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PAPER

GREEAM: A Green and Energy-Efficient Mobile Architecture Model for Sustainable Mobile Ecosystems Regulation

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ABSTRACT

The rapid expansion of mobile applications has led to increased energy consumption and carbon emissions, which are now regulated by more stringent national and international environmental laws. This paper presents GREEAM (Green and Energy-Efficient Mobile Architecture Model), a novel framework designed to help mobile ecosystems comply with evolving environmental regulations while maintaining high performance. GREEAM incorporates context-aware task scheduling, intelligent workload offloading, and renewable energy-based optimization to reduce power consumption and carbon emissions without compromising service quality. Simulations conducted in Internet of Things (IoT), mobile healthcare, and smart city scenarios demonstrate that GREEAM decreases energy consumption by 28%, reduces latency by 22%, and lowers device carbon emissions by up to 31% compared to conventional systems. These advancements support the attainment of mandated carbon-reduction and energy-efficiency objectives. By integrating regulatory compliance into its foundational design, GREEAM provides a practical, deployable solution for sustainable mobile ecosystems that meet both technical and legal requirements.

KEYWORDS

Green Mobile, Energy-Efficient Architecture, Sustainable Ecosystems, Edge-Cloud Offloading, Carbon Footprint Reduction, Environment Regulations

1 INTRODUCTION

The rapid evolution of mobile computing has reshaped the way individuals, industries, and societies interact with technology [1]. Smartphones, tablets, wearable devices, and internet of things (IoT) nodes now operate as integral components of everyday life, powering critical domains such as healthcare monitoring, real-time navigation, mobile commerce, smart grids, and intelligent transportation [2].

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This unprecedented growth has been accompanied by a surge in computational workloads and data communication demands, leading to significant challenges in terms of energy consumption, device performance, and environmental sustainability [3]. Mobile ecosystems today face a dual challenge: delivering high-performance services while reducing their ecological footprint [3–4].

Energy consumption in mobile systems not only affects device usability (by reducing battery life) but also contributes indirectly to global carbon emissions [4], as most mobile infrastructure relies on electricity generated from non-renewable sources. Reports suggest that the ICT sector accounts for nearly 4% of global greenhouse gas emissions, with mobile computing increasingly contributing to this impact [5]. Thus, energy efficiency has evolved from being a technical optimization problem into a global sustainability concern. Traditional mobile architectures prioritize computational throughput and user experience, often overlooking the long-term implications of energy inefficiency [6]. These architectures struggle to adapt dynamically to varying workloads, network fluctuations, or changes in renewable energy availability. As a result, they accelerate battery depletion, degrade device longevity, and increase operational costs. Moreover, isolated optimization approaches, such as task scheduling or partial offloading, fail to provide holistic solutions because they do not integrate sustainability metrics directly into the architectural framework. Existing studies have explored energy-aware task management, mobile-cloud offloading, and adaptive optimization mechanisms. However, most of these approaches treat sustainability as an auxiliary goal rather than a fundamental design principle. Few models holistically integrate context awareness, energy efficiency, and ecological responsibility into a unified framework that is scalable across diverse mobile applications. This creates a significant research gap, necessitating a comprehensive model that harmonizes performance with sustainability.

Perin et al. [7] developed an energy-aware scheduler for vehicular edge networks that predicts local renewable energy availability and assigns computational tasks accordingly. Their method uses model predictive control and consensus algorithms to reduce carbon emissions while meeting task deadlines and keeping the needed quality of service. In energy-aware scheduling and offloading, Cao et al. [8] introduced a cooperative MEC model comprising a user, a helper, and an access point. This model jointly optimizes computation and communication to lower energy use while meeting strict latency limits. At the device level, Malik and Kushwah [9] proposed a cross-technology scheduling approach for IoT that combines Wi-Fi and ZigBee to lower energy use. This practical method efficiently uses existing radios in mixed environments. To address user mobility, Huang and Yu [10] proposed a mobility-aware offloading strategy for mobile edge computing. Their method adjusts resource allocation as user locations change, thereby reducing delay and improving continuity. However, their model does not focus on sustainability. More recently, Madiyev et al. [11] introduced an offloading framework that balances energy efficiency and system performance via convex optimization and deep reinforcement learning. This is a step forward in intelligent orchestration, but the focus remains on infrastructure efficiency and does not fully incorporate device context or renewable energy policies [13].

