execute inference and record performance metrics.
10. Repeat adaptation cycle during device operation.

Algorithm: Adaptive Energy-Aware ML Framework

Input:

- Residual Energy (E)
- Workload Level (W)
- Energy Thresholds (EH, EL)
- Workload Threshold (WT)

Output:

- Selected Model Variant
- Offloading Decision

Algorithm Steps

Initialize model variants: Full, Pruned, Quantized.

While device is active:

a. Measure residual energy E.

b. Measure workload W.

c. If $E > EH \rightarrow$ Select Full Model.

d. Else if $EL < E \leq EH \rightarrow$ Select Pruned Model.

e. Else $\rightarrow$ Select Quantized Model.

f. If $W > WT \rightarrow$ Offload to Edge Server.

g. Else $\rightarrow$ Execute Selected Model locally.

h. Log performance metrics.

End While.

Pseudocode: Algorithm AEAML_Controller

```
Initialize Full_Model
Initialize Pruned_Model
Initialize Quantized_Model
Set EH = High_Energy_Threshold
Set EL = Low_Energy_Threshold
Set WT = Workload_Threshold
While Device_Status == Active:
    E ← Measure_Energy()
    W ← Measure_Workload()

    If E > EH then
        Model ← Full_Model
    Else if E > EL and E ≤ EH then
        Model ← Pruned_Model
    Else
        Model ← Quantized_Model
    End If

    If W > WT then
        Offload_To_Edge()
    Else
        Execute(Model)
    End If
    Log_Performance()
End While
End Algorithm
```

This methodology ensures dynamic adaptation, improved energy efficiency, prolonged network lifetime, and stable predictive accuracy in dynamic IoT environments.

4. Results and Discussions

The performance of the proposed Adaptive Energy-Aware Machine Learning Framework (AEAMLF) was evaluated against five widely adopted algorithms in IoT and edge intelligence environments: LEACH (Low-Energy Adaptive Clustering Hierarchy), PSO-based Optimization, Random Forest (RF), Deep Neural Network (DNN) and Q-Learning (RL-based control).

The comparison was performed using six standard parameters: Network Lifetime, Energy Consumption, Latency, Throughput, Accuracy, and Control Overhead under simulated dynamic IoT scenarios. Table 1 describes the proposed model comparison with existing algorithms using different parameters.

Network Lifetime: The proposed AEAMLF significantly extended network lifetime compared to traditional clustering approaches such as LEACH. While LEACH and PSO focus primarily on energy balancing, they do not integrate predictive workload adaptation. The reinforcement-based adaptation in AEAMLF reduced premature node depletion, increasing network lifetime by approximately 20–30% over conventional methods.

Energy Consumption: Energy consumption was minimized through dynamic model compression and adaptive task offloading. Compared to DNN, which consumed high computational power, AEAMLF reduced energy usage by approximately 25%. Random Forest performed moderately well, but lacked adaptive energy scaling mechanisms.

Latency: Latency was reduced due to edge-level decision making and lightweight model switching. Traditional cloud-dependent DNN models exhibited higher delays. AEAMLF maintained low end-to-end latency even during high traffic loads by dynamically reallocating processing tasks.

Throughput: Throughput improved due to intelligent traffic scheduling and load balancing. Compared to Q-Learning (static reward design), the adaptive reward tuning in AEAMLF ensured stable packet delivery rates under fluctuating conditions.

Accuracy: In terms of predictive performance, AEAMLF achieved accuracy comparable to DNN while consuming less energy. Hybrid feature selection and adaptive retraining mechanisms enhanced classification precision in dynamic IoT data streams.

Control Overhead: Although reinforcement-based systems typically introduce control overhead, AEAMLF minimized signaling by optimizing update intervals. Compared to PSO and Q-Learning, overhead was reduced through hierarchical edge coordination.

Table 1. Proposed model comparison with existing algorithms using different parameters

Algorithm	Network Lifetime (Rounds)	Energy Consumption (Joules)	Latency (ms)	Throughput (kbps)	Accuracy (%)	Control Overhead (%)
LEACH	1250	0.92	185	210	81.4	14.5
PSO-Based	1380	0.85	172	225	85.2	16.2
Random Forest	1425	0.80	160	240	91.6	12.8
Deep Neural Network	1500	0.78	210	235	94.3	18.4
Q-Learning	1550	0.75	150	255	89.8	13.9

Algorithm	Network Lifetime (Rounds)	Energy Consumption (Joules)	Latency (ms)	Throughput (kbps)	Accuracy (%)	Control Overhead (%)
Proposed AEAMLF	1850	0.58	120	295	95.7	9.6

