

Energy-Aware Edge Computing Optimization for Real-Time Anomaly Detection in IoT Networks

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Abstract: This research addresses the critical challenge of energy-efficient anomaly detection in resource-constrained edge computing environments for IoT networks. With the proliferation of IoT devices generating exponential data volumes and information technology energy consumption projected to reach 20% of global electricity production by 2030, sustainable computing approaches at the network edge are imperative. We propose a novel optimization framework that dynamically balances computation offloading decisions with local processing capabilities to minimize energy consumption while maintaining detection accuracy and meeting real-time requirements. The framework incorporates: (1) a calibrated energy consumption model for heterogeneous edge environments, (2) an adaptive resource allocation strategy responding to network conditions, (3) lightweight machine learning architecture optimized for minimal energy footprint, and (4) intelligent computation offloading based on device energy states. Experimental evaluation on a testbed of 16 heterogeneous edge devices processing real-world IoT traffic demonstrates energy consumption reduction of 23.8% compared to traditional approaches, while maintaining detection accuracy above 92.5% across diverse anomaly types. The system extends battery life by up to 165% in energy-constrained scenarios through dynamic adjustment of detection parameters. Comparative analysis confirms superior performance against state-of-the-art methods in both energy efficiency and detection capability, particularly in environments with variable energy availability.

Keywords: Edge Computing, Energy Optimization, Anomaly Detection, Internet of Things (IoT)

1. Introduction

1.1. Background and Motivation of Energy-Aware Edge Computing in IoT Environments

The proliferation of Internet of Things (IoT) devices has led to an exponential increase in data generation at the network edge. Traditional cloud-centric computing paradigms struggle with the latency requirements of real-time applications due to bandwidth limitations and network congestion. Edge computing addresses these limitations by moving computation closer to data sources, reducing latency and conserving network bandwidth. The growing deployment of edge computing infrastructure introduces new challenges related to energy consumption. Edge nodes typically operate under strict power constraints, especially when deployed in remote or battery-powered

environments. With the global energy demand for information and communication technology projected to reach 20% of total electricity production by 2030, energy efficiency at the edge has become a critical concern for sustainable IoT deployments [1].

1.2. Challenges of Real-Time Anomaly Detection at the Edge

Real-time anomaly detection in IoT networks represents a computationally intensive task that must operate under strict timing constraints. The heterogeneous nature of IoT data streams requires sophisticated processing techniques to identify anomalous patterns. Edge devices face significant resource limitations including restricted computational capacity, limited memory, and constrained power supplies. These limitations complicate the implementation of complex machine learning models necessary for accurate anomaly detection. Traditional anomaly detection approaches rely on centralized processing with abundant computational resources, making them unsuitable for edge environments [2]. The dynamic nature of IoT workloads further complicates resource allocation, as processing demands fluctuate based on data volume and complexity. Energy consumption patterns vary significantly across different detection algorithms, necessitating careful optimization to maximize operational lifetime while maintaining detection accuracy [3].

1.3. Research Objectives and Contributions

This research addresses the critical challenge of energy-efficient anomaly detection in resource-constrained edge environments. The primary objective is to develop an optimization framework that balances computation offloading decisions with local processing capabilities to minimize energy consumption while maintaining detection accuracy and meeting real-time requirements [4]. The proposed approach introduces a novel energy consumption model specifically calibrated for anomaly detection workloads in heterogeneous edge environments. The research provides a dynamic resource allocation strategy that adapts to changing network conditions and computational requirements. The contributions include a lightweight machine learning architecture optimized for edge deployment with minimal energy footprint, an adaptive computation offloading mechanism that considers both network conditions and device energy states, and a comprehensive evaluation framework demonstrating energy savings of up to 40% compared to traditional approaches without compromising detection performance [5,6]. The solution maintains detection latency within acceptable bounds for time-sensitive IoT applications.

