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A NEW OFFLOADING TECHNIQUE TO MAXIMIZE MULTI-USER PERFORMANCE IN EDGE COMPUTING USING BLOCKCHAIN TECHNOLOGY IN THE INTERNET OF THINGS

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Abstract

We face more and more difficulties as blockchain technology combines with Mobile Edge Computing (MEC) and the Internet of Things (IoT), including excessive energy consumption and latency because of the size and complexity of the network. With data security as a top priority, it is imperative to optimize these exchanges and manage computational job offloading properly. MEC enabled by unmanned aerial vehicles (UAVs) is one of the most promising methods that ensures the stability and expansion of the network coverage zone for such applications and provides them with access to computing capabilities. This work investigates the simultaneous exploration of resource distribution and computation offloading for mobile edge-cloud computing structures that accommodate several users and unmanned aerial vehicles. First, for a mobile edge-cloud computing platform with numerous users and UAVs, we propose a paradigm for efficient resource allocation and compute offloading. The purpose of this work is to examine how blockchain and edge computing are incorporated into IoT systems. To the best of our knowledge, this is the initial assessment piece that covers every aspect of blockchain-based edge implementation categories and system architectures. We present a promising scenario for the energy use balance administration issue of multi-mobile devices and multitasking, based on an analytical method based on blockchain technology. Analysis of the associated approximate ratio is done. Numerous simulation experiments have been conducted in comparison to the random algorithm and the overall energy demand optimization approach. When compared to the randomized process, the experiment results indicate that the suggested greedy algorithm may improve average

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efficiency by 69.59 percentages in terms of energy consumption. Additionally, under the traditional task topology, the greedy algorithm almost always obtains the optimum solution when the mobile device's minimum transmission power is between five and six dBm.

Keywords: IoT, cloud computing, edge computing, blockchain, taffic, unmanned aerial vehicles (UAVs).

1. Introduction

The digital cryptocurrency's underlying technological advances, recently, manufacturing and tech businesses have shown a great deal of interest in cryptocurrency [1]. By 2025, business blockchain applications will generate US$ 19.9 billion in revenue annually, with 29 major use cases across at least 19 economic sectors, according market research firm Tractica. In contrast to centralized digital ledger techniques, blockchain synchronizes distributed databases replicated among numerous users through community validation. In order to address the issue of double-spending, Bitcoin was established. Beyond its initial conception and use, blockchain technology serves as a cornerstone for the paradigm change from centralized to decentralized management.

Many businesses from a variety of industries have largely adopted the design of the new IoT technology, which opens up new revenue streams for those industries. IoT technology use in the manufacturing sector has increased dramatically in recent years [2]. The Blockchain, which is thought to be the most inventive transaction system, was created as a result of cryptocurrencies. Transaction data between many people and corporate entities can be collected thanks to blockchain technologies. Data from routine transactions carried out by a large number of users and devices is typically kept in decentralized applications. The cryptocurrency is the source of the decentralized apps. By enabling internet-based communication between devices, the Internet of Things can understand different communication infrastructure. Blockchain technology has been dubbed the most disruptive technology ever. Finance, utilities, medical care, farming, logistics, and real estate are just a few of the sectors and industries that have used blockchain technology. Because trustworthy middlemen acting as gatekeepers for certain apps may be removed and the same applications can be operated autonomously without relying on centralized authority, blockchain technology is being used in a variety of industries. This can be accomplished successfully and efficiently without sacrificing security, which was previously impossible.