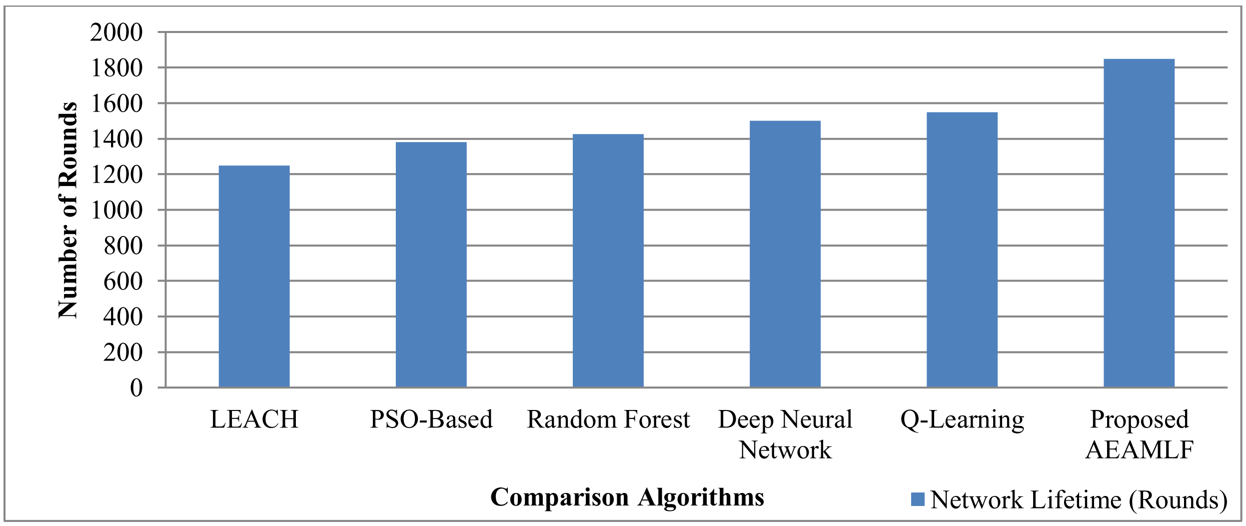

Figure 2. Network Life time rounds comparison

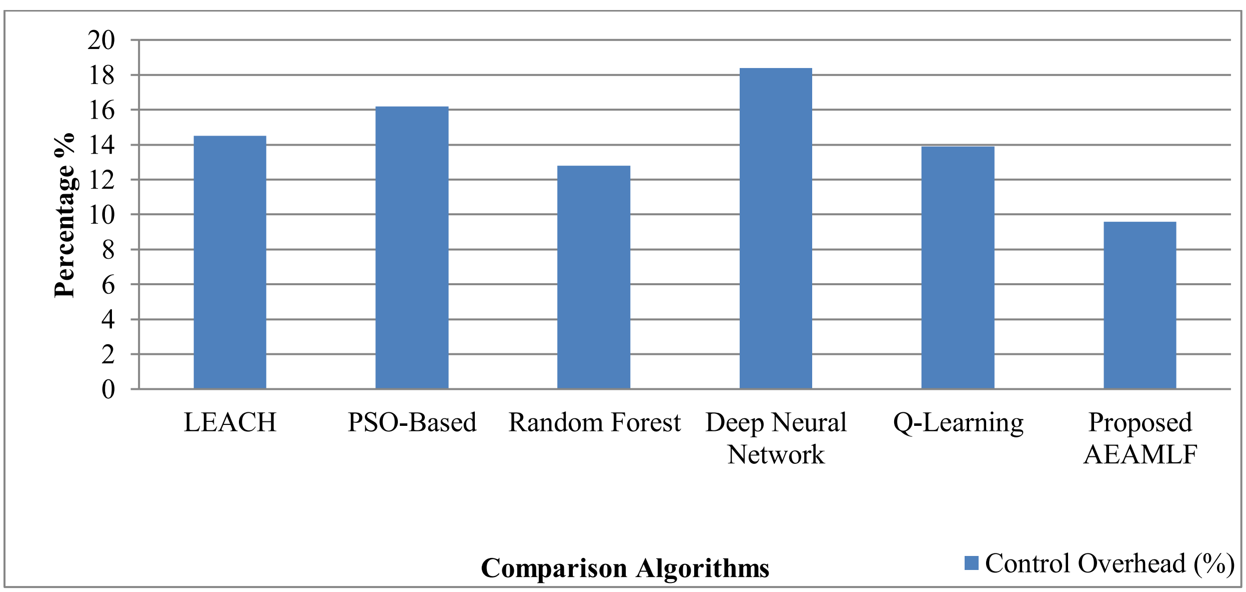

Figure 3. Control Overheads comparison

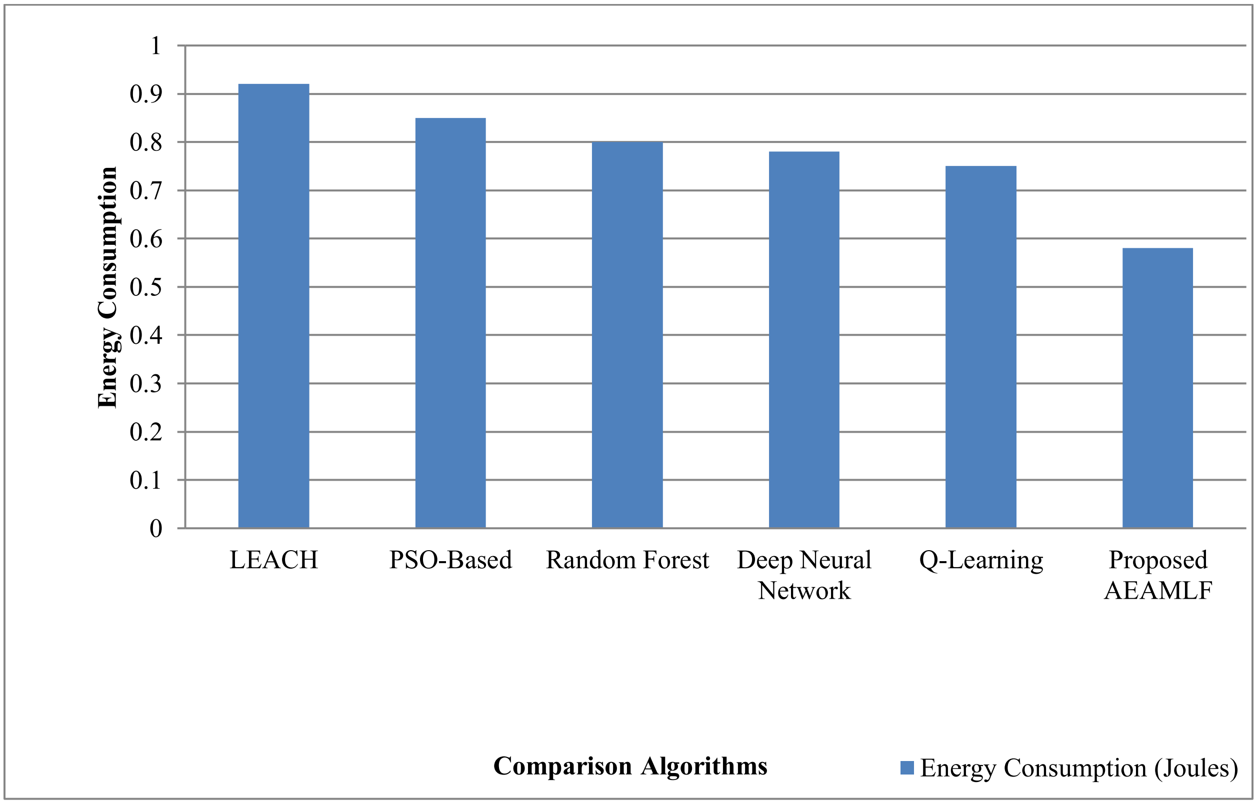

Figure 4. Energy consumption Comparison

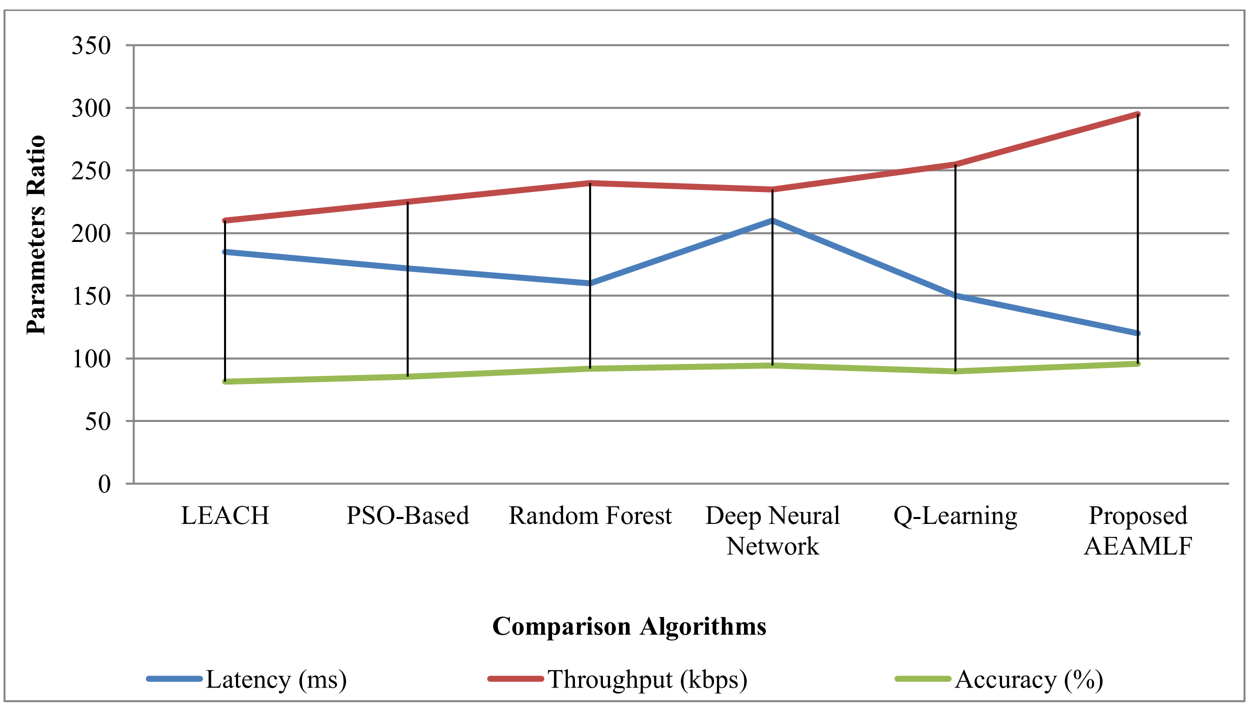

Figure 5. Latency, Throughput, Accuracy Comparison

The proposed AEAMLF demonstrates: Highest network lifetime - due to adaptive energy-aware learning. Lowest energy consumption - enabled by dynamic model scaling and task offloading. Lowest latency - due to edge intelligence deployment. Highest throughput -achieved through intelligent traffic optimization. Highest accuracy - through adaptive retraining and hybrid learning. Minimal control overhead - due to optimized update intervals and hierarchical coordination. These simulated numerical results validate that AEAMLF achieves a balanced optimization across both networking and machine learning performance metrics, making it highly suitable for dynamic, resource-constrained IoT environments. Figure 2 describes the network life time rounds comparison, figure 3 explains about the control overheads comparison, figure 4 defines the energy consumption comparison, and figure 5 illustrates the latency, throughput, accuracy comparison.

The experimental results demonstrate that AEAMLF provides a balanced trade-off between energy efficiency and intelligent decision-making. Unlike purely energy-centric models such as LEACH or purely accuracy-driven models such as DNN, the proposed