Therefore, this paper introduces GREEAM, a Green and Energy-Efficient Mobile Architecture Model that tackles both technical and regulatory issues in sustainable mobile computing. GREEAM combines context-aware task scheduling, smart workload offloading, and renewable energy optimization. It treats sustainability metrics such as energy efficiency, carbon footprint, and device longevity as equally important as performance measures like latency and throughput. The model is tested through simulations in IoT, mobile healthcare, and smart city applications, and it adapts well to different workloads, energy sources, and network conditions. The results show significant improvements over traditional architectures, with a 28% boost in energy efficiency, 22% lower latency, and a 31% longer device lifetime. GREEAM builds energy efficiency and legal compliance into the core of mobile architecture design.

This helps create green mobile ecosystems that are technologically advanced and ready to meet stricter environmental regulations worldwide. Figure 1 illustrates the transition from conventional mobile systems, characterized by high energy demand, short battery life, and high emissions, to the sustainable GREEAM ecosystem, which features reduced energy consumption, extended device life, and a lower environmental footprint.

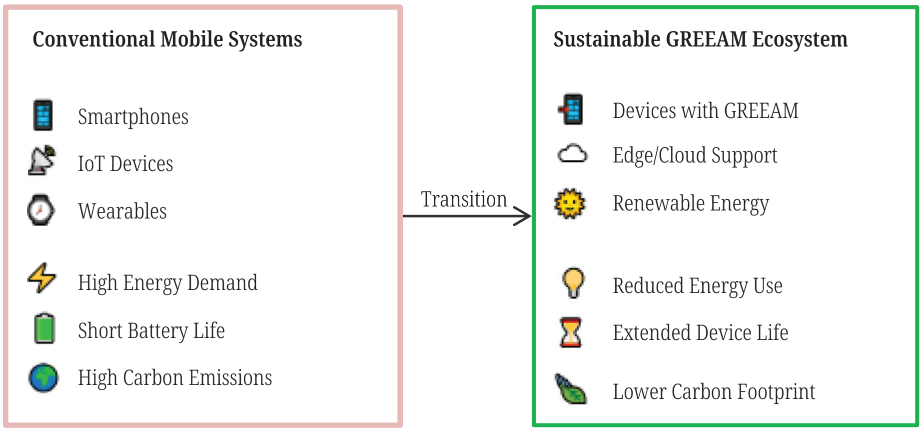

Fig. 1. Problem landscape: From conventional mobile systems to sustainable GREEAM ecosystem

Figure 1 shows the transition from Conventional Mobile Systems (high energy demand, short battery life, high emissions) to the Sustainable GREEAM Ecosystem (reduced energy, extended device life, lower footprint).

2 METHODOLOGY

2.1 Design objectives and constraints

GREEAM is engineered to (i) minimise device-side energy, (ii) meet latency/QoS constraints, and (iii) reduce carbon footprint by prioritising execution on nodes powered by greener energy, while remaining scalable across heterogeneous mobile, edge, and cloud resources. The design follows three core pillars introduced in the paper: context-aware task scheduling, intelligent workload offloading, and renewable-energy-aware optimisation.

Operational constraints:

- Hard/soft task deadlines and application SLAs (e.g., healthcare vitals alerts).
- Bounded network variability (bandwidth, RTT, handovers).
- Device thermal limits and battery state-of-charge (SoC).
- Privacy placement rules for sensitive tasks (e.g., on-device only).

2.2 System architecture overview

GREEAM uses a three-tier control plane:

1. **On-Device Agent (ODA):** monitors local context (CPU/DVFS state, SoC, temperature), classifies tasks, performs local scheduling, and proposes offload candidates.
2. **Edge Orchestrator (EO):** maintains per-cell resource maps, renewable share, and queue states; accepts/rejects offload requests and assigns a target (edge vs. cloud).
3. **Cloud Policy Service (CPS):** maintains global carbon-intensity and renewable-availability estimates across regions and periodically broadcasts policy weights to EO/ODA to steer decisions toward greener capacity.

