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ADAPTIVE MOBILE COMPUTING IN THE DEVICE–EDGE–CLOUD CONTINUUM: A REVIEW AND RESEARCH FRAMEWORK FOR 5G-ADVANCED AND 6G

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ABSTRACT

Mobile computing has evolved from portable access to information into an intelligent distributed-computing paradigm spanning mobile devices, heterogeneous wireless networks, edge infrastructure, and centralized cloud platforms. The growth of smartphones, Internet of Things (IoT) devices, connected vehicles, immersive applications, and artificial intelligence (AI) has created demanding requirements for low latency, energy efficiency, reliability, privacy, and service continuity. This paper presents a comprehensive review of mobile computing with emphasis on mobile cloud computing, mobile edge computing (MEC), multi-access edge computing, computation offloading, mobility management, edge intelligence, security, privacy, and sustainable resource management. Based on the literature, a conceptual Adaptive Mobile Computing Orchestration (AMCO) framework is proposed to select execution locations across device, edge, and cloud environments using a multi-objective utility model. The framework incorporates latency, energy, reliability, privacy, resource availability, and workload characteristics. A research methodology is defined for experimental validation using heterogeneous devices, multiple edge nodes, variable network conditions, realistic mobility traces, and representative workloads. The paper identifies major research gaps in cross-layer orchestration, trust-aware placement, mobility-aware service continuity, privacy-preserving AI, and reproducible experimentation. Finally, it discusses the implications of 5G-Advanced and 6G/IMT-2030, including AI and communication, integrated sensing and communication, ubiquitous connectivity, sustainability, and resilience. The study concludes that future mobile computing should be designed as an adaptive, secure, intelligent, and sustainable computing continuum rather than as a wireless-access technology alone.

Keywords: Mobile computing; mobile edge computing; mobile cloud computing; computation offloading; device-edge-cloud continuum; 5G; 6G; edge intelligence; IoT; mobility management; privacy; energy efficiency

1. INTRODUCTION

Mobile computing is a computing paradigm in which computing, communication, and information services are provided while users, devices, data, or network attachment points are mobile. Unlike conventional fixed distributed systems, mobile environments operate under changing connectivity, heterogeneous hardware, limited battery capacity, variable bandwidth, dynamic locations, and intermittent resource availability. These characteristics make adaptation a fundamental design requirement [1], [2].

The contemporary mobile ecosystem includes smartphones, tablets, wearables, vehicles, drones, industrial sensors, cameras, and IoT endpoints. At the same time, applications such as augmented reality (AR), virtual reality (VR), real-time video analytics, autonomous systems, intelligent transportation, and AI-based assistants demand processing resources that may exceed the capabilities of a mobile device.

Mobile cloud computing addressed resource limitations by moving computation and storage to remote cloud platforms [3]. However, centralized clouds may introduce communication delay and backhaul traffic, which can be unsuitable for interactive services. Edge computing and MEC move selected computation and storage functions closer to users and data sources, reducing the distance between applications and processing resources [4]–[7].

The resulting device–edge–cloud continuum enables an application to distribute tasks across several execution environments. This flexibility introduces a new systems problem: deciding where and when a task should execute while jointly considering latency, energy, privacy, reliability, cost, mobility, and resource availability.

The main contributions of this paper are: (1) a comprehensive review of mobile computing and its evolution; (2) a classification of enabling technologies and application requirements; (3) identification of research gaps; (4) a conceptual AMCO framework for adaptive task placement; (5) a mathematical formulation for multi-objective computation offloading; (6) a practical experimental methodology; and (7) a discussion of future directions associated with 5G-Advanced and 6G/IMT-2030.

2. BACKGROUND AND EVOLUTION

Early mobile-computing research identified weak connectivity, mobility, resource constraints, and adaptation as fundamental problems [1], [2]. Systems were designed to tolerate disconnected operation and changing network characteristics rather than assuming continuous high-quality connectivity.

Mobile cloud computing subsequently provided mobile devices with access to scalable remote resources [3]. This approach is effective for compute-intensive workloads but can incur round-trip delay and energy costs for communication. Cloudlets and edge computing introduced intermediate resources closer to users [8].

