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

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Abstract: The proliferation of Internet of Things (IoT) installations has resulted in an increased number of sensing, communication, storage, and computation operations performed by devices with limited resources. A typical cloud-centric approach results in unnecessary communication overhead, latency, and additional energy expenditure to transport large volumes of raw sensor data to remote datacenters. The proposed design uses adaptive sampling, data aggregation, compression, a workload-aware offloading mechanism, dynamic voltage/frequency scaling where available, and container consolidation and renewable-energy awareness, and carbon-aware workload placement, all of which are aligned with the direction of current Multi-access Edge Computing (MEC) standardization, and are now considering energy management, power information, and application-specific energy policies as first-class concerns.

Keywords: Edge Computing; Sustainable Internet of Things; Energy Efficiency; Multi-access Edge Computing; Green Computing; Dynamic Offloading; Resource Orchestration; Energy Harvesting; Carbon-Aware Computing; IoT Optimization.

I. INTRODUCTION

The Internet of Things connects sensing, actuation, communication, and computation across smart homes, healthcare, agriculture, transportation, manufacturing, and cities. As IoT deployments scale, the energy[8] consumed by sensing and wireless transmission becomes a system-level concern, particularly for battery-powered devices and remotely deployed nodes. Recent reviews identify data transmission as a major contributor to IoT energy use and discuss aggregation, compression, duty cycling, low-power hardware, energy harvesting, offloading, and computational intelligence as important mitigation techniques. [1]Edge computing complements IoT by moving selected computation and storage functions closer to data sources. The architectural rationale is to reduce the distance that data must travel, decrease backhaul traffic, and support latency-sensitive services. This paper therefore [2]addresses the following research question: How can sensing, communication, data processing, edge resource management, and cloud coordination be jointly organized to reduce the total energy and environmental cost of sustainable IoT services while maintaining application-level quality of service? [5]The proposed framework is also motivated by recent work on distributed learning and edge intelligence, which identifies energy efficiency, heterogeneous resources, privacy, robustness, and secure real-time inference as coupled research challenge

II. PROPOSED LAYERED FRAMEWORK

The proposed framework, named LEES-IoT (Layered Energy-Efficient and Sustainable IoT), separates functions into six operational layers and one cross-layer management plane. The architecture [3]is intended to be deployable over heterogeneous IoT and MEC environments rather than tied to a particular vendor.

III. ARCHITECTURAL OVERVIEW

Layer	Primary Functions	Energy/Sustainability Mechanisms
L1: Sensing & Device	Sensing, actuation, local filtering, battery/energy state	Adaptive sampling, sleep scheduling, duty cycling, local event detection
L2: Communication	Wireless/wired connectivity and routing	Packet reduction, aggregation, low-power protocols, link selection
L3: Edge Data Reduction	Filtering, aggregation, compression, feature extraction	Transmit only useful information; computation-vs-transmission trade-off
L4: Edge	Task execution, containers/VMs,	Offloading, DVFS, consolidation, idle-node sleep,

Computing	accelerators	workload placement
L5: Orchestration & Sustainability	Global policy, resource allocation, energy/carbon monitoring	Multi-objective optimization, renewable awareness, carbon-aware scheduling
L6: Cloud/Service	Long-term storage, model training, global analytics	Batch scheduling, archival compression, workload migration to efficient resources
Cross-layer plane	Telemetry, security, prediction, policy enforcement	Energy monitoring, QoS monitoring, forecasting, secure policy control

IV. METHODOLOGY

Because the present work proposes a framework, its quantitative validation[4] should be performed using a reproducible experimental or simulation study. The following methodology is recommended for future implementation and validation. A simple adaptive sampling rule is:

$$f(t+1) = \text{clip}[f(t) + \alpha \cdot A(t) - \beta \cdot B(t), f_{\min}, f_{\max}] \quad (1)$$

where f is the sensing frequency, $A(t)$ represents application-relevant activity or prediction uncertainty, $B(t)$ represents battery/energy pressure, α and β are control coefficients, and clip bounds the resulting frequency. This is a control policy rather than a fixed algorithm; the coefficients should be tuned experimentally.