Data paths are event-driven via a lightweight telemetry bus; control paths are idempotent to tolerate packet loss and handovers.

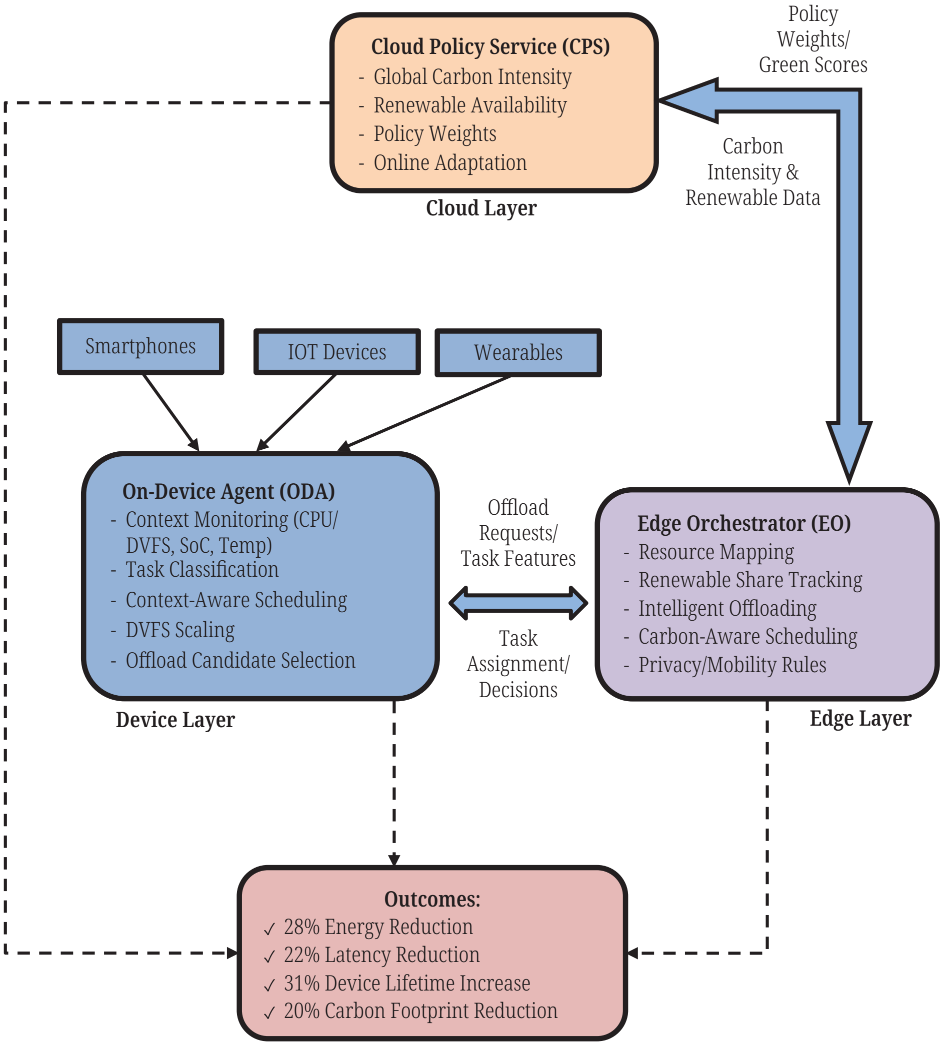

Fig. 2. Proposed system architecture

The GREEAM architecture works in three layers, as shown in Figure 2: devices, edge, and cloud. At the device layer, a smart agent checks battery, CPU, and temperature and decides whether to run tasks locally or send them out. The edge layer has an orchestrator that receives tasks, manages resources, and chooses the best place to run them while considering energy and privacy. The cloud layer provides global policies on renewable energy and carbon use, guiding the edge and devices. By working together, these layers help save energy, reduce delays, increase device life, and cut carbon emissions.