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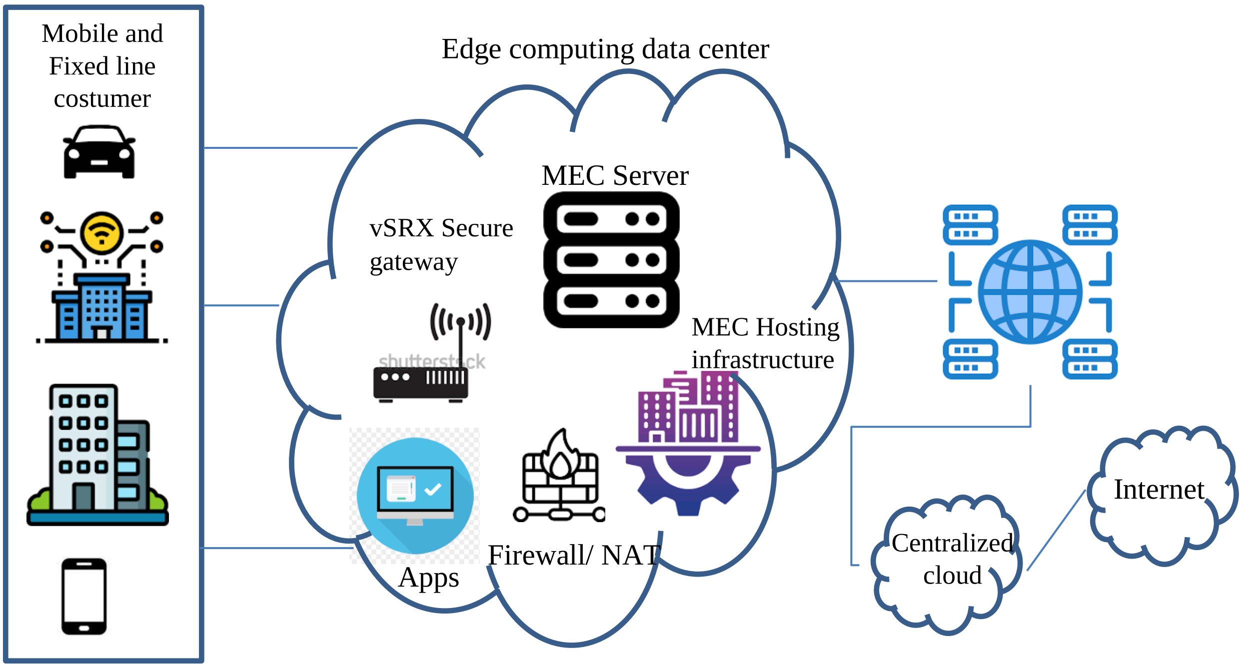

Figure 1. Platform for Multi-Access Edge Calculating

Multi-access edge calculating is regarded as the logical next step in data processing and computing in Figure 1. In conventional network environments, servers and other assets are frequently located in different places, which frequently means that cloud computing is located far from data-producing network equipment. MEC is a common architecture used by businesses [3]. It boosts efficiency by enabling networks to process data more effectively. Previously remote cloud-based IT service settings are now closer to devices that generate data. One significant benefit is that immediate processing of data can occur with reduced latency, which facilitates quicker information analysis and distribution.

Furthermore, maintaining security is crucial in the contexts of MEC and IoT. The integration of such structures with blockchain systems is being investigated in recent research trends; this adds another level of complexity even though it improves security [4]. Even while this integration is beneficial for security and trust in decentralized computing systems, it tends to spike energy consumption, operational costs, and occasionally causes delays. IoT devices can include blockchain-based technologies into the system and edge servers may communicate securely and transparently, creating a dependable environment for data processing and interchange. The task-offloading procedure is made more difficult by the need for more complex administration of blockchain operations due to the progress in security measures. The aforementioned difficulties are addressed in certain research in this area. However, as far as we are aware, typical machine learning methods have been used primarily recent studies on offloaded tasks in complex blockchain platforms with MEC enabled for IoT.

These studies usually only look at a small several samples and don't optimize their systems, which leads to unworkable solutions. There is a significant lack of novel sophisticated algorithms that can handle large-scale multiuser situations, making existing methods unfeasible. Furthermore, current models frequently overlook crucial links in these

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intricate networks and fail to account for all system features in an understandable way, which raises latency, energy consumption, and expenses. On the basis of UAV-mobile edge computing, several related system concepts have recently been introduced. These devices move computationally intensive tasks from a portable gadget to a more powerful resource located at the radio access network's (RAN) edge. The majority of these designs aim to reduce energy usage, allocate radio and computational resources effectively, and/or satisfy the latency needs of mobile users.