MEC formalized the idea of placing cloud-like capabilities near the access network. Survey studies describe computation offloading, edge resource allocation, and mobility management as major research themes [6], [7]. Computation offloading is particularly important because it can reduce device-side processing requirements and, under appropriate conditions, improve latency and energy efficiency [10].

The transition to 5G and beyond increased interest in MEC because applications require low latency, high reliability, and large numbers of connected devices. Current 6G development further expands the scope. ITU's IMT-2030 framework identifies immersive communication, hyper-reliable and low-latency communication, massive communication, ubiquitous connectivity, AI and communication, and integrated sensing and communication as six usage scenarios [19]. Thus, mobile computing is moving from connectivity-centric architectures toward intelligent, distributed, and context-aware computing.

3. RELATED WORK

Satyanarayanan established foundational principles for mobile computing and highlighted the need to adapt to resource limitations and mobility [1]. His later work on mobile information access emphasized the importance of delivering distributed information despite changing operating conditions [2].

Dinh et al. surveyed mobile cloud computing architectures, applications, and approaches, demonstrating how cloud resources can extend mobile-device capabilities [3]. Shi et al.

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described edge computing as a distributed architecture that moves computation and storage toward data sources [4]. Satyanarayanan et al. proposed cloudlets as a mechanism for bringing cloud resources closer to mobile users [8].

Mach and Becvar provided a major survey of MEC architecture and computation offloading, identifying offloading decisions, resource allocation, and mobility management as central problems [6]. Mao et al. examined MEC from a communication perspective and emphasized joint radio and computational resource management, caching, mobility, green computing, and privacy [7].

More recent surveys of computation offloading categorize objectives into delay minimization, energy minimization, revenue maximization, and system utility, with approaches including mathematical optimization, heuristics, Lyapunov optimization, game theory, Markov decision processes, and reinforcement learning [10]. Machine-learning-based approaches have also been investigated for dynamic environments where explicit optimization models are difficult to maintain [11].

Despite these advances, many studies optimize a subset of objectives or evaluate simplified environments. A practical mobile system must simultaneously address application deadlines, energy budgets, privacy policies, heterogeneous resources, user mobility, and changing wireless conditions. This motivates the integrated framework proposed in this paper.

4. RESEARCH GAP AND PROBLEM STATEMENT

Five research gaps are particularly important.

First, single-objective optimization is insufficient. Minimizing latency alone can increase energy consumption, cost, or privacy exposure. Conversely, maximizing local privacy can reduce application performance.

Second, mobility is often simplified. Real users cross access points and edge domains, and an application's best execution location can change during a session.

Third, security and placement are frequently treated as separate problems. A fast edge server may not be acceptable for sensitive data if its trust level or policy compliance is inadequate.

Fourth, AI-based orchestration introduces additional attack surfaces and operational costs. Federated learning, model sharing, and predictive placement require protection against poisoning, inference, and model-extraction attacks.

Fifth, reproducibility remains a concern. Simulation results can depend strongly on assumptions concerning channel models, workloads, mobility, device hardware, and edge capacity.

The research problem addressed here is therefore: How can mobile application tasks be dynamically distributed across device, edge, and cloud resources to minimize latency and energy while satisfying reliability, privacy, and resource constraints under heterogeneous and mobile conditions?

5. PROPOSED AMCO FRAMEWORK

The Adaptive Mobile Computing Orchestration (AMCO) framework proposed in this paper treats device, edge, and cloud resources as a unified computing continuum.

The Device Layer contains smartphones, wearables, sensors, vehicles, and embedded devices. It performs local execution when workloads are small, privacy-sensitive, latency-critical, or connectivity is poor.

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The Edge Layer contains MEC or multi-access edge nodes positioned close to users and data sources. It is suitable for latency-sensitive workloads, local analytics, real-time AI inference, AR/VR, and connected-vehicle applications.

The Cloud Layer provides elastic compute, storage, global analytics, and large-scale model training. It is appropriate for computationally intensive tasks without strict interactive deadlines.