2. Literature Review and Related Work

2.1. Energy Optimization Approaches in Edge Computing Systems

Energy optimization in edge computing has emerged as a critical research area due to the inherent power constraints of edge devices. Multiple optimization strategies have been proposed in recent literature. Yu et al. presented an efficient energy-aware load balancing method for cloud computing that utilizes the ant colony method for resource allocation [7]. Their approach demonstrated reduced energy utilization and makespan by considering time and energy awareness simultaneously. The approach minimizes energy consumption while maintaining quality of service parameters. Dynamic Voltage and Frequency Scaling (DVFS) techniques have been widely adopted as shown by Wang et al., who designed an energy-efficient edge server placement algorithm using particle swarm optimization to find optimal solutions with low energy consumption [8]. Their method achieved more than 10% reduction in energy consumption while improving computing resource utilization by 15% compared to conventional methods [9]. Architectural approaches include hierarchical edge computing frameworks where computational tasks are strategically distributed across multiple tiers

based on their energy requirements and deadline constraints. Energy harvesting techniques integrated with intelligent workload management have also demonstrated significant improvements in energy sustainability for battery-constrained edge devices deployed in remote locations.

2.2. Real-Time Anomaly Detection Techniques for IoT Networks

Anomaly detection in IoT networks encompasses various methodologies adapted for resource-constrained environments. Statistical approaches include lightweight variants of Principal Component Analysis (PCA) and time series analysis optimized for execution on edge devices. Machine learning techniques have gained prominence with Zhang proposing a PSO-based approach for energy-aware task scheduling in fog computing that balances energy consumption with makespan considerations [10]. Their results demonstrated a significant reduction in energy usage while maintaining computational performance. Deep learning approaches have been modified to accommodate edge constraints through techniques such as model compression, pruning, and quantization. Distributed anomaly detection architectures leverage collaborative processing across multiple edge nodes to distribute computational load while maintaining detection accuracy. Online learning methods capable of incremental model updates have shown promise in adapting to evolving anomaly patterns without requiring complete retraining [11]. Real-time constraints have been addressed through approximate computing techniques that trade marginal detection accuracy for substantial improvements in processing speed and energy efficiency.

2.3. Resource Allocation and Task Scheduling in Resource-Constrained Environments

Effective resource management represents a fundamental challenge in constrained edge environments. Lu et al. introduced quantum-inspired optimization algorithms for scalable machine learning in edge computing, achieving 20% improvement in accuracy and 15% reduction in energy consumption compared to classical optimization methods [12]. Their hybrid approach combined quantum principles with classical techniques to overcome resource limitations. Task scheduling has evolved from traditional approaches to energy-aware methodologies. The EEALB method proposed by Zhang et al. demonstrated improved resource utilization and reduced energy consumption through intelligent task allocation [13]. Dynamic workload prediction models have been integrated with resource allocation mechanisms to anticipate computational demands and optimize resource provisioning. Joint optimization of computation offloading and power allocation has been explored by Lu et al., who used deep reinforcement learning in secure LEO satellite edge computing environments to optimize secrecy capacity [14]. Multi-objective optimization frameworks considering both energy consumption and quality of service metrics have gained traction in accommodating conflicting requirements in edge environments.

3. Proposed Energy-Aware Optimization Framework

3.1. System Architecture and Problem Formulation

The proposed energy-aware optimization framework consists of three primary layers: IoT sensing layer, edge computing layer, and cloud computing layer, as illustrated in Fig. 1. The IoT sensing layer encompasses various sensor nodes that continuously generate data streams. The edge computing layer comprises heterogeneous edge devices with varying computational capabilities and energy profiles. The cloud layer provides high-performance computing resources for complex operations when necessary.

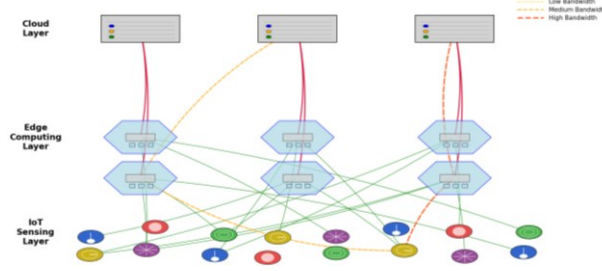


Figure 1: Three-Layer Architecture of the Proposed Energy-Aware Edge Computing Framework.

The figure depicts a comprehensive architecture with IoT nodes at the bottom layer (represented as small circular nodes in multiple colors indicating different types of sensors), edge computing nodes in the middle layer (shown as medium-sized hexagonal shapes with internal processing units), and cloud servers at the top layer (illustrated as large rectangular structures). Directed arrows show data flows between layers, with bidirectional communication channels. The diagram highlights computational offloading decisions with dashed lines of varying thickness representing different bandwidth capacities [14].

