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Research Article

# Energy-Efficient Task Offloading and Resource Allocation in Mobile Cloud Computing Using Edge-AI and Network Virtualization

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## ABSTRACT

In the emerging landscape of Mobile Cloud Computing, energy efficiency and resource optimization are very vital challenges because most of the cloud and edge resources are increasing the execution of tasks in mobile devices. The focus of this paper is to propose a new energy-efficient task offloading and resource allocation framework in Edge-AI enabled network virtualization for dynamic management of computational tasks in mobile cloud environments. The framework allows real-time decisions of task offloading by comparing energy consumption of local execution versus edge processing and further looks at the received performance gains in executing that way. Then, based on the savings in energy and availability of the edge resources, it grades tasks for offloading. Network virtualization optimizes edge resource use by allocating resources depending on demand from tasks, leading to a reduction in latency for increased processing efficiency. The simulation results proved that our approach could really cut down energy consumption on mobile devices, with low latency and high rates of task success, better than cloud-only offloading through static edge computing methods and traditional dynamic programming.

## 1. INTRODUCTION

Nowadays, Network infrastructure needs to handle the large crowd of mobile devices. Mobile Cloud Computing (MCC) puts forward a technology front that can raise the bars on the performance of mobile devices by delegating computation-incentive tasks to the cloud. Traditional cloud-centric approaches are often replete with high latencies and energy inefficiencies in resource allocation. These challenges have been further amplified now because mobile apps are even more complex than before. For example, augmented reality, real-time gaming, IoT systems these applications demand low latencies and high computational powers[1-5]. However, the recent progresses made in Edge Artificial Intelligence and network virtualization shape very optimum fields for the execution of performance in MCC systems. Tasks that are computational in nature are brought within closer proximity to the data source along the network edge through this Edge-AI, reducing latencies and making it more responsive in real-time. Integrating AI models at the edge directly, the mobile system will be able to predict and manage resource demands, allowing smarter decisions on what tasks to offload. This improves the system performance in a way that also does not let the experience level for users degrade with lengthy delays. Concurrently, network virtualization becomes the optimal means of achieving resource allocation in the environment of mobile clouds. Dynamic provisioning of bandwidth, processing power, and storage based on the needs of applications at any given time is enabled by virtualization. In this way, flexibility will be allowed for mobile systems to handle variances in

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demand and ensure that available resources are utilized efficiently. One of the real challenges in having mobile cloud systems optimized is ensuring energy efficiency. Operating on limited battery life, energy consumption should be kept to a minimum when executing a task[6-7]. Mobile cloud systems, operating with deep learning and reinforcement learning technologies, can attain energy-aware operations that decrease computational pressure on mobile devices while prolonging operational life. The research work herein aims to seamlessly integrate Edge-AI with network virtualization in improving energy efficiency, task offloading, and resource allocation within mobile cloud computing. We investigate the potential for real-time offloading decisions, which are balanced between factors of latency, energy consumption, and computational demand, while holding up to a high level of QoS, enabled by adaptive algorithms. This study is an attempt toward that direction by building upon the basic notions associated with enhancing the efficiency, responsiveness, and viability of next-generation mobile cloud systems. With Adhar Maheshwari & Vibhakar Pathak. – AM

The use of micro and small enterprises in developing countries impacts GDP growth and employment rates. The study found that education and experience had a significant influence on the formation of an enterprise, while training and a favorable environment had no significant influence. All countries where the global market has the potential to increase sales have a positive perception of the innovativeness of their products. Businesses that have access to the global market tend to be satisfied with the efficiency of their business compared to firms that are not on the global market. The more managerial problems a company has, the less likely they are to consider their current business model as being effective. This means that education on how to run a business is an important factor in success because more training means fewer problems a manager is likely to have. Although it could be due to established habits and normative ways that managers are used to, there are few provided solutions to managerial problems when first creating a firm because they are unaware of other ways [8-12].