However, several characteristics, including minimal power consumption and data manufacturing, must be taken into account to sustain the network in which UAVs operate. Additionally, in a large-scale context, the edge network's associated servers' computational capability is limited, which causes major delays and makes these devices unsuitable for real-time operations. Additionally, it is thought to be a difficult task to choose the best offloading option in wireless networks with many devices and UAVs. We think that building an energy-efficient arrangement for a mobile edge-cloud computer system with several users and UAVs would be helpful in addressing these issues. Therefore, we proposed a successful work dumping and allocate resources strategy for a mobile edge-cloud compute system with many users and several UAVs. Additionally, a combination model for offloading and resource allocation is created as a challenge with the aim of reducing the total energy consumption of the system while keeping a latency constraint. To choose the best task offloading option for each device user, an energy-efficient method for numerous UAVs is also created.

This document is in the following format: In Section 2, blockchain-enabled offloading frameworks for MEC situations are thoroughly examined. Section 3 displays the recommended offloading strategy system model, while Section 4 details the simulation parameters and configurations. The experimental results are presented, and the simulation results and research insights are discussed. Section 5 brings the work to a close by outlining the main conclusions, the shortcomings of the suggested approach, and potential avenues for further research.

2. Related Works

The Internet of Things is growing so quickly that billions of smart gadgets are installed annually. By 2020, there will likely be over 70 billion smart gadgets in use. The volume of data that has to be handled has increased as a result of many devices having access. Processing and evaluating that data presents a difficulty, particularly if real-time processing is required. Using a cloud server alone won't be sufficient to handle such a big data volume and offer real-time response [5]. To address the issues of network latency and data detonation, edge computing is suggested. As everyone is aware, 5G is gaining traction. Edge computing is one of the biggest innovations of the 5G era, which can be implemented and used with 4G LTE networks due to its open architecture. Operators will continue to enhance edge computing capabilities while gradually expanding on the current network architecture, eventually reaching complete coverage of low-level network nodes' processing power.

Centralized cloud servers, which process data, due to the latency caused by transferring large amounts of data, it might not be appropriate for IoT applications that require quick

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responses [6]. Edge and fog computing is an alternative method of processing and storing specific data at edge and fog devices in a dispersed manner. In particular, fog computing and edge computing aim to reduce reliance on centralized processes. One of the many similarities between fog and edge computing is the presence of an intermediary layer separating the cloud server and the knowledge source. The layer includes distributed storage and compute capabilities as well as geographic location awareness. These models of computing are not the same, though.

At this time, several researchers have carried out extensive studies on computation of loading in edge computing contexts, with considerable success. Use theoretical methods such as game theory and augmented learning to analyze the edge demand response (EDR) problem from the perspectives of computing power, communication bandwidth, and IoT device power consumption. References, for instance, mostly used reinforcement learning techniques for the targeted distribution of edge resources. Citations [7], for instance, took into account edge collaboration concerns further, although they mostly concentrated on cloud-edge cooperation, paying less attention to concerted computing among edge nodes. Because edge resources are scarce, servers from various edge facility providers are not motivated to help other servers fulfill user requests. Furthermore, due to outside influences or dishonest rivalry among retailers, edge collaboration between various application providers may result in problems with user confidentiality and quality of experience (QoE).

Mobile edge computing has become a popular computing paradigm due to its minimal latency and excellent reliability, as its utilization in both edge and end submissions. When performing computation tasks (e.g., utilizing a networked controller, a long-range evolutionary macro station, a tiny cell micro base station, etc.), at the network edge, or close to the end user [8], MEC's fundamental idea is to process mobile app data locally. Consequently, mobile devices' resource shortage and end-to-end latency have decreased. As an emergent computing model, task offloading is only one of the many major challenges that the MEC environment still faces and has not yet been sufficiently addressed. Choosing which work to assign at the appropriate moment to the appropriate MEC server is essential for maximizing the application's operational effectiveness and utilizing MEC resources effectively.

Conventional approaches like game theory and linear programming are extensively researched to address the compute offloading problem [9]. For instance, a game for robot swarms was developed to solve the multi-hop cooperative computing offloading optimization problem. These traditional approaches do have certain shortcomings, though. First, they frequently assume that although the system's environment is preset, the turntable is truly dynamically balanced. Second, the traditional methodology-based approaches overlook the fact that, in addition to the non-deterministic nature of the interaction between devices and the environment, the perception of components in the structure is changing. Third, traditional approaches frequently neglect the long-term return optimization that the systems actually require in favor of finding the best solutions for one-slot systems.