framework integrates adaptive learning, energy awareness, and dynamic environment responsiveness. The findings confirm that combining reinforcement learning with energy-aware optimization significantly enhances IoT system sustainability while maintaining high predictive accuracy and throughput. Overall, AEAMLF outperforms conventional algorithms across most evaluation metrics, making it suitable for next-generation dynamic IoT environments requiring intelligent, scalable, and energy-efficient operation.

5. Conclusion and Future Enhancement

This paper presented an Adaptive Energy-Aware Machine Learning Framework (AEAMLF) designed for dynamic and resource-constrained IoT environments. The proposed model integrates adaptive learning, reinforcement-based optimization, and energy-aware task scheduling at the edge layer to enhance system sustainability and intelligence simultaneously. Unlike traditional protocols such as LEACH, which primarily focus on clustering efficiency, or purely learning-driven models such as Deep Neural Network, which emphasize predictive accuracy at the expense of energy, AEAMLF provides a balanced optimization framework. The comparative analysis demonstrated that the proposed approach significantly improves network lifetime, reduces energy consumption, lowers latency, increases throughput, enhances prediction accuracy, and minimizes control overhead. By combining adaptive reinforcement mechanisms similar to Q-Learning with intelligent workload distribution, the framework ensures real-time responsiveness and efficient resource utilization in dynamic IoT scenarios. The integration of energy-aware scheduling and adaptive model scaling makes AEAMLF particularly suitable for smart cities, industrial IoT, and healthcare monitoring systems.

However, several limitations remain. First, the current evaluation is based on simulated environments, which may not fully capture real-world uncertainties such as hardware failures, communication interference, or unpredictable environmental changes. Second, reinforcement-based adaptation introduces computational complexity that could be challenging for ultra-low-power sensor nodes. Third, scalability in extremely large heterogeneous IoT deployments requires further validation. Finally, security aspects such as adversarial attacks and data poisoning were not deeply addressed in this study.

Future research can extend this framework by integrating federated learning for privacy preservation, lightweight deep reinforcement learning for faster convergence, and blockchain-based trust management for secure IoT communication. Real-world prototype implementation on edge devices would provide deeper validation. Additionally, incorporating explainable AI mechanisms could improve transparency in decision-making processes. Overall, AEAMLF establishes a strong foundation for next-generation energy-efficient intelligent IoT systems, paving the way toward scalable, adaptive, and sustainable edge intelligence architectures.

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