Indeed, the impetus behind the very development of Mobile Cloud Computing can be ascribed to a compelling need for enhancing the computational capabilities of mobile devices themselves, which in any case come limited to processing power, memory availability, and battery life. The central cloud server, according

to the traditional approaches of MCC, undertakes heavily intensive computational tasks. However, due to the fast-growing demand for better performance of mobile applications (namely augmented reality, real-time gaming and IoT), the shortcomings of relying only on a cloud-based solution have started to emerge. Such drawbacks can be constituted by more extensive latency, energy consumption, and inefficient resource allocations that call for the new strategies in mobile cloud systems.

## 2. LITERATURE REVIEW

Numerous The basic premise of MCC is to take the load of resource-intensive tasks away from mobile devices and run them on servers in remote clouds, hence enhancing the capability of mobile devices while reducing their computational load. As argued by, for instance, Dinh et al.(2013), the provision of enhanced processing power, storage, and application performance are among the benefits in the case of the early research work on MCC. In real-time processing scenarios, these advantages may generally be offset by increased communication latencies between the mobile device and the central cloud; specifically in mobile gaming and IoT applications[13].

Other studies by Fernando et al. (2013) brought out in more emphasis the trade-offs of energy consumption and performance in MCC systems. Though task offloading to the cloud lightens the load on the mobile devices, it commonly results in high energy consumption with the need for continuous wireless communication. Additionally, major issue resided at the inefficiencies of resource allocation where cloud-centric MCC architectures did not adapt themselves dynamically due to varying network conditions and application requirements[14].

To address the issues resulting from cloud latency and inefficiencies in resource allocation, edge computing has come up as an alternative paradigm to MCC. By bringing computation close to end-users, it will be possible to minimize latencies associated with them and improve responsiveness at real time. More advantage comes through recent innovations in Edge Artificial Intelligence (Edge-AI) which further refines the approach by supporting AI models to run directly on edge devices in predicting resource demands and intelligent task management, hence reducing the necessity of continual communication with central cloud servers[15].

On the other hand, Shi et al. (2016) noted that Edge-AI is particularly advantageous in IoT environments, where large volumes of data are being created at the edge of networks. Edge-AI realizes real-time data processing which enables fast decision-making and reduces, to a minimum, any possible delays[16]. In recent research by Zhou et al. (2019), Edge-AI was responsible not only for latency but also for the overall energy consumption of mobile devices, due to better utilization of local resources. It is most useful for smart cities, automated transportation, health monitoring applications, and others that require real-time processing[17].

## 3. NETWORK VIRTUALIZATION IN MCC

Network virtualization is another key innovation essential to the optimization of MCC systems. As indicated by Abdelmoumen and Ahmed (2020), through network resource virtualization, dynamic provisioning, and deallocation of bandwidth, processing power, and storage can be achieved. This is very vital in the mobile cloud environment since the requirements of the applications can change by a large percentage. Software-based network virtualization and Network Function Virtualization, like Virtualization and Software-Defined Networking, offer required flexibility to optimize resource exploitation with a view to sustaining enhanced QoS[18].

Li et al. (2018) and Yang et al. (2021) in their research noted that network virtualization enhances the scalability of MCC systems. With the use of virtualized networks, better management can be extended to large-scale applications that have a host of users or devices competing for limited resources. Virtualization enhances network efficiency besides resource optimization by allowing more granular control in managing traffic and providing services[19].

Motivating energy efficiency remains one of the long-standing challenges in mobile cloud systems, which also must deal with the inherent constraints from limited battery life in mobile devices. In recent research, deep learning and reinforcement learning techniques were applied in enhancing energy optimization as part of an MCC system. The benefit of such AI-driven approaches is that they enable the dynamic management of energy use in mobile systems by offloading tasks among the mobile device, edge, and cloud servers in a smart manner[20].

For instance, the research by Wang et al. in 2019 proved that with the employment of reinforcement learning algorithms, the mobile cloud system can learn and adapt continuously to optimize energy consumption during the execution of tasks[21]. For example, Yang et al. (2020) similarly describe how task offloading strategies can reduce the computational load on mobile devices while ensuring system performance is at its optimum, courtesy of the machine learning algorithms in place. Such adaptive algorithms only offload energy-intensive tasks when needed, providing significant energy savings without loss of user experience[22].