For a transmission of b bits over a selected link k , a simplified communication-energy model is:

$$E_{\text{tx}}(k) = b \cdot e_{\text{tx}}(k) + E_{\text{startup}}(k) + E_{\text{retry}}(k) \quad (2)$$

where e_{tx} is the effective energy per bit and the other terms represent radio activation and retransmission energy. The model can be extended using measured hardware power states.

The framework introduces a transmission-value score:

$$V_{\text{data}} = \Delta E_{\text{network}} + \Delta E_{\text{storage}} - E_{\text{processing}} - \lambda \cdot \Delta Q \quad (3)$$

where $\Delta E_{\text{network}}$ and $\Delta E_{\text{storage}}$ are estimated energy savings, $E_{\text{processing}}$ is additional local processing energy, ΔQ is the change in application quality, and λ weights quality loss. Data is processed locally when V_{data} exceeds a configurable threshold.

For task i , total completion time can be approximated as:

$$T_i = T_{\text{upload}} + T_{\text{queue}} + T_{\text{compute}} + T_{\text{download}} \quad (4)$$

and total task energy as:

$$E_i = E_{\text{device}} + E_{\text{network}} + E_{\text{edge}} + E_{\text{cloud}} \quad (5)$$

Algorithm 1: LEES-IoT Energy-Aware Orchestration

Input:

Device telemetry D , network telemetry N , edge/cloud telemetry R
Application constraints Q
Renewable/carbon information G
Candidate execution locations P

Repeat every control interval:

1. Collect D , N , R , Q , G .
2. Estimate workload, battery state, renewable availability and carbon intensity.
3. Adapt device sampling rate using application value and energy pressure.
4. Aggregate/filter/compress data when predicted savings exceed processing cost.
5. For each task i and location p in P :
Estimate latency $T(i,p)$
Estimate energy $E(i,p)$
Estimate traffic $B(i,p)$
Estimate carbon $C(i,p)$
Check security, capacity and deadline constraints.

6. Solve:

minimize $wE \cdot E + wL \cdot L + wT \cdot B + wC \cdot C + wR \cdot \text{ViolationPenalty}$

subject to QoS, resource, battery and security constraints.

