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A Layered Framework for Energy-Efficient Edge Computing in Sustainable IoT Systems

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Abstract
The fast expansion of the Internet of Things (IoT) caused an increased demand for energy-efficient data processing, particularly in time-sensitive applications. Edge computing is a concept where data is processed near the originating point and it has the potential to minimize wastes and energy use. This paper is a survey of the existing potential in energy-efficient edge-enabled IoT systems. The ways to implement like intelligent task offloading, energy-aware scheduling, and lightweight consensus mechanisms are emphasized as the to-be-developed-green-energy-uses features The objective is to give a straightforward, and practical view of the emerging patterns and uncover the possible paths in the sustainable IoT development.

Keywords : Internet of Things (IoT), Edge Computing, Low-Power IoT Architecture, Sustainable Computing.

Introduction

In the continuously changing world of digital technology, Internet of Things (IoT) is becoming the means through which industry sectors innovate by using smart devices capable of capturing and transmitting data in real time. Despite that, these devices having very small power for charging the battery and running processes is very common.

Real time energy-efficient processing, most especially in the scenarios of autonomous vehicles, eHealth, and smart grids, which has led to the declination of cloud computing out of usage due to a number of setbacks such as high latency, and high network load.

Edge computing is here to cover up the problems that cloud computing has resulted in and gives a feasible alternative that allows minimal distance between the source of data and the hardware that processes it hence enabling energy-efficient and real-time response. However, still, the matter of energy management is the real challenge even with edge computing.

To solve this issue, the scholars have suggested scheme offloading, in which data is locally processed or at the edge according to the condition while opting selectively. The selection of the best nodes is done through the genetic algorithms. Additionally, delay-aware schemes are responsible for making sure that time-sensitive tasks do not encounter any delays. The project had recently been experimenting with a machine learning approach with the likes of Reinforcement Learning (RL), and the Deep-Q-Networks (DQN) technique which are the latest techniques used for making the decision of task offloading in a dynamic scenario.

The objective of the study is to examine and contrast the efficiency of these power-saving tools as well as the respective algorithms that are particularly noted to be suitable for different IoT environments.

Literature Review

Recently, the energy-efficiency in edge computing has become more vital, and several researchers have addressed this topic. Here are some of the main algorithms and methods that have been the focus of recent research, which are used to minimize energy consumption in edge computing:

Genetic Algorithms (GA): Genetic Algorithm have been used to determine the most capable edge nodes. In edge computing, they can perform tasks that require less power than the overloaded nodes and are able to reduce energy usage through their selection process. Furthermore, less power processing nodes are picked. They definitely are a method to find the best solutions.