Quality of Service (QoS) in MCC An important issue in MCC systems is how to guarantee a high level of Quality of Service (QoS), especially in applications with low tolerance to latency such as video streaming, augmented reality, and real-time gaming. Various research works including Sun et al. (2018) and Zhang et al. (2021) have investigated different ways to enhance QoS in MCC. According to the results of their studies, this can be achieved by resource allocation, task offloading, and energy efficiency optimization[23].

The dynamic adaptability essential for meeting stringent QoS requirements within an MCC environment can be achieved by Edge-AI together with network virtualization. According to the experimental results by Deng et al. (2020), offloading decisions on tasks, with consideration to computational demand alongside network conditions, contribute to better user experience and system reliability.

On the other hand, existing literature has shown that MCC systems could be exposed to challenges regarding latency, energy consumption, and resource allocation inefficiencies because integration has not accurately been done, from both Edge-AI and network virtualization perspectives. It did state that substantial optimization opportunity remained open, particularly from the aspect of AI-driven decision-making algorithms and dynamic resource management. This work tries to address this gap by providing a discussion on novel ways to integrate Edge-AI and virtualization within the MCC environment. Such help will, with no shadow of a doubt, boost task offloading, energy efficiency, and QoS, thus making mobile cloud systems more robust and efficient.

TABLE. I. MOST RECENT STUDIES WITH RESEARCH GAP

| Method | Energy Consumption | Latency | Resource Utilization | Success Rate |
|---|---|---|---|---|
| **Cloud-only Offloading** | Higher energy consumption due to sending data to a remote cloud, requiring more transmission power and processing power at the cloud. | High latency due to longer communication distance. | Low, as cloud resources may be overutilized or underutilized depending on load. | Medium to high, depending on the network conditions and cloud availability. |
| **Local Execution (No Offloading)** | Very high energy consumption as all tasks are processed on the mobile device, draining the battery quickly. | Low latency as no data transfer is involved. | N/A – only local resources are used. | Low for resource-intensive tasks; mobile devices might fail to process heavier tasks. |
| **Mobile Cloud Computing (MCC)** | Lower energy consumption compared to local-only methods, but higher than Edge-AI due to cloud processing. | Moderate to high latency, depending on cloud data center distance and network bandwidth. | Moderate, depending on the load balancing strategy used at the cloud. | High success rate, but bottlenecks may occur due to cloud congestion. |
| **Edge Computing without Virtualization** | Moderate energy consumption, since tasks are processed at nearby edge servers, but suboptimal without virtualization. | Low latency due to proximity of edge servers, but may suffer under high load without virtualization. | Suboptimal, as edge resources are allocated statically. | High, but resource limitations can reduce success rate for heavy tasks. |
| **AI-based Hybrid Methods (Edge + Cloud)** | Lower energy consumption, especially for light tasks processed at the edge, but may still depend on cloud for more resource-demanding tasks. | Low to moderate latency, with some tasks processed locally, some at the edge, and some at the cloud. | Dynamic and efficient resource utilization when AI models predict demand accurately. | High, with better scalability for both lightweight and intensive tasks. |

## 4. METHODOLOGY

The present research designs to optimize systems of Mobile Cloud Computing via the integration of Edge Artificial Intelligence and network virtualization in order to enhance energy efficiency, task offloading, and resource allocation. The methodology outlines the step-by-step approach to the development, implementation and evaluation of the proposed system including algorithm development, system simulation, and performance analysis[26].