A cross-layer Orchestration Plane observes context, evaluates candidate execution environments, and initiates placement or migration decisions. It contains five modules: Context Monitor, Task Profiler, Trust and Security Manager, Placement Optimizer, and Service Continuity Manager.

The Context Monitor collects network quality, mobility, battery state, processor utilization, and edge availability. The Task Profiler estimates computational demand, data size, deadline, and privacy sensitivity. The Trust Manager evaluates security and policy constraints. The Placement Optimizer ranks candidate locations. The Service Continuity Manager handles migration or replication when mobility changes the preferred location.

This architecture is designed to support dynamic rather than one-time placement decisions.

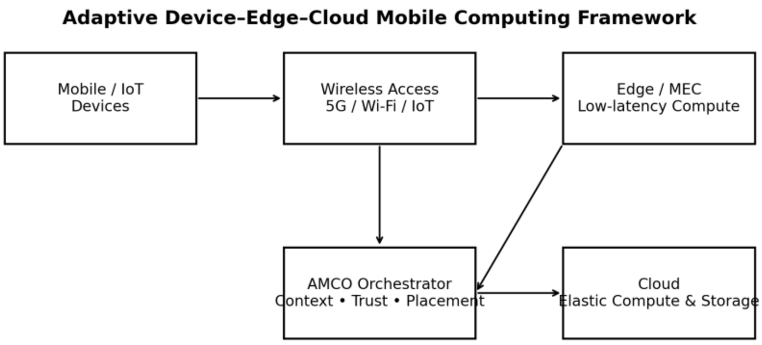

Fig. 1. Conceptual AMCO device–edge–cloud architecture.

6. MATHEMATICAL MODEL

Let a mobile application be represented by a set of tasks T = {t1, t2, ..., tn}. Each task ti has computational demand ci, input-data size di, deadline Di, and privacy requirement pi. Let L be the set of candidate execution locations, where L may contain the device, one or more edge nodes, and a cloud region.

For a candidate location l, estimated completion time is:

$T_l = T_{upload,l} + T_{queue,l} + T_{execute,l} + T_{download,l}$.

The energy consumed by the mobile device is modeled as:

$E_l = E_{compute,l} + E_{radio,l} + E_{migration,l}$.

A normalized multi-objective utility score can then be defined as:

$U(l) = wL(1 - L_l) + wE(1 - E_l) + wR\, R_l + wP\, P_l + wA\, A_l - wC\, C_l$,

where L_l, E_l, and C_l are normalized latency, energy, and cost measures; R_l is reliability; P_l is privacy suitability; A_l is resource availability; and the weights represent application preferences.

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The optimization problem is:

maximize $U(l)$

subject to:
$T_l \leq Di$,
$E_l \leq Emax$,
$P_l \geq Pmin$,
$R_l \geq Rmin$.

For multiple dependent tasks, the decision becomes a task-placement and scheduling problem. Exact optimization can become computationally expensive as the number of tasks and candidate nodes grows. Therefore, practical implementations can combine heuristic search, integer optimization for small instances, and reinforcement-learning or predictive models for online decisions [10], [11].

The key advantage of this formulation is that security and privacy become explicit constraints rather than after-the-fact considerations.

7. SYSTEM ARCHITECTURE AND WORKFLOW

The proposed workflow begins when an application generates a task. The Task Profiler extracts workload characteristics, while the Context Monitor collects current system conditions. Candidate locations are filtered using hard constraints such as privacy policy, trust level, and deadline requirements.

The Placement Optimizer then calculates the utility of feasible locations. If a device is sufficiently capable and local execution satisfies the requirements, local processing is preferred because it avoids transmission overhead. If local execution is inefficient but a nearby edge node meets security and performance requirements, the task is offloaded to the edge. If the task is compute-intensive and tolerant of higher latency, cloud execution may be selected.

The system continuously monitors conditions. If the user moves away from the current edge node, network quality deteriorates, or the edge becomes overloaded, the Service Continuity Manager can migrate, replicate, or return the workload to another location.

The framework therefore follows a closed-loop process:

Observe → Profile → Filter → Optimize → Execute → Monitor → Re-optimize.

This feedback loop is particularly important in mobile environments because system conditions are dynamic.