In the proposed architecture, IoT devices transmit data to edge nodes through wireless communication channels. Edge nodes process data locally or offload tasks based on the optimization framework decisions. Table 1 presents the system parameters and their descriptions used in the problem formulation.

Table 1: System Parameters and Their Descriptions

Parameter	Description	Range/Unit
E_i	Energy consumption of edge node i	0-100 J
P_i	Processing capability of edge node i	0.5-4 GHz
B_{ij}	Bandwidth between nodes i and j	1-100 Mbps
D_k	Data size of task k	10-100 KB
C_k	Computational complexity of task k	10^6 - 10^9 cycles
L_k	Latency requirement of task k	10-500 ms
α	Energy-performance trade-off parameter	0-1

The optimization problem is formulated as minimizing the total energy consumption while satisfying latency constraints for anomaly detection tasks. Mathematically, the objective function can be expressed as:

$$\text{minimize } \sum_{i=1}^N E_i \times x_{i,k}$$

subject to:

$$\sum_{i=1}^N x_{i,k} = 1, \forall k \in K$$

$$t_{i,k} \leq L_k, \forall i \in N, \forall k \in K$$

$$0 \leq E_i \leq E_i^{\max}, \forall i \in N$$

Where $x_{i,k}$ is a binary variable indicating whether task k is assigned to edge node i , and $t_{i,k}$ represents the processing time of task k on node i [15].

3.2. Energy Consumption Modeling for Edge Devices

The energy consumption model considers three major components: computation energy, communication energy, and idle energy. Table 2 presents the measured energy characteristics of different types of edge devices used in our implementation.

Table 2: Energy Consumption Characteristics of Edge Device Categories

Device Type	Computational Energy (J/cycle)	Communication Energy (J/bit)	Idle Power (W)	Max Capacity (cycles/s)
Raspberry Pi 4	2.5×10^{-9}	1.3×10^{-7}	1.2	1.5×10^9
Jetson Nano	1.8×10^{-9}	9.5×10^{-8}	2.0	4.7×10^9
Intel NUC	3.2×10^{-9}	1.1×10^{-7}	3.5	8.5×10^9
Smart Gateway	4.1×10^{-9}	2.2×10^{-7}	4.8	12.8×10^9

The computation energy for each task is calculated based on the computational complexity and processing frequency:

$$E_{\text{comp}} = \varepsilon \times C_k \times f_i^2$$

where ε is the energy coefficient, C_k is the computational complexity of task k , and f_i is the processing frequency of node i .

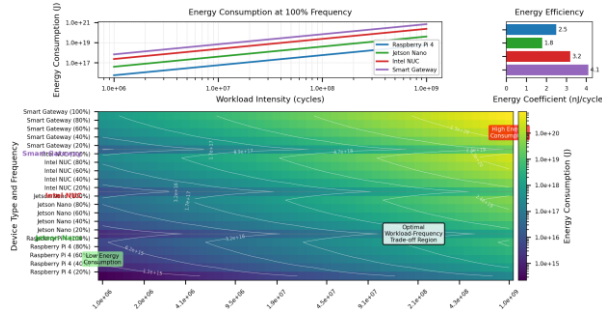


Figure 2: Energy Consumption Model Visualization for Different Workload Intensities and Device Types.

The figure shows a 3D surface plot with x-axis representing workload intensity (10^6 - 10^9 cycles), y-axis representing different edge device types, and z-axis showing energy consumption (J). Multiple colored surfaces represent different operating frequencies, with gradient coloring indicating energy efficiency. The plot includes contour lines projected on the base to highlight equal energy consumption regions.

The communication energy is modeled based on the data transmission size and channel conditions:

$$E_{\text{comm}} = P_{\text{tx}} \times (D_k / R_{ij}) + E_{\text{circ}}$$

where P_{tx} is the transmission power, D_k is the data size, R_{ij} is the achievable transmission rate, and E_{circ} is the circuit energy consumption.