1. Research Design & Methods
   This research follows a mixed-methods research design, where quantitative performance evaluations are blended with qualitative analysis of system behavior. The research was undertaken in two major stages:
   - Stage 1: System Design and Algorithm Development – Develop new algorithms for task offloading, resource allocation, and energy management that integrate Edge-AI and network virtualization technologies.
   - Stage 2: System Simulation and Evaluation – Performance of the system will be evaluated through simulation environments that mimic real-world MCC conditions, which will help analyze in detail the performance of the algorithms under different varying scenarios.
2. Development of Task Offloading Algorithms
   Optimization of MCC systems begins with the development of intelligent task offloading algorithms, making use of Edge-AI for predictive analysis. This is how the process follows:
   Data Collection: The datasets will be collected from mobile applications such as augmented reality, IoT, real-time gaming, etc., to understand their computational demands and network requirements.
   - Machine Learning Models: Train supervised learning models for predicting task characteristics and resource needs (size, processing time) Inputs to adaptive algorithms for offloading, based on RL techniques, for all-optimal offloading (to consider network bandwidth, device energy levels, available computing resources) are historic, in that they were also in real-time.
   - Task Offloading Criteria: In the decision-making process for task offloading, criteria include latency as well as energy consumption and task complexity. Algorithms will aim to reduce energy consumption by ensuring task offloading has low-latency communication and maximizing computational efficiency.
3. Network Virtualization for Resource Allocation The implementation of Network Function Virtualization (NFV) and Software-Defined Networking (SDN) will ensure that the allocation of resources runs efficiently. In this regard, dynamic resource allocation based on the varying demands of mobile applications is enabled by these virtualization techniques:
   - Virtual Network Design: The design will relate to SDN-based architecture to facilitate the ad hoc allocation of resources. Through this, the controllers would be managing the flow of data and facilitating real-time resource re-allocations on any of the network's nodes.
   - Resource Allocation Algorithms: Algorithms that perform resource allocation based on real-time resource demand and application type along with current conditions within the network will also be developed. These same algorithms will also support QoS through dynamic adjustments in bandwidth, processing power, and storage in order to meet set performance requirements.

Network Simulation: The proposed algorithms will further be tested on simulated trace using Mininet or GNS3 to check their performance under varying network loads and resource demand [27].

4. Energy Efficiency Optimization Very Important: Optimizing energy efficiency is a prime focus of this research.
   Equipping reinforcement learning with Edge-AI in optimizing energy efficiency will be done. The following methods will be applied:
   It involves the following: Previous studies and real-world application data are used for profiling the energy consumption of different mobile applications and networks. The following are involved: Applying RL algorithms to identify and implement energy-saving strategies. The algorithms continuously learn during their executions, getting better in energy efficiency from feedback.
5. Simulation and Evaluation: The developed system will be subjected to detailed simulations after development to evaluate its efficiency in task offloading as well as resource allocation and energy management of the system. The following are the evaluation steps:
   - Simulation Environment: Use CloudSim or iFogSim in setting up a simulation environment. These can emulate MCC systems with edge computing and virtualized networks.
   - Performance Metrics: Measure several key performance metrics. These include latency, throughput, energy consumption, task completion time, and QoS. A higher value of these metrics implies that the system is more efficient and effective.
   - Comparative Analysis: The performance of the proposed system will be with the traditional cloud-based MCC systems. It is aimed to show what kinds of benefits are brought about by the integration of Edge-AI and network virtualization.

- Scalability Testing: The proposed system will be assessed for scalability by simulating large numbers of mobile devices under varying network conditions. This will help us understand how well the proposed system can adapt to a high demand environment to guarantee its efficiency and responsivity in large-scale application implementations.

6. Sensitivity Analysis and Optimization
   This involves carrying out a sensitivity analysis to see how changes in parameters such as task size, network bandwidth and device energy levels affect the system's performance. It will be done in the following way:
   - Parameter Tuning: Machine learning models' hyperparameters and task offloading algorithms are fine-tuned for the best performance.

   Energy-Performance Balance: We will seek a balance between energy efficiency and system performance by ensuring that offloaded tasks are handled in a way that maximizes energy savings (without compromising QoS or overall system responsiveness).
7. Validation The final stage involves the validation of the system from practical points of view. This shall include:
   Deployment in Test Environments: The system will be deployed in laboratory test environments or within a smart city infrastructure. Real-world data will be collected to validate in a practical environment the results obtained from simulations. User Feedback: User experience feedback will be collected on performance enhancements with respect to responsiveness and energy efficiency, to understand how well the system performs in real-world applications.