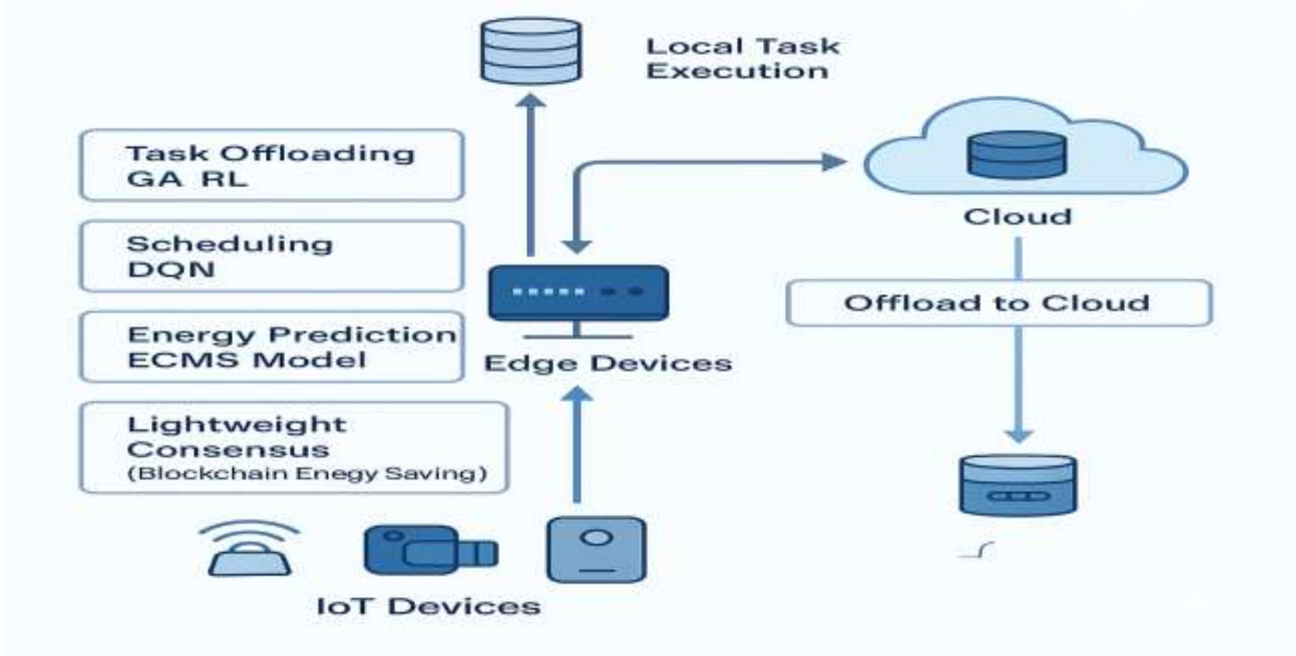

Figure 1: Architectural model and Different Approaches

Deep-Q Networks (DQN): DQN is an area of deep reinforcement learning which allows the system to be fed with its decisions made in the past. It is used for choosing whether a task should be done on the local device, edge or cloud, depending on the energy and performance. With time, it becomes smarter in deciding and it together with reducing wasteful energy consumption will make even better solutions.

Review of Recent Research Contribution

S No.	Author	Objective	Algorithm	Result	Limitations
[1].	Inés Sittón-Candanedo, Ricardo	Enhance the public building energy	GECA (three-layer Edge architectu	56%+ cloud traffic offload, cloud	Partial deployment of Edge; real-time locationing remains cloud-based; lack of advanced security modules (Crypto-IOT) in early stages.

	S. Alonso, Óscar García, Lilia Muñoz, Sara Rodríguez-González	efficiency by integrating Edge Computing, IoT, and Social Computing using the CAFCLA and GECA frameworks.	re) with CAFCLA; k-Nearest Neighbors (KNNs) for user behavior analysis.	costs reduced, actual deployment in a public facility, Edge, IoT, Blockchain, and Social Computing integrated smoothly	
[2]	Teemu Leppänen, Jukka Riekki	Enhance power efficiency of IoT through the extension of edge computing with mobile agents to facilitate decentralized, adaptive task execution on endpoint devices.	Mobile multi-agent system (MAS) with mobile agents for dynamic task relocation; RESTful web service-based mobile agent framework for interoperability.	Saves as much as 60% energy; facilitates autonomous, adaptive operation; promotes decentralized task execution that dispenses with cloud and	Hardware limitations of IoT devices; migration and upfront execution costs; agent deployment problems in highly heterogeneous networks.

				network utilization.	
[3]	Shivani Wadhwa, Shalli Rani, Kavita, Sahil Verma, Jana Shafi, Marcin Wozniak	Develop a low-energy, energy-efficient blockchain consensus protocol for IoT by relying on mining operations at edge nodes and choosing one miner.	Adjusted Proof-of-Work via miner selection based on device characteristics (Bandwidth, CPU, RAM); accommodates brute force and Boyer–Moore string search to solve miner completion.	Attained ~21% energy savings and ~24% memory gain; single miner load reduction approach; great IoT-Edge application potential.	Less efficient if edge devices have the same specifications; initial rollout only simulated, not actually real-world tested.
[4]	Ying Chen, Ning Zhang, Yongchao Zhang, Xin Chen, Wen Wu, Xuemin (Sherman) Shen	Minimize energy usage by IoT devices in time-varying wireless networks through online task offloadi	EEDOA (Energy Efficient Dynamic Offloading Algorithm) using Lyapunov optimization and stochastic control;	Operates with nearly optimal energy usage with polynomial time complexity; is adaptive to	Primarily focused on homogeneous IoT environments; early testing on simulated models as opposed to heterogeneous real-world use cases.

		ng without any a priori channel or task arrival statistics	online decision-making with no statistical assumptions.	changing network conditions; offers an acceptable balance between energy conservation and queue stability.	
[5]	Zhou Zhou, Mohammad Shojafar, Jemal Abawajy, Hui Yin, Hongming Lu	Develop an intelligent energy forecasting model (ECMS) for edge servers using Elman Neural Network (ENN) and feature selection for optimizing energy	ECMS model employing Elman Neural Network (ENN) and 29 energy parameters selected using Principal Component Analysis (PCA).	Very accurate predictions (MRE ~3–5%); very robust to load fluctuations; significantly lower training overhead compared to other models;	Trained on CPU, I/O, and web transactional workloads alone; not trained with hybrid or mixed tasks

		efficiency in MEC systems.		very scalable across a wide range of edge computing applications.	