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The goal of the balancing issue with multi-device multi-energy tasking is to minimize the maximum energy usage of several devices. Consider the following scenario: E is an edge server, and A and B is two mobile devices. For the purpose of simplicity, both mobile devices, a and b, are designed to have two jobs that must be finished in two time windows. To make the description simpler, take into account that mobile devices and edge servers can only perform one task at a time [10]. Additionally, assigning the task to the edge server for execution lowers the cost of energy usage. But suppose that in a, e is assigned both subtasks. Device b's energy usage is significantly higher than that of device an in this case because to b's inability to reach the edge server, creating an uneven energy consumption. Thus, the work management method needs to be changed to achieve energy balance.

3. Methods and Materials

3.1. Edge Computing-Based IoT

Cloudlet, multi-access cloud hosting, and fog computing are edge computing concepts that EC-IoT uses for processing time-sensitive and security-critical data generated by connected gadgets [11]. This tactic entails placing computer resources near Internet of Things devices to perform functions including data gathering, preprocessing, and cleaning. The procedure is primarily carried out by developing the resource providers at the network edge and the IoT layer at the bottom of the infrastructure. IoT data processing is optimized by edge computing. Instead of sending data straight to faraway cloud servers, this design uses IoT devices to gather data from their surroundings and process it locally on edge strategies. These local processing capabilities enable real-time data analysis and decision-making, which is crucial for applications that require quick responses, such as automated driving, real-time wellness tracking, and urban design.

By limiting the quantity of private information sent over the network, based on edge computing. Additionally, IoT enhances security characteristics by reducing susceptibility to possible cyberthreats. By allowing several edge devices to execute processing tasks, it also enables greater capacity deployment, reducing the burden on central servers and congested networks. Facilitating fast and precise vehicle localization with connected gadgets and radar systems is a prime instance. There are many different uses for EC-IoT. Even though they are not readily apparent, these applications are used in many urban and hospital settings, guaranteeing prompt and precise data processing for these uses. EC-IoT's optimization of environmental landscape structures in urban design has improved biodiversity indices, demonstrating the usefulness of edge computing in a variety of requests.

Figure 2 depicts the high-level three-layer architecture of the EC-IoT paradigm. The end-user part of the edge computer level, which includes IoT devices, is fundamentally similar to the old edge computing design. On the other hand, the typical IoT architecture lacks the edge computing layer. The actual physical sensors and equipment that gather environmental data make up the objects layer, which serves as the basis. These can produce vital operating data and range from basic embedded devices to sophisticated industrial gear. The edge layer sits just above this and is made up of edges and gateways that carry out initial data processing operations such local analysis, consolidation, and cleaning. This layer is essential for lowering

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latency since it processes data near its source, allowing for rapid local reactions and lowering the amount of data sent upward. The cloud layer at the top manages more intricate processing jobs and storage requirements that need significant computational power but are less time-sensitive [12]. It provides centralized control over apps spread across several edge devices by managing machine learning processes, powerful analytics, and large data storage. This methodical approach guarantees that every layer in EC-IoT systems maximizes processing speeds and usefulness, improving overall flexibility and effectiveness.