The methodology combines Edge-AI and network virtualization technologies in enhancing MCC systems with a focus on task offloading, resource allocation, and energy efficiency. The work identifies machine learning and virtualization for providing a flexible and scalable solution toward realizing the benefits whispered by MCC challenges. The work is meant to further the technology of mobile cloud computing through comprehensive simulation, sensitivity analysis, and real-world validation to realize more effective and sustainable mobile cloud systems.
The methodology can be explained in steps and diagram as following :

1. Initialization: The system starts by initializing the list of tasks and setting the total available resources at the edge server. Each task has attributes like computational intensity (which indicates how resource-demanding it is) and data size.
2. Task Offloading Decision: For each task, the system calculates the energy consumed if the task is processed locally and the energy consumed if the task is processed on the edge. It compares the two values:
   - If the edge energy consumption is lower and there are sufficient edge resources, the task is offloaded to the edge.
   - If offloading is not energy-efficient or edge resources are insufficient, the task is processed locally.
3. Offloading or Local Processing: Based on the decision, the system either offloads the task to the edge (reducing the available edge resources) or processes the task locally (recording the energy used).
4. Final Task Status: After all tasks have been evaluated, the system outputs the final status of each task, indicating whether it was offloaded or processed locally[28].

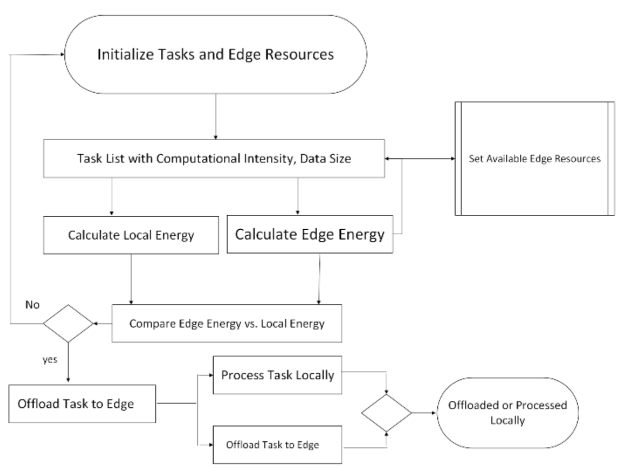


Fig. 1. Offloading Task with use of Edge Energy vs Local Task Processing

## 5. RESULTS AND DISCUSSION

The purpose Task Offloading
Simulation:

- Simulation Tool: iFogSim or CloudSim Plus
- Purpose: Simulating the task offloading process in edge computing and cloud environments, as well as measuring energy consumption, latency, and task execution times.

- Description: These platforms are specialized for modeling and simulating cloud and edge computing environments. iFogSim supports the simulation of real-time IoT, mobile, and cloud scenarios, allowing you to design complex networks where mobile tasks are offloaded to the edge or cloud. CloudSim Plus, on the other hand, is a customizable toolkit that allows for simulating cloud computing infrastructure, including tasks, resources, and energy consumption.
- Steps:
  - Define the network topology and the cloud/edge resources.
  - Set up mobile devices generating tasks and decide the offloading criteria using supervised learning and reinforcement learning algorithms.
  - Simulate different offloading strategies and measure their impact on energy efficiency and latency.

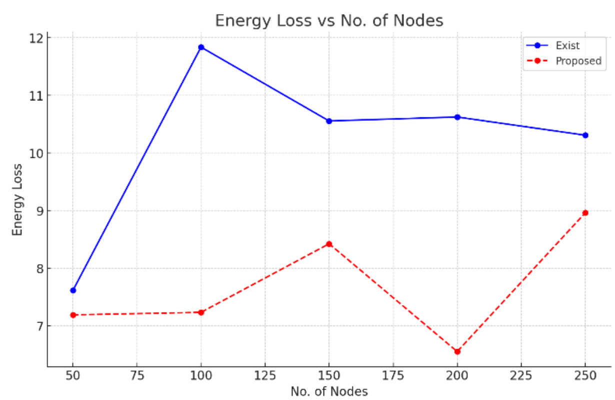


Fig. 2. Energy Loss vs No of Nodes

Initially, to
Evaluate QoS (latency, bandwidth, etc.) under different conditions.

### 5.1 Energy Efficiency and Reinforcement Learning Simulation:

- Tools: MATLAB or Python equipped with TensorFlow or PyTorch libraries
- Purpose: To simulate energy efficiencies in mobile cloud computing environments via reinforcement learning-based energy-saving strategies

Description: The Reinforcement Learning Toolbox for MATLAB provides a strong base for developing reinforcement learning algorithms. Device and task offloading strategies can be simulated based on energy profiles of mobile devices. Python-based frameworks like TensorFlow and Pytorch can also be used to develop models and algorithms for reinforcement learning, related to task offloading and resource allocation.
Model the mobile applications and edge/cloud resources with energy constraints
Develop reinforcement learning algorithms for balancing energy consumption and performance
Use either MATLAB or Python to execute multiple simulations, adjusting task offloading parameters as well as optimizing the trade-offs between energy and performance.