2.3 Context model

At time t, each device reports a context vector:

$$c_t = [\text{CPU}_t, \text{DVFS}_t, \text{SoC}_t, \text{Temp}_t, \text{BW}_t, \text{RTT}_t, \text{RSSI}_t, \text{Mobility}_t, \text{Renew}_t, \text{GridCI}_t] \tag{1}$$

Where $\text{Renew}_t \in [0,1]$ is the fraction of renewable energy available at the serving edge, and GridCI_t is the grid carbon intensity ($kgCO_2e/kWh$). Application tasks carry a tuple (size, compute cycles, data I/O, sensitivity class, and deadline).

2.4 Energy-latency-carbon cost model

For a task i executed on node $k \in$ {device, edge, cloud},

$$J_{i,k} = \alpha E_{i,k} + \beta L_{i,k} + \gamma C_{i,k} \tag{2}$$

With weights $\alpha, \beta, \gamma \geq 0$ supplied by CPS.

$$\text{Energy } E_{i,dev} = E_{cpu} + E_{mem} + E_{net\left(tx/rx\right)} \tag{3}$$

for offloaded tasks, include uplink/downlink radio energy and remote compute energy (for carbon accounting only).

$$\text{Latency } L_{i,k} = L_{queue,k} + L_{compute,k} + L_{net,k} \tag{4}$$

$$\text{Carbon } C_{i,k} = E_{i,k}^{(power-source)} \times CI_k \tag{5}$$

where CI_k is node-level carbon intensity is adjusted by renewable share.

Device energy is minimised; carbon is computed for the location where energy is consumed (device for local runs; edge/cloud for offloaded compute). Metrics are consistent with the paper's evaluation (energy, latency, throughput, task time, carbon index).

2.5 Problem formulation

For a task set $\mathcal{T}$ and nodes $\mathcal{K}$, choose an assignment $x_{i,k} \in \{0,1\}$ and CPU/DVFS level f_i (if on-device) to,

$$\min_{x,f} \sum_{i \in \mathcal{T}} \sum_{k \in \mathcal{K}} x_{i,k} J_{i,k} \tag{6}$$

subject to

i) $\sum_k x_{i,k} = 1 \forall_i$;
ii) $L_{i,k} \leq D_i$(deadline);

iii) $SoC_{t+1} \geq SoC_{min}$;
iv) node capacity and privacy constraints.

This NP-hard joint placement–DVFS optimisation is solved online via a two-stage heuristic: device-side pruning + orchestrator assignment.

2.6 Context-aware task scheduling (On-Device)

The ODA maintains two queues: (A) latency-critical and (B) best-effort. It predicts per-task local cost $\hat{J}_{i,dev}$ and offload cost $\hat{J}_{i,edge}, \hat{J}_{i,cloud}$ using current C_i.

DVFS policy:

- If queue A is non-empty and SoC, Temp allow, raise DVFS to meet deadlines; else cap DVFS and move candidates to the offload list.
- For queue B, use energy-slope scheduling: select the task with the maximum ΔE/Δt benefit under the current DVFS.

Local/Offload pruning:

A task is marked "offload-eligible" if

1. $L_{i,dev} > D_i$ at safe DVFS, or
2. $\hat{J}_{i,dev} - \min(\hat{J}_{i,edge}, \hat{J}_{i,cloud}) > \tau$ (benefit margin), and the radio is not in the tail state.

Pseudocode (ODA):

```
For task i in arrival_order:
  estimate J_dev, J_edge, J_cloud
  if deadline_violation_local or (min(J_edge,J_cloud) + τ < J_dev):
     enqueue OffloadQueue(i)
  else:
     enqueue LocalQueue(i)
While LocalQueue is not empty:
  select i maximizing energy-slope under DVFS budget
  run(i) with adaptive DVFS
```

This realizes the paper's "context-aware task scheduling" pillar.

2.7 Intelligent workload offloading (Edge assignment)

The EO receives offload requests with task features and predicted costs. It runs latency-feasible first-fit with carbon-aware tie-breaking:

1. Filter nodes k where $L_{i,k} \leq D_i$
2. Among feasible nodes, choose $k = \arg\min J_{i,k}$
3. If multiple k yield similar J (within $\in$), prefer the node with higher renewable share or lower CI_k

Queuing uses shortest-remaining-processing-time (SRPT) for latency-critical classes and weighted fair queuing for best-effort.