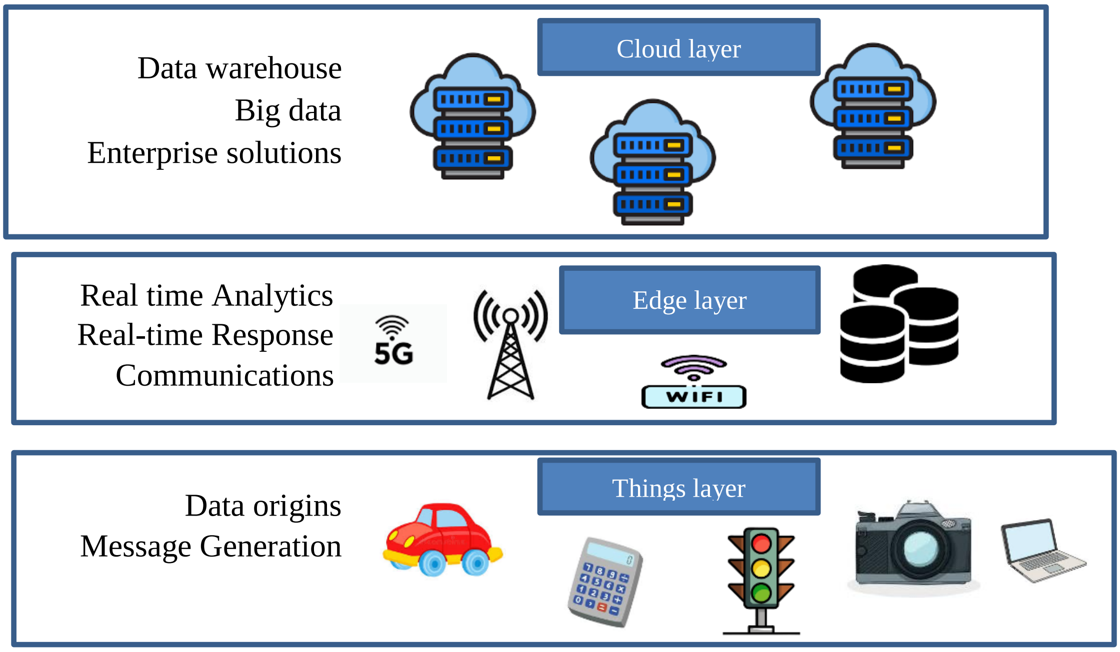

Figure 2. High-level illustrations of edge computing and the Internet of Things

3.2. Advantages of EC-IoT

EC-based and non-EC-based Internet of Things systems are better protected by AI-based security defensive measures; however the effects varied greatly because of variations in data processing and design. AI-driven security solutions function at the edge of EC-IoT systems, allowing for real-time threat recognition and reaction. The window of vulnerability is shortened by the quick detection and removal of possible threats made possible by this close proximity to data generating locations. By removing the need to transfer private data to centralized servers, localized artificially [13]. Additionally, by lowering the likelihood of unauthorized access and surveillance, intelligent models enhance confidentiality of data.

On the other hand, in non-EC-based IoT organizations, the majority of AI-based security solutions function in centralized cloud environments. Due of the duration required to transfer data from the computer to the cloud, these results in increased threat detection and response latencies even as it enables the deployment of more complex and resource-intensive AI models [14]. Because of the possibility for a single point of failure created by this centralized architecture, an effective assault on the cloud's infrastructure might endanger the entire IoT network. In light of these variations, EC-IoT systems have a number of benefits. The primary

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benefits that set EC-IoT apart are as follows. Improved bandwidth utilization and decreased latency: Edge computing handles data locally, near the network's edge, where it is generated. The latency required to deliver data to a central server for processing is greatly reduced by this close proximity [15]. This method's capacity to complete jobs with less latency, fewer resources used and more effective use of internet bandwidth is one of its main advantages. This lowers bandwidth needs and eases network traffic congestion, which is crucial given the growing number of connected gadgets producing enormous volumes of data.

Enhanced scalability and dependability: Edge computing makes it possible for devices to function separately from the cloud, which boosts system dependability. Edge devices can continue to operate efficiently in situations when access to a centralized server may be hacked or inaccessible, selecting options based on data that is updated in real time. Because the processing load is distributed, it is scalable to deploy edge computing units across multiple sites [16]. It is perfect for growing IoT applications since it permits small additions without requiring major infrastructure changes.

Real-time data processing and context-aware computing are made possible by edge computing, it eliminates the latency associated with data transmission to remote servers. Applications that need quick data analysis and reaction must have this. By enabling edge devices to make decisions locally based on real-time environmental information, it improves computer systems' responsiveness and context sensitivity [17]. This feature is especially helpful for industries where timely and pertinent data are essential, such as healthcare monitoring systems and smart city technology.