7. Execute selected placement and resource policy.

8. Measure actual energy and QoS.

9. Update prediction/model parameters using observed error.

End Repeat

V. COMPARATIVE ANALYSIS

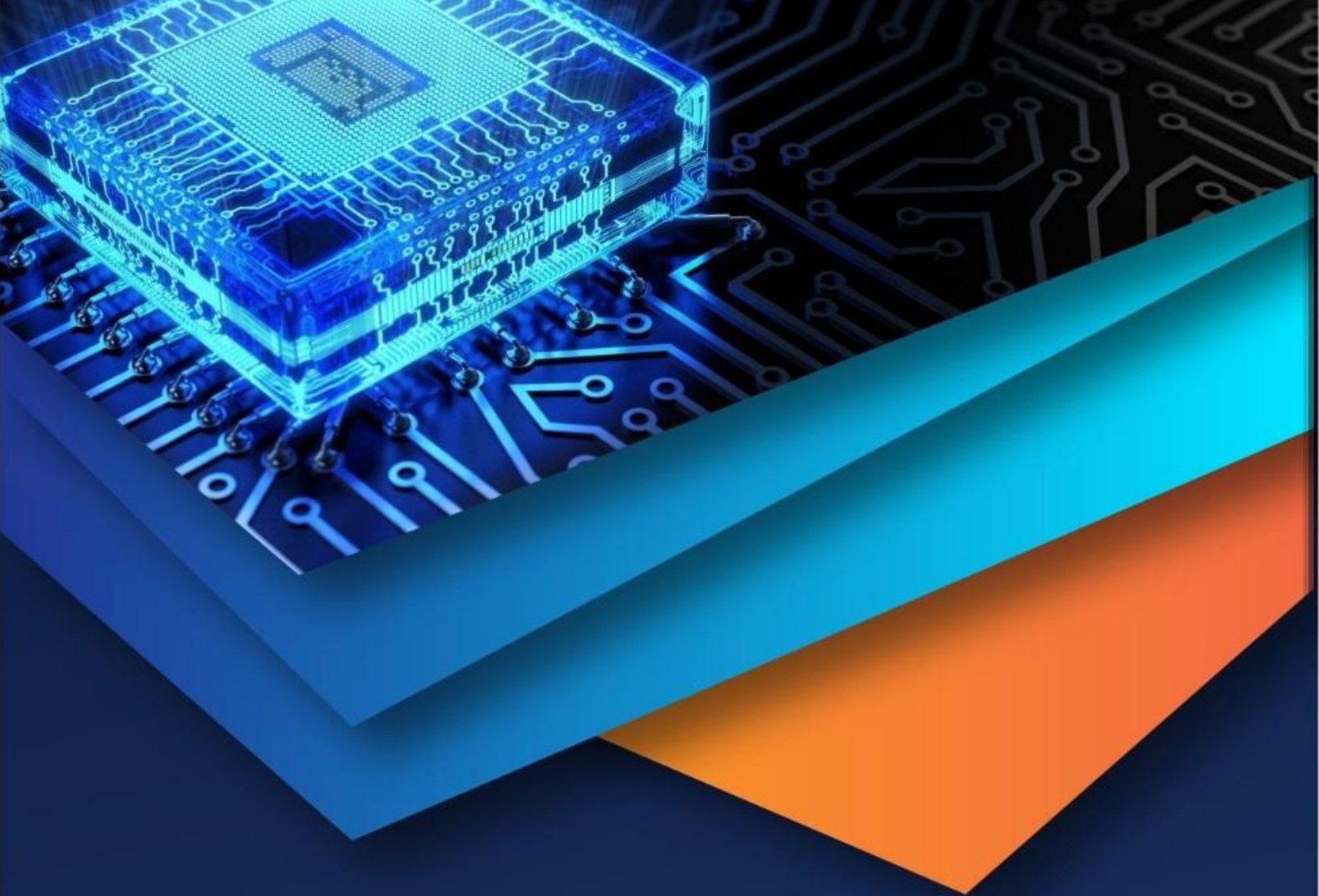
Dimension	Cloud-centric IoT	Conventional Edge	Proposed LEES-IoT
Data processing	Mostly centralized	Near source	Adaptive source + edge + cloud
Energy awareness	Usually secondary	Often resource-specific	Cross-layer
Offloading	Cloud-oriented	Latency/load-oriented	Energy/latency/carbon/QoS-aware
Data reduction	Optional	Often gateway-based	Adaptive and policy-controlled
Renewable awareness	Possible but external	Possible	Explicit orchestration input
Carbon awareness	Depends on provider	Often absent	Explicit optimization objective
Device battery state	Limited use	May be considered	First-class scheduling input
Security	Cloud/service focused	Distributed edge concerns	Cross-layer policy and isolation
Optimization scope	Centralized	Edge-centric	Device-to-cloud continuum

VI. CONCLUSION

This paper proposed the LEES-IoT framework for a layered approach to energy-efficient edge computing[6]. The paper's argument is that sustainability cannot be achieved by optimized IoT devices, networks, or edge servers in isolation, but rather through cross-layer information exchange about sensing, communications, data reduction, computation, orchestration, and cloud coordination in a management plane. The framework [9] combines adaptive sensing, data reduction, energy-aware offloading, resource consolidation, renewable-aware scheduling, and carbon-aware placement. A mathematical formulation and evaluation methodology were provided to establish reproducibility. The framework is deliberately [7] presented as a research architecture and evaluation plan. Its effectiveness must be demonstrated through controlled experiments or simulations rather than assumed. Future implementations should measure actual power consumption on representative IoT and edge hardware, evaluate multiple workloads and network conditions, and report energy, latency, traffic, reliability, and carbon metrics together. Such validation can [10] identify which combinations of mechanisms provide sustainability gains without jeopardizing the responsiveness and dependability of IoT services.

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