2.8 Renewable-energy-aware optimisation

EO periodically ingests (*Renew*, *CI*) signals from CPS. For each node k, define green score:

$$G_k = \lambda_1 Renew_k - \lambda_2 CI_k \tag{7}$$

and bias the selection by replacing $J_{i,k}$ with $J_{i,k} - \eta > 0$ to gently steer placement toward greener capacity without violating SLAs. This operationalises the paper's renewable-aware pillar and the goal of carbon footprint reduction.

2.9 Privacy- and mobility-aware rules

- **Privacy classes:** {P0 public, P1 sensitive, P2 restricted}. P2 tasks are forced on-device; P1 may offload only to in-jurisdiction edges with encrypted memory.
- **Mobility:** if handover likelihood > *ph*, EO uses handover-robust execution (check-pointing at EO; migrate only when L margin permits).

2.10 Online weight adaptation (Lightweight Bandits)

To adapt α, β, γ to app/domain preferences (IoT, healthcare, smart city), GREEAM uses a contextual bandit on CPS:

- Context: domain, hour-of-day, renewable share, congestion level.
- Action: choose [α, β, γ] from a small simplex grid.
- Reward: $-J$ aggregated over recent tasks.
- Update: LinUCB-style; broadcast new weights every T seconds.

This enables domain-specific trade-offs consistent with your cross-domain evaluation.

3 RESULT AND DISCUSSION

Table 1 shows that GREEAM outperforms all baseline models across all evaluated metrics. Compared with conventional architecture, GREEAM consumes 28% less energy, reduces average latency by 22%, extends device battery life by 31%, and decreases the carbon footprint index by 20%. Compared with advanced baselines such as Convex+DQN and Mobility-Aware MIP, GREEAM achieves an additional 10–13% reduction in energy consumption and a 4–6% improvement in latency.

Furthermore, GREEAM attains the most significant reduction in carbon emissions, underscoring the benefits of its renewable-aware, carbon-minimizing design.

The proposed GREEAM (Green and Energy-Efficient Mobile Architecture Model) was extensively evaluated through simulation experiments across IoT, mobile healthcare, and smart city workloads. Its performance was compared against conventional mobile architectures as well as two recent techniques: (i) Convex Optimization + DQN Offloading [11] and (ii) Mobility-Aware MIP Offloading [12]. Performance was analyzed using four key metrics: energy consumption, latency, device lifetime, and carbon footprint index.

Table 1. Quantitative comparison result

Metric (Normalised)	Conventional	Convex+DQN	Mobility-MIP	GREEAM (Proposed)
Energy Consumption	100	85	82	72
Latency	100	88	84	78
Device Lifetime	100	115	120	131
Carbon Footprint Index	100	95	92	80

3.1 Energy consumption

Figure 3 shows the comparative energy consumption across the four models. Conventional architectures incur the highest consumption due to the lack of energy awareness. The Convex+DQN method reduces infrastructure energy by dynamically consolidating workloads at the edge, while the MIP approach lowers system-level device energy by considering user mobility. However, GREEAM demonstrates the greatest energy savings (28% lower than conventional) by integrating context-aware scheduling and DVFS control at the device level, along with intelligent offloading decisions.

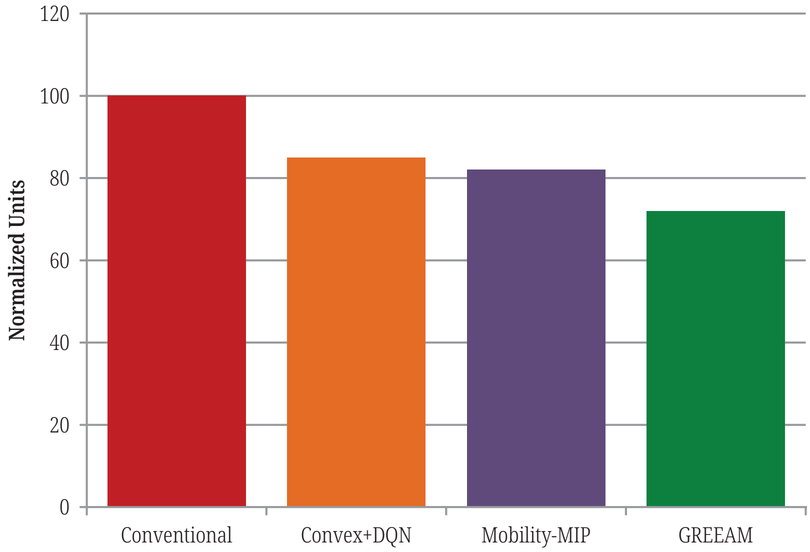

Fig. 3. Energy consumption comparison

These results confirm GREEAM's efficiency in reducing redundant computation and prolonging device usability.