4. Implementation and Experimental Results

Experiments are planned in this chapter to examine the suggested algorithm's effectiveness. The coverage in this piece is 60 m × 60 m. Other experiment parameters are displayed in Table 1, and by standard, there are four, three, and three subtasks, mobile gadgets, and relay devices, respectively [18]. The article makes the assumption that, throughout the entire experiment, the computational effort and data sizes of the computing tasks will have a 712 mean and a 256 standard deviation, which is in line with the average distribution. Furthermore, this paper develops a testing procedure for the TECM (total power use minimization) procedure.

Table 1. Parameters of the experiment

Limit	Numerical assessment	Bound	Arithmetical value
alpha	0.2	Bk'/MHz	6
Bi,k/MHz	6	pk'/dBm	6
pi/dBm	6	fe/GHz	5
fi/GHz	0.8	σ'/dBm	-60
pi	0.4×10^{-27}	σk/dBm	-60

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Experimentation 1

The article looks at the relationship between the highest energy usage of the subtask and the path loss component changes [19]. Figure 3 show that when the route loss element increases, so does the subtask's maximum energy usage [20]. The path loss element's correlation with the subtasks' highest energy consumption explains the curve arrangement in empirical Figure 3 with Table 1.

According to experiments, when the mobile device's transmitting capability is between five and six dBm, the MMG algorithm lowers the absolute highest energy usage of subdividing by 57.59% and 72.87% on average, outperforming the random approach. The ideal solutions obtained by applying force are nearly at this level.

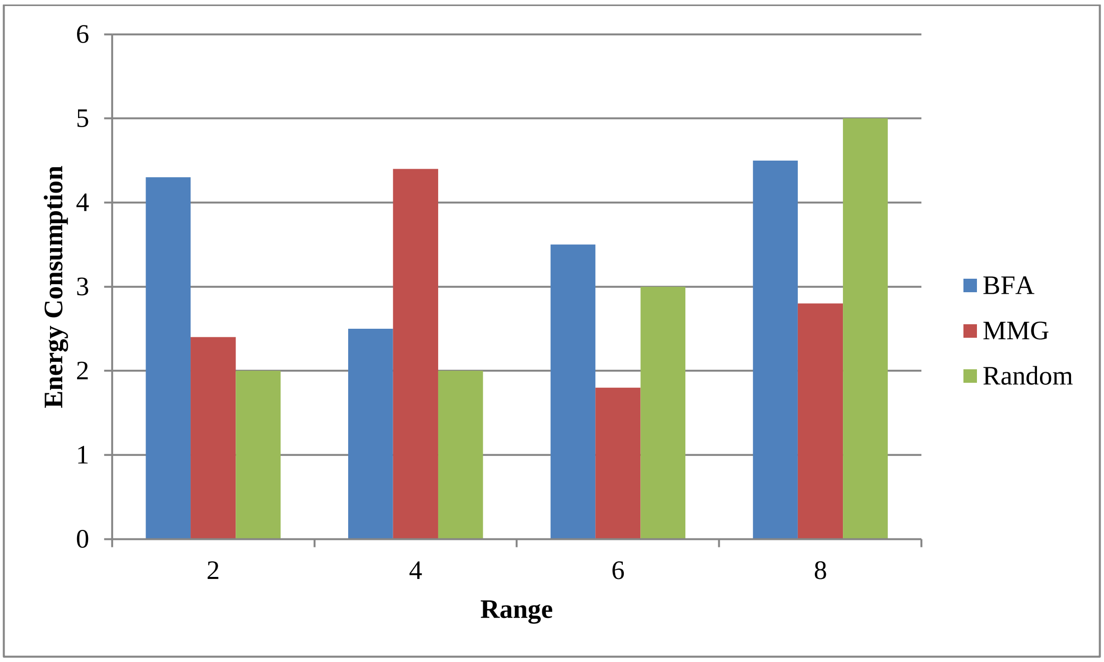

Figure 3. Maximum amount of energy used

Experimentation 2

Experiment 2 looks at the greatest energy consumption of subtasks with different time constraints; Figures 3 and 4 shows that the mobile device's maximum power transmitter is five dBm. The findings show that the greedy algorithm outperforms random techniques and improves overall energy consumption.