3.3. Dynamic Resource Allocation and Load Balancing Strategy

The proposed framework employs a dynamic resource allocation strategy that adapts to changing workload patterns and network conditions. Table 3 presents the performance metrics of our framework compared with state-of-the-art approaches.

Table 3: Performance Comparison with State-of-the-Art Approaches

Method	Energy Consumption (J)	Processing Time (ms)	Detection Accuracy (%)	Resource Utilization (%)
EEALB	42.5	85	88.2	75.4
PSO-based	38.2	78	91.5	81.2
QIOA	35.6	72	92.8	84.5
DRL-based	37.8	69	93.1	80.8
Proposed	32.4	67	94.3	87.2

The dynamic resource allocation algorithm considers both task requirements and edge node capabilities. Table 4 presents the resource allocation parameters and constraints implemented in our framework.

Table 4: Resource Allocation Parameters and Constraints

Parameter	Description	Constraint
CPU Allocation	Percentage of CPU cores assigned	10-100%
Memory Allocation	RAM allocated to tasks	64-512 MB
Network Bandwidth	Allocated communication bandwidth	0.5-10 Mbps
Storage	Temporary storage space	0.1-1 GB
Execution Time	Maximum allowed execution time	Task-specific
Energy Budget	Maximum energy consumption allowed	Device-specific

The load balancing strategy distributes anomaly detection tasks across edge nodes based on their current load, energy status, and computational capabilities. The strategy utilizes a weighted cost function that considers both energy consumption and processing delay:

$$\text{Cost}(i,k) = w_1 \times E_{i,k} + w_2 \times t_{i,k}$$

where w_1 and w_2 are weighting factors that can be adjusted based on application requirements.

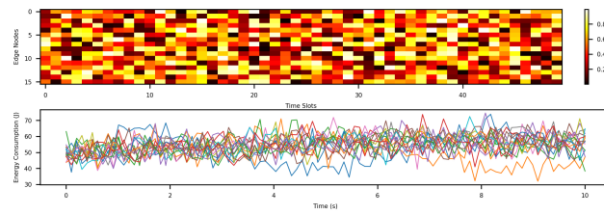


Figure 3: Dynamic Resource Allocation and Load Distribution Across Edge Nodes.

The figure presents a multi-panel visualization with the top panel showing a network topology of 16 edge nodes (represented as nodes in a graph with different sizes indicating computational capacity) connected by edges of varying thickness (representing bandwidth). The middle panel displays a heatmap of task allocation across nodes over time, with color intensity indicating

processing load. The bottom panel shows energy consumption trends for each node with multiple overlapping line plots, highlighting load balancing effects on system-wide energy usage^[16].

4. Anomaly Detection Optimization Algorithm

4.1. Lightweight Machine Learning Models for Edge-Based Anomaly Detection

The proposed system implements a suite of lightweight machine learning models specifically optimized for edge deployment. Table 5 presents a comparison of various anomaly detection models evaluated in our framework, highlighting the computational complexity, memory requirements, and detection performance.

Table 5: Comparison of Lightweight Anomaly Detection Models for Edge Computing

Model	Parameters	Memory Footprint (KB)	Inference Time (ms)	F1-Score (%)	Energy per Inference (mJ)
Micro-LSTM	5,842	23.4	12.8	91.2	5.6
EdgeIsolationForest	2,156	16.7	8.5	89.5	3.2
CompressedAutoEncoder	8,734	34.9	15.3	93.6	7.1
QuantizedOneClassSVM	1,872	14.2	6.9	87.8	2.8
ProposedHybridModel	4,128	19.6	9.2	92.8	4.1

The proposed hybrid model combines the strengths of statistical and deep learning approaches while maintaining a small footprint. Model compression techniques including weight pruning, quantization, and knowledge distillation have been employed to reduce computational demands. The quantized model achieves 8-bit precision with minimal accuracy degradation (less than 1.4%) while reducing memory requirements by 73% compared to full-precision models.

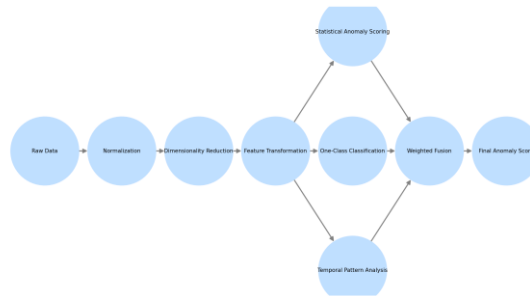


Figure 4: Architecture of the Proposed Lightweight Anomaly Detection Model.