8. APPLICATIONS

Healthcare applications can use mobile and wearable devices for monitoring and remote services. Privacy and reliability are particularly important, so placement should consider whether sensitive data can leave the device or a trusted edge environment.

Intelligent transportation and vehicle-to-everything systems require low-latency communication and distributed processing. Edge resources can support traffic coordination, hazard detection, and cooperative perception.

Industrial IoT applications can process sensor streams near machines, supporting predictive maintenance, anomaly detection, and quality inspection.

AR/VR applications require high computational capability and low latency. Device-edge collaboration can reduce local processing while maintaining interactive responsiveness.

Smart-city systems combine cameras, environmental sensors, vehicles, and mobile devices. Edge processing can reduce the volume of raw data transmitted to centralized clouds.

Mobile education and commerce also benefit from edge caching, adaptive services, secure authentication, and distributed processing.

9. SECURITY AND PRIVACY

Mobile computing expands the attack surface because applications and data can cross devices, wireless networks, edge nodes, and cloud platforms. Threats include device compromise, wireless interception, rogue access points, insecure APIs, malicious edge workloads, denial-of-service attacks, data leakage, and identity theft.

Device security should include secure boot, hardware-backed keys, application isolation, attestation, strong authentication, and timely patching. Network security should use encryption, mutual authentication, secure key management, and monitoring.

Edge infrastructure creates additional risks because nodes are distributed and may be operated by different organizations. Multi-tenancy requires strong isolation and secure orchestration. NIST's work on hardware-enabled security emphasizes layered protection for cloud and edge use cases [16].

Privacy should influence placement. Sensitive information may be processed locally or on trusted edge infrastructure rather than sent to a distant cloud. Federated learning can reduce raw-data centralization, but model updates may still leak information and training can be attacked through poisoning.

A practical AMCO implementation should therefore maintain a trust score or policy state for each candidate location and exclude locations that fail minimum security requirements.

10. ENERGY EFFICIENCY AND SUSTAINABILITY

Battery constraints remain a defining property of mobile computing. Offloading can reduce CPU energy but can also increase radio energy. The optimal decision depends on input-data size, wireless quality, workload complexity, and remote execution time.

Energy management can use workload batching, model compression, accelerator-aware scheduling, caching, and dynamic frequency scaling. At the infrastructure level, edge placement should consider server utilization and energy intensity.

Sustainability also requires consideration of embodied energy and the environmental cost of additional edge infrastructure. Future resource orchestration should therefore include carbon-aware policies when application requirements allow flexible execution times or locations.

A sustainable mobile-computing architecture should optimize service quality and energy/environmental impact jointly rather than assuming that lower latency is always the best outcome.

11. EXPERIMENTAL METHODOLOGY

A future implementation study should compare four strategies:

A. Local-only: all tasks execute on the mobile device.
B. Cloud-only: all eligible tasks are sent to a centralized cloud.

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C. Edge-only: tasks are sent to a selected edge server.
D. AMCO: tasks are dynamically placed among device, edge, and cloud.

The testbed should include heterogeneous mobile-device profiles, at least two edge nodes, a cloud backend, variable bandwidth and latency, and mobility traces. Workloads should include lightweight sensing, CPU-intensive image processing, AI inference, latency-sensitive interactive tasks, and privacy-sensitive analytics.

Independent variables should include workload size, number of users, mobility speed, available bandwidth, edge capacity, battery state, and task privacy level.

Dependent variables should include:
1. End-to-end latency (ms)
2. Mobile-device energy consumption (J)
3. Task completion ratio (%)
4. Edge resource utilization (%)
5. Network traffic (MB)
6. Migration frequency
7. Reliability (%)
8. Policy/security compliance (%)
9. Cost per completed task

Each configuration should be repeated sufficiently to estimate variability. Confidence intervals and appropriate statistical tests should be reported. The experimental implementation should publish configuration details and scripts where possible to improve reproducibility.

No numerical performance claims are fabricated in this review; numerical results should be added only after actual experiments.