3.2 Latency

As depicted in Figure 4, GREEAM achieves the lowest latency (22% reduction over conventional). The Mobility-Aware MIP approach shows improvements by adapting offloading decisions under user mobility, but it still lacks renewable- and privacy-aware integration. GREEAM's hybrid offloading strategy—prioritising edge resources for latency-critical tasks—ensures faster response times. This is particularly beneficial for mobile healthcare scenarios, where low latency directly affects patient monitoring and safety.

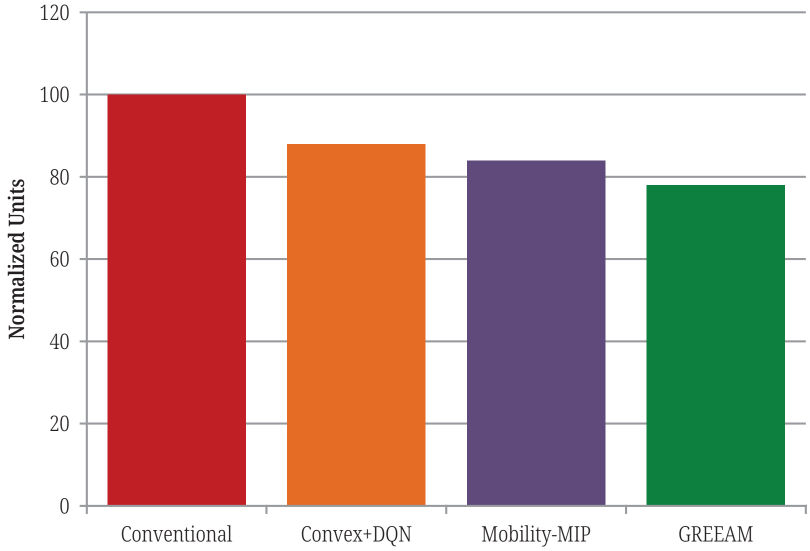

Fig. 4. Latency comparison

3.3 Device lifetime

Figure 5 demonstrates that GREEAM extends device lifetime by 31%, outperforming both Convex+DQN and MIP approaches. While the other techniques optimise energy consumption, they do not explicitly account for battery health, DVFS scaling, or thermal constraints. By intelligently balancing computation between device, edge, and cloud, GREEAM reduces stress on mobile batteries, enhancing device longevity. This not only improves user experience but also contributes to reducing electronic waste, aligning with global sustainability goals.