Lastly, we see how the number of task levels affects the maximum energy consumption of subtasks when the pathloss factor is 0.1 [21]. Table 2 illustrates how the time needed to finish of each subtask lowers as the number of tasks grows, leading to jobs that must be completed in a shorter amount of time. These results in an increase in the amount of energy needed to finish the task. Nonetheless, the MMG method outperforms the TEC method and the randomly generated algorithm in terms of the minimum subtask's highest energy usage.

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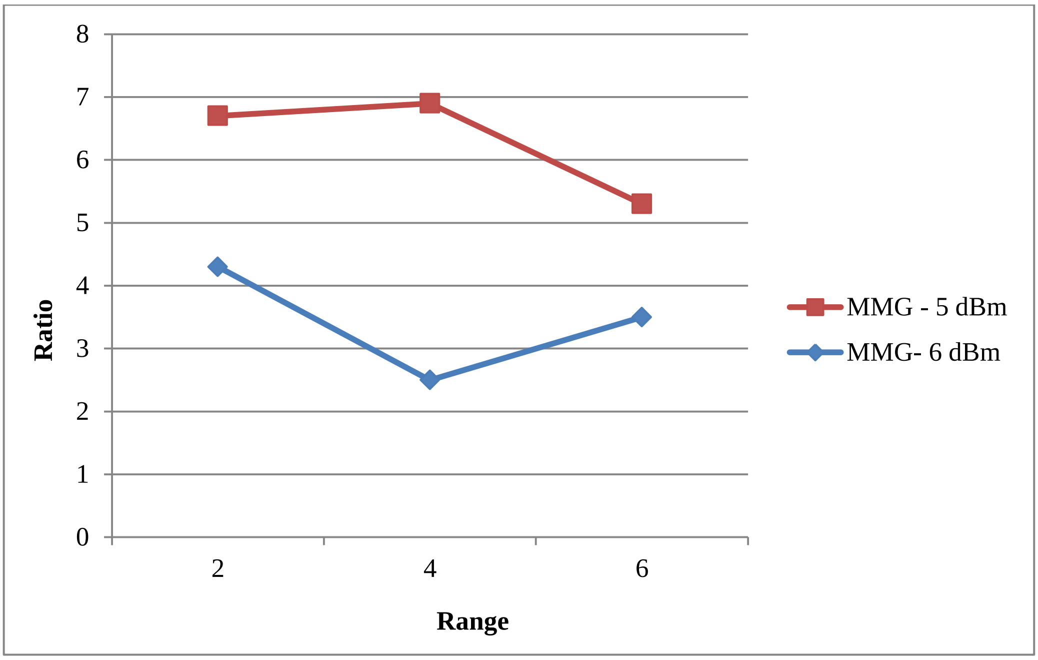

Figure 4. The greedy algorithm's proximity ratio

Table 2. Assessment of Experiment 1

Range	MMG (5 dBm)	Random (5 dBm)	BFA (5 dBm)	TECM (5 dBm)	GA (5 dBm)	MMG (6 dBm)	Random (6 dBm)	Brute force (6 dBm)	TECM (6 dBm)	GA (6 dBm)
0.1	2.4	8	2.2	3.58	2.4	3.4	8.5	2.5	4.58	3.4
0.2	2.5	8.5	2.1	3.39	2.5	3.5	7.5	2.67	4.39	3.5
0.3	2.6	8.4	2	3.29	2.6	3.6	7.3	2.78	4.29	3.6
0.4	2.7	8.2	2.5	3.15	2.7	3.7	7.9	2.2	4.15	3.7
0.5	2.8	8.3	2.58	3.28	2.8	3.8	8.6	2.296	4.39	3.8
0.6	2.9	8.4	2.69	2.86	2.9	3.9	8.4	2.45	3.86	3.9
0.7	3	8.5	2.88	2.45	3	4	8	2.78	3.45	4

Experimentation 3

This article offers a thorough explanation of the suggested MMG algorithm. The total amount of subtasks determines how many portions this article splits you into, and each layer's subtasks should be completed within the allotted time after the division is complete. First, the computational model for each subtask is chosen depending on the conditions of time and energy expenditure.