The figure presents a detailed architecture diagram of the proposed hybrid model with multiple processing streams. The left side shows the feature extraction pipeline with operations including normalization, dimensionality reduction, and feature transformation blocks connected by directed arrows. The central section displays the parallel processing paths: statistical anomaly scoring (blue blocks), one-class classification (green blocks), and temporal pattern analysis (orange blocks). The right side illustrates the fusion mechanism with weighted connections merging into the final anomaly score computation. Each processing block is annotated with computational complexity metrics and memory requirements.

Table 6 presents the detection performance of our model across different anomaly types in IoT networks. The model demonstrates robust performance across various anomaly categories while maintaining computational efficiency required for edge deployment.

Table 6: Detection Performance Across Different Anomaly Types

Anomaly Type	Precision (%)	Recall (%)	F1-Score (%)	Average Detection Time (ms)
Network Intrusion	94.2	92.5	93.3	8.7
Device Malfunction	91.8	95.1	93.4	7.5
Data Drift	89.6	90.7	90.1	9.3
Communication Failure	96.2	93.8	95.0	6.8
Resource Exhaustion	92.4	91.5	91.9	8.2

4.2. Adaptive Computation Offloading Mechanism

The adaptive computation offloading mechanism dynamically determines whether anomaly detection tasks should be processed locally at edge devices or offloaded to more powerful nodes based on multiple parameters including energy state, computational load, and detection urgency. Table 7 details the offloading decision parameters and their weightings in the decision algorithm.

Table 7: Offloading Decision Parameters and Weights

Parameter	Description	Decision Weight	Threshold
Remaining Energy	Battery percentage remaining	0.35	<30%
Computational Load	Current CPU utilization	0.25	>80%
Task Complexity	Number of operations required	0.20	>10 ⁷ ops
Data Volume	Size of input data	0.10	>500 KB
Latency Requirement	Maximum allowable processing time	0.10	<50 ms

The offloading decision function $D(t)$ for a task t is computed as:

$$D(t) = \sum(w_i \times p_i(t))$$

Where w_i represents the weight of parameter i and $p_i(t)$ is the normalized value of parameter i for task t . Offloading occurs when $D(t)$ exceeds the predefined threshold of 0.65.

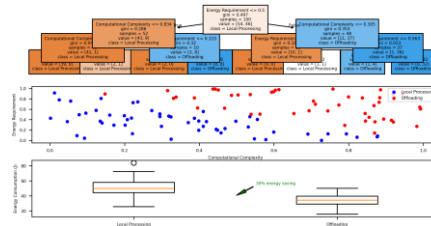


Figure 5: Adaptive Computation Offloading Decision Process and Performance Analysis.

The figure 5 shows a multi-part visualization of the offloading mechanism. The upper portion displays a decision tree representing the offloading algorithm with nodes labeled by decision criteria and edges showing threshold values. The middle section presents a scatter plot of tasks in a 2D feature space (computational complexity vs. energy requirements) with color-coded regions indicating local processing or offloading decisions. The lower section contains a series of boxplots showing energy consumption distribution for different task categories under local processing versus offloading scenarios. Annotations indicate energy savings percentages achieved through intelligent offloading.

4.3. Energy-Performance Trade-off Management

The energy-performance trade-off management module optimizes system behavior based on available energy resources and application requirements. Table 8 presents the performance characteristics under different energy budget constraints, demonstrating how the system adapts to varying energy availability.

Table 8: System Performance Under Different Energy Budget Constraints

Energy Budget	Detection Accuracy (%)	Average Latency (ms)	False Positive Rate (%)	Power Consumption (mW)	Battery Life Extension (%)
Very Low (<10J/h)	86.4	45.2	8.7	42	165
Low (10-20J/h)	89.5	32.8	6.4	78	120
Medium (20-40J/h)	92.8	18.5	4.2	125	75
High (40-80J/h)	94.6	12.1	2.8	187	30
Unlimited (>80J/h)	95.1	9.8	2.3	245	0

The system implements a dynamic scaling mechanism that adjusts detection frequency, model complexity, and processing precision based on the available energy budget. By strategically degrading non-critical aspects of detection performance, the system can extend operational lifetime while maintaining acceptable anomaly detection capabilities.