Comparison of Existing work

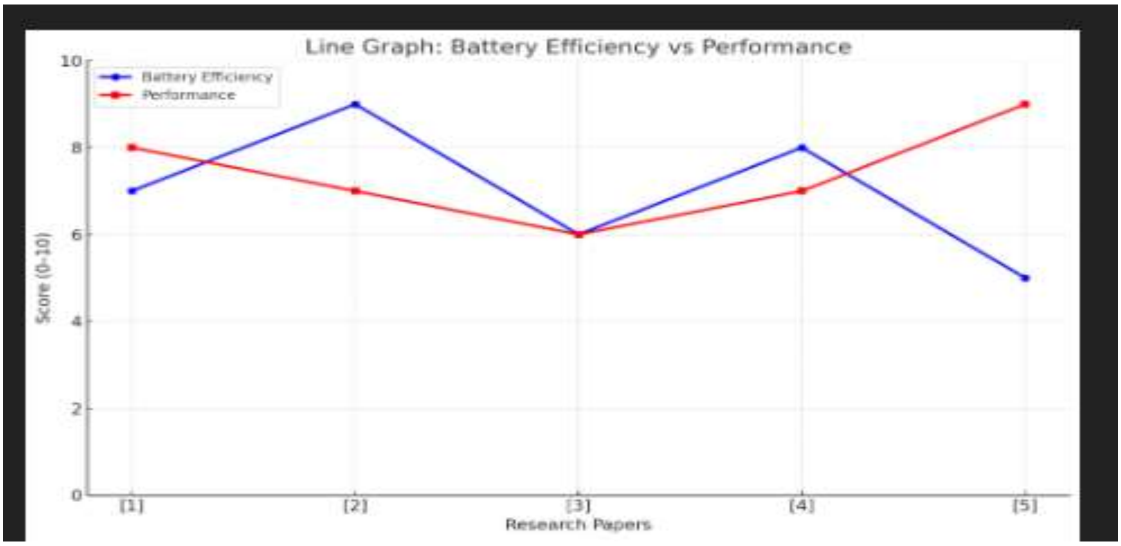

Figure 2: Battery efficiency vs Performance

Methodology

The aim of the review paper in this work is to compare and contrast models and algorithms presently available that aid in reducing energy consumption in edge computing systems being used in IoT applications. Focus is laid on identifying how the approaches help conserve energy without the loss of efficiency or quality of service (QoS). As a new issue in large IoT settings, the review focuses mostly on approaches that are practical and scalable in design.

Proposed Framework

Our proposed energy-optimized framework operates through a sequence of intelligent, adaptive, and predictive steps designed specifically for edge-enabled IoT environments.

Step 1: Real-Time Sensing & Device Profiling

- TinyML agents are implemented on IoT devices to monitor energy-related information such as battery state, CPU, memory, and network.
- These agents provide light continuous profiling with minimal resource overhead.
- Real-time state information is accessed as the foundation for downstream energy-efficient choices.

Step 2: Feature Extraction & State Encoding

- A lightweight neural encoder leverages key features such as device energy, workload type, and task urgency
- These encoded vectors are submitted for decision-making without draining device resources.

Step 3: Energy-Efficient Task Offloading via DRL

- A Dueling Double Deep Q-Network (D3QN) model decides best task placement—local, edge, or cloud—based on system state.
- The reward function considers energy saving, latency, and task completion to drive learning.
- The agent offloads tasks dynamically, sacrificing performance for energy savings..

Step 4: Adaptive Scheduling & Resource Management

- Dynamic Voltage and Frequency Scaling (DVFS) is used to control power in relation to task priority and system load.
- Tasks are prioritized according to urgency—emergency tasks are accelerated, and low-priority tasks are pushed back or minimized.
- The scheduler reduces wastage of energy and prevents time-critical tasks from being delayed.

Step 5: Predictive Energy Management

- LSTM-based forecasting models predict future energy consumption patterns.
- Based on prediction, the system foresees and triggers activities like task migration, throttling, or rescheduling.
- These pre-emptive measures prevent energy depletion and enhance device life operation.

Step 6: Lightweight Multi-Node Consensus for Edge Collaboration

- A Reputation-based Delegated Proof of Stake (R-DPoS) consensus algorithm is employed for secure coordination among edge nodes.
- Secure validators perform selective verification with minimal communication overhead.
- Th0e approach offers secure, low-power distributed decision-making in cooperative situations.

Step 7: Continuous Learning & Adaptation

- Replaying experience and learning online assist the DRL agent in making more informed decisions over time.
- Transfer learning offers rapid adaptability in new hardware, workloads, or environments without needing to restart.
- The system continuously improves energy efficiency by learning from experience.