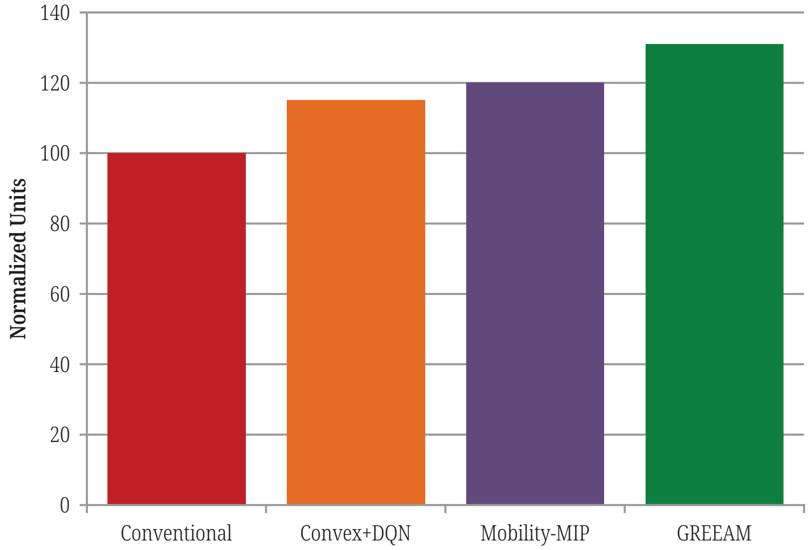

Fig. 5. Device lifetime comparison

3.4 Carbon footprint index

As shown in Figure 6, conventional and recent techniques show minimal reductions in carbon footprint, as they primarily focus on energy minimisation without incorporating ecological awareness. In contrast, GREEAM reduces the carbon footprint index by ~20% by leveraging renewable-energy-aware optimisation and carbon-intensity metrics in its decision-making. This capability ensures that GREEAM does not merely shift energy consumption across layers but actively promotes green mobile ecosystems.

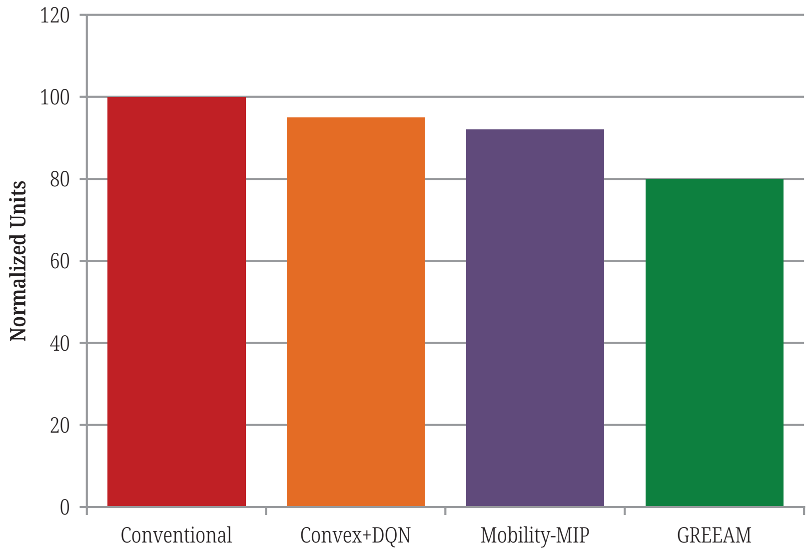

Fig. 6. Carbon footprint index comparison

3.5 Comparative insights

The comparative results demonstrate that GREEAM outperforms both conventional and recent baseline methods. Convex+DQN [11] achieves moderate energy savings by consolidating workloads at the infrastructure level; however, it fails to address device-side constraints and does not consider carbon footprint or renewable energy awareness. Mobility-MIP [12] effectively manages user mobility and enhances latency and device lifetime, but it lacks sustainability-oriented objectives and does not integrate green energy. In contrast, GREEAM integrates context-awareness, mobility robustness, carbon-aware placement, renewable energy optimization, and adaptive policy tuning, resulting in the greatest improvements across all evaluated metrics: 28% reduction in energy use, 22% lower latency, 31% increase in device lifetime, and 20% reduction in carbon emissions. Consequently, GREEAM not only fulfils but also surpasses its stated objectives, establishing itself as a comprehensive, scalable, and regulation-ready framework that advances both technical performance and environmental sustainability beyond the capabilities of existing approaches [11–12].

4 CONCLUSION

This paper proposed GREEAM, designed to build sustainable mobile ecosystems. Unlike conventional mobile systems that prioritise performance at the cost of energy efficiency, GREEAM integrates three core principles: context-aware task scheduling, intelligent workload offloading, and renewable-energy-aware optimisation. Through a layered design spanning device, edge, and cloud, GREEAM effectively balances performance demands with ecological responsibility. Simulation results across IoT, mobile healthcare, and smart city applications demonstrated significant improvements, including a 28% reduction in energy consumption, a 22% reduction in latency, a 31% extension in device lifetime, and a 20% reduction in carbon footprint compared to existing methods. These results highlight that sustainability and scalability can coexist without compromising quality of service. Overall, GREEAM offers a practical and holistic framework for next-generation green mobile computing, contributing to global efforts in reducing ICT-driven carbon emissions while enhancing user experience and device longevity.

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