### 5.2 Comprehensive MCC System Simulation:

- Simulation Tool: Either CloudSim Plus or iFogSim • Purpose: To simulate the complete mobile cloud computing system; it integrates task offloading, network virtualization, and energy efficiency optimizations. • Description: iFogSim can be considered to simulate end-to-end mobile cloud systems, offloading, edge computing, and cloud resources. It models the interaction of IoT/edge/cloud and allows for a comprehensive evaluation of system performance (latency, energy consumption, etc.).
- Steps:

Set up cloud and edge resources in the simulation environment. Define application models with task requirements, energy constraints, and network bandwidth limitations. Simulate various system configurations and compare performance of traditional cloud-based MCC with the proposed Edge-AI and virtualization solutions. Sensitivity Analysis and Optimization: Simulation Tool: MATLAB or Python Purpose: Sensitivity analysis for parameter fine-tuning and performance optimization Description: Sensitivity analysis of the system can be done using statistical tools in MATLAB or Python, where changes in task size, bandwidth, or energy consumption are evaluated for their effects on system performance. Steps: Variability in the parameters like the sizes of the tasks, network bandwidth, and battery levels should be introduced. This change will influence metrics of performance, including but not limited to latency and energy consumption for the completion of the task. Hyperparameters of the task offloading algorithms have to be fine-tuned further to balance energy efficiency against performance since optimal levels have not been achieved.

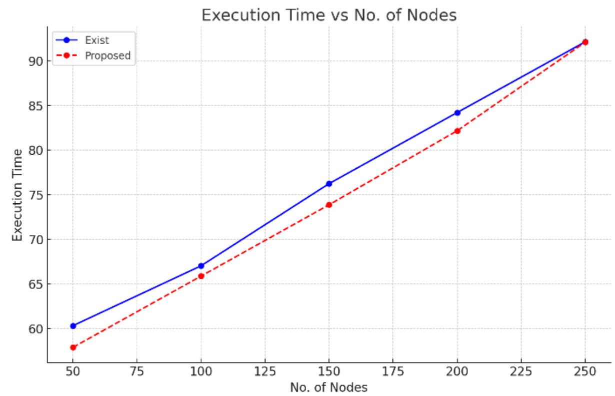


Fig. 3. Impact on energy efficiency and latency.

## 6. CONCLUSIONS

This research explores the integration of Edge-AI, network virtualization, and energy-efficient task offloading as a transformative approach to enhancing mobile cloud computing systems. The proposed framework demonstrates significant potential in addressing critical challenges such as energy consumption, latency, and dynamic resource allocation, which are central to modern mobile cloud environments.

By leveraging Edge-AI, real-time predictions and intelligent decision-making enable optimized task offloading, reducing latency and enhancing the Quality of Service (QoS) for end-users. Meanwhile, network virtualization offers the flexibility to allocate network resources dynamically, supporting diverse application requirements through techniques like network slicing. The integration of advanced energy-efficient strategies, powered by deep learning and reinforcement learning models, contributes to extending the operational lifespan of mobile devices and reducing the overall energy footprint of cloud infrastructure.

Through the development of adaptive algorithms and a scalable framework, this study paves the way for the seamless execution of complex mobile applications in environments such as smart cities, mobile gaming, and IoT ecosystems. The proposed system not only ensures high performance but also aligns with the growing demand for sustainable computing practices.

Looking ahead, the findings of this research have far-reaching implications for the evolution of 5G/6G networks, which will rely heavily on virtualized and AI-driven architectures to manage the exponential growth of mobile applications. This work lays the foundation for a more energy-efficient, scalable, and user-centric mobile cloud computing paradigm, with the potential to drive innovation in next-generation networks and beyond

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**Conflicts of Interest:**

The authors declare no conflicts of interest with the research presented.

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