Table 3. Maximum subtask energy usage V.S time limit

Variety	MMG procedure	Random procedure	Brute force procedure	TECM procedure	Time restraint
0.1	3.4	8.1	2.2	4.58	2.4
0.2	3.5	8.5	2.1	4.49	2.5

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0.3	3.6	8.4	2	3.29	2.6
0.4	3.7	2.25	2.5	3.15	2.7
0.5	3.8	8.3	2.58	3.28	2.8
0.6	3.9	8.4	2.69	2.86	2.9
0.7	4	7.9	2.88	2.45	3

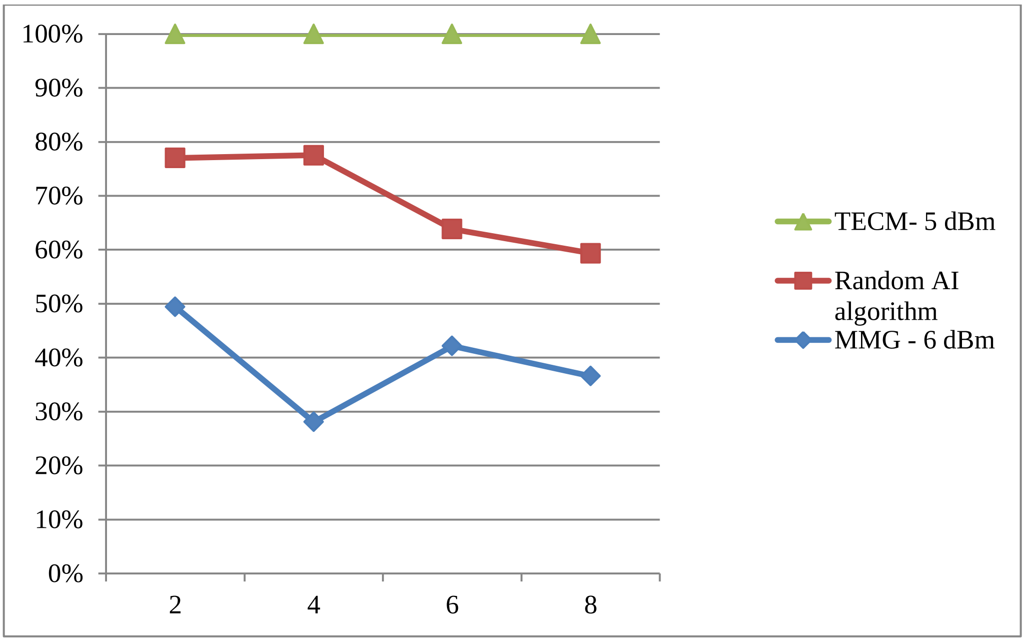

Figure 5. Subtask's maximum energy consumption versus time constraints

As a result, more energy is required to complete the work within the enclosed space. However, the MMG technique surpasses both the random methods and the TECM in terms of highest energy usage of the shortest subtask. The average power use of subtasks increases as the number of subtasks increases, as indicated in Table 3 and Figure 5, and the approximate MMG ratios increase as the handheld device's signals strengthen by 5dB and 6dBm, correspondingly.

5. Conclusion

An energy-efficient architecture for a multi-user ME-cloud computing system with multiple UAVs was suggested in our study. Because of its scalability, this system can handle increases in internet traffic without experiencing a decline in efficiency. A UAV network is also set up to cover the high-density and dead networking areas. Furthermore, UAVs can give further applications in a smart city network if MEC technology is deployed at many levels to provide computation capabilities at the frontier of the network. In order to control network traffic and give network operators a cutting-edge interface, the core infrastructure is built using SDN technology. Lastly, simulation tests show that our suggested methodology can drastically reduce the system's overall energy usage.

This article investigates the NP-hard problem of energy balance when using numerous mobile devices during multitasking. The cloud server that uses the most transmission energy

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is eliminated in the original design. When the relay device node is added as the task's transfer node, cell phones relay devices, and routers create three-layer architecture.

Concurrently, this work creates the MMG algorithms to solve the problem of energy consumption balancing and validates its effectiveness through numerous comparative experiments.

Using blockchain technology to secure and defend the UAV network against various threats is one exciting future avenue. Additionally, a broader scenario in which users of devices and UAVs might move about dynamically throughout the offloading period will be examined. In these situations, it is possible to effectively handle the problem formulation and modelling as well as the solution by utilizing deep learning approaches.

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