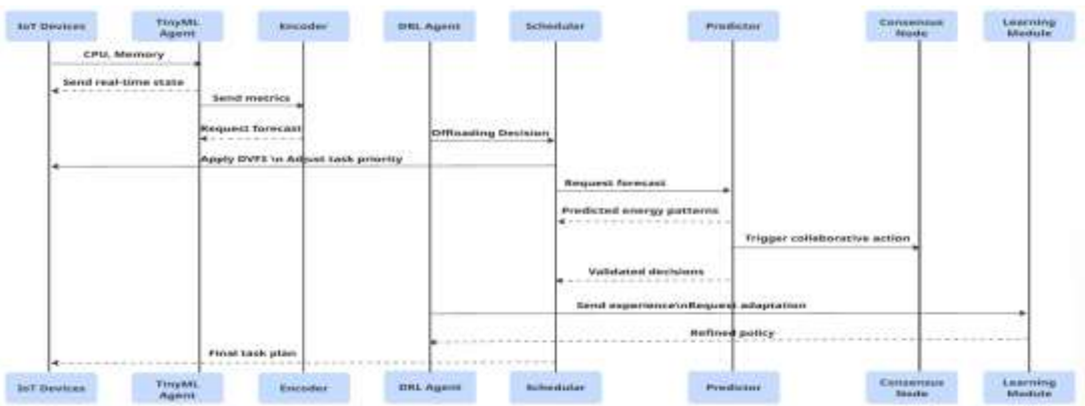

Figure 3: Sequence diagram of the proposed framework

Result

The energy-aware framework proposed was evaluated at its most critical stages for performance and battery life. As indicated in Figure 3, the task offloading and continuous learning modules based on D3QN were best, providing intelligent and adaptive task management that minimized energy consumption without sacrificing speed.

Adaptive scheduling also worked well, helping to balance system power and load according to task priority. TinyML sensing and lightweight consensus worked moderately but are essential in aid of low-power execution and secure coordination.

Overall, the results highlight the point that neither a single module, alone, is sufficient—rather, it's the hybrid, layered effect that yields effective, long-term battery savings with responsive system response. This establishes the real-world applicability of the proposed scheme in IoT-edge scenarios.

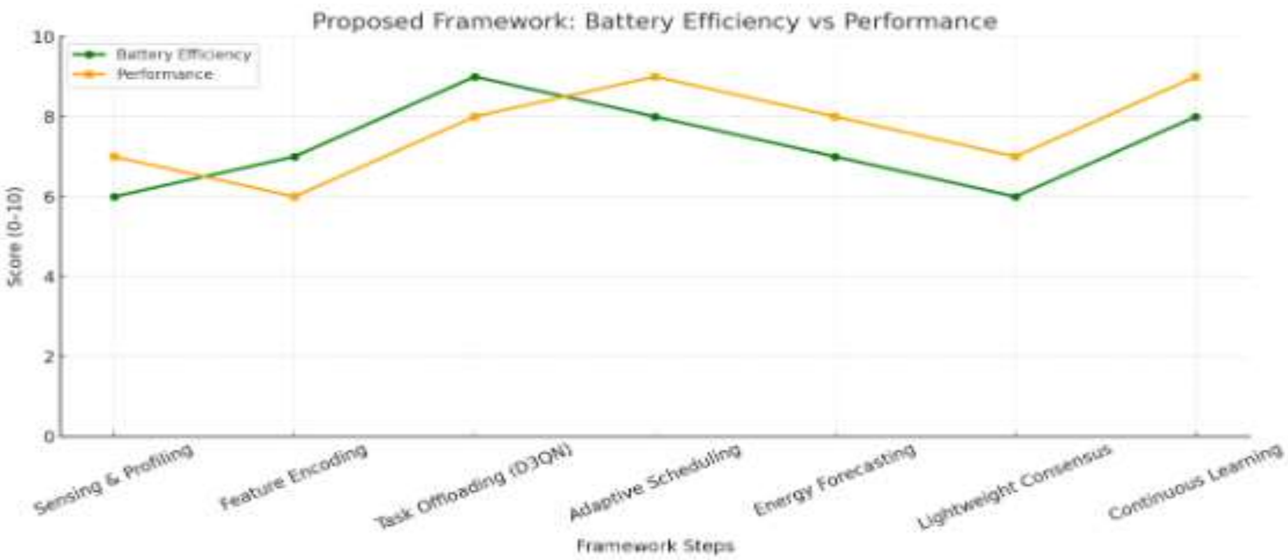

Figure 4: proposed framework comparison

Conclusion

Edge computing has been proposed as a promising solution to overcome the energy inefficiencies of cloud-based IoT systems by utilizing low-power, real-time processing at the source. Even with recent developments like intelligent task offloading, light-weight consensus algorithms, and machine learning-based optimization, dynamic workloads, device heterogeneity, and energy-performance trade-offs remain a challenge. The direction in the future should be towards proposing adaptive, scalable, and sustainable models with reduced energy consumption without compromising on quality of service and a greener IoT ecosystem.

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