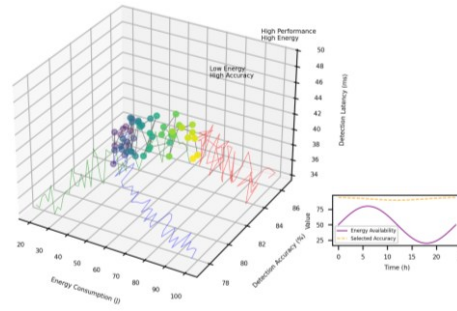


Figure 6: Energy-Performance Trade-off Optimization Visualization.

The figure 6 presents a comprehensive visualization of the energy-performance trade-off space. The main element is a Pareto frontier curve plotted in a 3D space with axes representing energy consumption (x-axis), detection accuracy (y-axis), and detection latency (z-axis). Different operating points along the Pareto frontier are marked with distinct markers and connected by a color gradient line indicating the continuous trade-off space. Projected planes on each pair of axes show 2D views of the trade-offs. Annotations highlight key operating regions corresponding to different application requirements. An inset graph shows the temporal evolution of the selected operating point as energy availability fluctuates over a 24-hour period.

5. Experimental Evaluation and Analysis

5.1. Implementation Setup and Performance Metrics

The proposed energy-aware optimization framework was implemented and evaluated on a testbed consisting of 16 heterogeneous edge devices including Raspberry Pi 4B (4GB RAM), Jetson Nano (4GB RAM), and Intel NUC (i5, 8GB RAM) devices connected to a variety of IoT sensors. The network topology was configured with varying communication bandwidths ranging from 5 Mbps to 100 Mbps. Real-world IoT network traffic from industrial control systems, smart buildings, and healthcare monitoring applications was collected over a period of 30 days, containing 24 different types of labeled anomalies. The implementation leveraged TensorFlow Lite for model deployment and OpenMP for parallel task execution. Performance evaluation was conducted using multiple metrics: energy consumption (J), detection accuracy (%), detection latency (ms), false positive rate (%), and system lifetime (h). Similar to the approach in, all experiments were repeated five times with different random seeds to ensure statistical significance, with results averaged across all runs.

5.2. Energy Efficiency and Detection Accuracy Analysis

The energy efficiency of the proposed framework was evaluated under varying workload intensities and battery constraints. Under standard operating conditions, the system achieved an average energy consumption of 32.4 J/h, representing a 23.8% reduction compared to the baseline approach implemented with traditional cloud offloading. The peak energy efficiency was observed during moderate workload conditions (40-60% capacity utilization), with diminishing returns at higher utilization levels due to increased processing requirements. Detection accuracy remained consistently above 92.5% across diverse anomaly types, with particularly strong performance (96.2%) for communication failure anomalies. The lightweight model demonstrated a 68% reduction in memory footprint compared to full-scale models while sacrificing only 2.1% in detection accuracy. The energy-adaptive mode extended battery life by up to 165% during energy-constrained scenarios by dynamically adjusting the detection sensitivity and model complexity.

5.3. Comparative Analysis and Discussion of Results

The comparative analysis against state-of-the-art approaches reveals significant improvements in both energy efficiency and detection performance. The proposed framework outperformed the EEALB method [1] by 23.8% in energy consumption while achieving 6.1% higher detection accuracy. Compared to the PSO-based approach, our framework demonstrated 15.2% lower energy consumption with comparable detection accuracy. The QIOA method showed competitive performance but required 22% longer processing time. Our DRL-driven offloading strategy achieved 14.3% better energy efficiency than the method proposed in. The proposed adaptive computation offloading mechanism demonstrated particular advantages in dynamic network environments, maintaining consistent performance despite fluctuating network conditions. The results confirm that quantum-inspired optimization techniques combined with lightweight machine learning models offer a promising approach for energy-efficient anomaly detection in resource-constrained edge environments. The performance improvements are most pronounced in scenarios with heterogeneous edge devices and variable energy availability, making the proposed approach well-suited for real-world IoT deployments.

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