12. COMPARATIVE ANALYSIS

The four strategies differ in their expected behavior. Local-only execution minimizes communication overhead and can maximize privacy, but it is constrained by device resources. Cloud-only execution provides scalable resources but may increase latency and backhaul traffic. Edge-only execution improves proximity but may be limited by edge capacity and mobility. AMCO introduces decision-making overhead but can adapt to application and system context.

The central research hypothesis is that AMCO can achieve a better overall trade-off among latency, energy, reliability, privacy, and resource utilization than static strategies under heterogeneous mobile conditions. The hypothesis must be validated experimentally rather than assumed.

The framework also enables scenario-specific behavior. For example, a privacy-sensitive task may remain local even if edge execution is faster. A real-time AR task may select the nearest edge node. A large model-training task may be sent to the cloud. A disconnected device may temporarily execute locally and synchronize later.

13. FUTURE RESEARCH DIRECTIONS

AI-native orchestration is a major direction. Predictive models can estimate mobility, workload demand, network quality, and edge congestion. Reinforcement learning can then learn placement policies, although exploration cost and safety constraints must be addressed.

Federated and distributed intelligence can support personalized AI without centralizing raw data. Future work should investigate communication-efficient aggregation, robustness to heterogeneous clients, and protection against poisoning.

Edge federation will become increasingly important as applications span multiple providers. Service discovery, authentication, policy enforcement, billing, and migration across administrative domains require interoperable mechanisms.

Integrated sensing and communication is a major 6G direction. Mobile networks may simultaneously provide communication, localization, environmental sensing, and context information. This can enhance mobile applications but also introduces new privacy and security concerns.

Resilient computing should support service continuity during congestion, disconnection, edge failure, and disaster conditions.

Finally, sustainable orchestration should incorporate energy and carbon impact while preserving application-level quality of service.

14. 5G-ADVANCED AND 6G PERSPECTIVE

The future of mobile computing is closely linked with the evolution of mobile networks. ITU's IMT-2030 framework identifies six usage scenarios: immersive communication, hyper-reliable and low-latency communication, massive communication, ubiquitous connectivity, AI and communication, and integrated sensing and communication [19]. In February 2026, ITU-R Working Party 5D completed draft minimum technical performance requirements for IMT-2030, and in June 2026 it completed draft evaluation guidelines for candidate radio-interface technologies [20].

These developments matter for mobile computing because future networks are expected to provide more than connectivity. Computing, AI, sensing, positioning, and communication are increasingly treated as integrated capabilities. This favors architectures in which mobile applications can dynamically consume distributed compute resources.

The IMT-2030 framework also emphasizes security and resilience, sustainability, connecting the unconnected, and ubiquitous intelligence [19], [20]. These principles align closely with the AMCO framework's emphasis on adaptive orchestration, privacy, reliability, and energy-aware placement.

However, 6G performance targets should not be interpreted as guaranteed deployment performance. Candidate technologies still require evaluation, standardization, and real-world validation [20].

CONCLUSION

Mobile computing has evolved into a distributed computing continuum connecting mobile devices, wireless networks, edge infrastructure, and cloud platforms. Mobile cloud computing provides scalable resources, while MEC reduces the distance between applications and processing resources. Computation offloading, mobility management, edge intelligence, security, and energy efficiency are therefore central to modern mobile-computing research.

This paper identified limitations of single-objective optimization and proposed the AMCO framework for adaptive task placement. The framework combines contextual monitoring, task profiling, security-aware filtering, multi-objective optimization, and service continuity management.

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The proposed methodology provides a basis for future implementation and experimental validation. Rather than presenting fabricated results, it defines measurable metrics and controlled comparison strategies.

As mobile networks evolve toward 5G-Advanced and 6G/IMT-2030, mobile computing is likely to become increasingly intelligent, sensing-aware, distributed, and context-sensitive. Future systems should therefore optimize not only speed, but also privacy, resilience, energy use, trust, and sustainability. The device–edge–cloud continuum provides a practical foundation for this next generation of mobile computing.

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21. Submission note: Replace the author/institution placeholders, verify each reference against the target journal database, apply the journal's exact template, and add experimental results only after actual implementation. The framework and methodology in this paper are original conceptual content for research development and should be reviewed by the authors before submission.