

Research Article

On Computational Offloading in Massive MIMO-Enabled Next-Generation Mobile Edge Computing

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Next-generation wireless communication networks are expected to support massive connectivity with high data rate, low power consumption, and computational latency. However, it can significantly enhance the existing network complexity, which results in high latency. To ease this situation, mobile edge cloud and massive multiple input and multiple output (MIMO) have recently emerged as the effective solutions. Mobile edge cloud has the ability to overcome the constraints of low power and finite computational resources in next-generation communication systems by allowing devices to offload their extensive computation to maximize the computation rate. On the other hand, MIMO can enhance network spectral efficiency by using large number of antenna elements. The integration of mobile edge cloud with massive MIMO also helps to increase the energy efficiency of the devices; as a result, more bits are computed with minimal energy consumption. In this work, a mathematical model is formulated by considering the devices' energy constraint, which is nonconvex in nature. Following that, to overcome this, we transformed the original optimization problem using the first approximation method and solved the partial offloading schemes. Results reveal that the proposed scheme outperforms the others by considering computational rate as a performance matrix.

1. Introduction

Future wireless communication networks are expected to connect massive devices to the Internet [1]. These devices would be intelligent, cost-effective, and energy efficient [2]. Moreover, such devices will provide diverse quality of services [3]. Some promising technologies for these networks are artificial intelligence/machine learning [4], autonomous vehicles [5], reflecting intelligent surfaces [6], backscatter communication system [7], unmanned aerial vehicles [8], nonorthogonal multiple access [9], and high frequencies such as millimeter wave, terahertz, and visible light communications [10]. However, there exist several challenges in the development of these networks [11]. The most critical issue

is the spectral efficiency due to the limited spectrum resources [12]. Another issue is the allocation of existing resources in efficient way [13]. Furthermore, security is also a big issue in both physical and network layers [14].

Recent advancements in the Internet of Things (IoT) and applications such as augmented reality [15], self-driving vehicles, smart cities [16], smart grids, and home automation have resulted in the concept of the Internet of Everything (IoE) [17], where a large number of computing and communication capable devices (e.g., sensors) are deployed [18]. The primary purpose of these sensor nodes is to collect a large amount of data generated from real-time applications and use it to manage traffic control systems [19], security [20], surveillance [21], and noise pollution control [22], as well as to assist existing

infrastructure. Similarly, the amount of data generated grows exponentially as IoT devices such as sensors, actuators, and smartphones become more widely used [23, 24]. These devices collect data from various applications, such as health care, monitoring, and security [25, 26]. In addition, these devices are small in size and have limited computing power and finite battery life [27]. However, the processing of the huge amounts of data that are produced by real-time applications must take place in an extremely condensed amount of time [28]. Due to their limited computational capabilities, these devices are unable to handle large amounts of data [29]. As a result, their quality of service (QoS) is highly compromised [30, 31]. Because of this, the need for a lot of computing power shows that users are moving away from traditional ways of communicating and toward computers [32, 33].

1.1. Related Work. In the last few decades, central clouds have been used to get around the problem of having too many computers. These central clouds enable on-demand access to massive storage and extensive computation [33–36]. In addition to this, these clouds are situated too far away from these devices, and as a result, they bring latency into the system [37]. As a result of this, relying on central clouds is insufficient [38]. However, to overcome the latency constraint imposed by central clouds, the mobile edge cloud (MEC) emerges as a practical solution, providing high computational capabilities in close proximity to these devices. The MEC enables these devices to offload their extensive computations in one of two ways: binary offloading or partial offloading. Within the framework of a binary offloading approach, the task in its entirety is computed either locally or at the MEC. In contrast, the task is divided in to two distinct segments within the framework of the partial offloading system [39]. A component of the task is carried out locally, while the remaining portion is offloaded to MEC so that it can be processed on a much larger scale. Thus, the perfect match of MEC with IoT attracted much attention from academia and industry and was identified as a critical technology beyond 5G/6G wireless networks [27, 40–43].

Recent work has focused on overcoming finite battery life constraints and limited computational capabilities by using either a partial or binary offloading scheme. The author of [15] investigates the concept of wireless power mobile edge cloud using a partial offloading scheme and maximizes end-user energy efficiency by optimally allocating the resources such as transmitted power and local chip computation and transmitting time using a mesh adaptive direct search algorithm. In [44], the author optimizes resource allocation and implements a partial offloading scheme to reduce the energy consumption of orthogonal frequency division multiple access-based mobile edge cloud networks. Simultaneously, the author describes task placement in [45] as a stochastic optimization problem, which will eventually lead to a deterministic approach for minimizing energy consumption via the dynamic offloading algorithm. In [46], the author investigates a binary offloading scheme based on optimal resource allocation over a stochastic wireless channel in order to reduce the MEC's energy consump-

tion, whereas in [47], the author optimizes the end-computation user's rate by allocating resources such as transmission time, chip computational capabilities, and mode selection variables that specify whether the task is computed locally or offloaded to MEC for further processing.

The literature shows that offloading tasks minimize energy consumption, either partial or binary offloading schemes. However, latency is also a critical performance metric for evaluating the MEC network's performance. As a result, considerable research has been conducted in the literature to address the time-sensitive application. In [48], an author formulates the latency minimization problem for single and multiple device scenarios by partially offloading the task to MEC and investigates the role of the intelligent reflecting surface in MEC. Simultaneously, the author formulates the mutual communication and computational resource allocation problem in [49] in order to minimize the weighted sum latency of all devices. Additionally, some work has been conducted that takes into account both energy consumption and latency constraints for time-sensitive applications [50, 51]. The authors in [51] formulate the multiobjective constraint optimization problem and investigate the trade-off between energy consumption and latency in this joint formulation. Simultaneously, the author of [51] investigates the weighted sum of the task's execution time and computational energy consumption while taking the transmission power constraint into account via a partial offloading scheme.

Furthermore, the researcher contributed significantly to the field by integrating orthogonal frequency division multiple access with MEC in order to further optimize communication resource utilization by considering profit [52, 53], latency [54], and energy efficiency [55] as performance metrics. In [52], the authors consider the price of computation and optimize end-users and MEC resources using the game theory approach. Simultaneously, the author in [53] considers the objective of mobile network profit maximization while taking the end-user's quality of service constraints into account by optimizing computational and communication resources jointly. As illustrated above, successive offloading to MEC reduces energy consumption and latency. In comparison, the success of the MEC network is mainly dependent on the performance of the communication links. Thus, its performance can be enhanced by integrating it with cutting-edge wireless communication technologies such as massive MIMO. Massive MIMO, as a critical technology for the 5th generation of communication systems, supports a large number of users while increasing spectral efficiency, system capacity, robustness, and energy efficiency.

Getting inspired by massive MIMO's advantage, some researchers started considering its integration with MEC. In [56], authors consider the concept of cell-free massive MIMO which enables mobile edge cloud and uses stochastic and queuing theory to analyze the impact of computational probability on energy consumption. In [57], a low complexity algorithm is designed to optimize the communication and computational resources by considering energy consumption as a performance metric for massive MIMO-enabled MEC. The above discussion shows that MEC can

overcome finite battery life constraints, but their performance mainly depends on the communication link. Simultaneously, massive MIMO is a cutting-edge technology of wireless communication that increases spectral efficiency. Integrating it with the MEC will dramatically increase the transmission rate, which directly leads to a higher computational rate.

1.2. Motivation and Contribution. The concept of smart cities includes a significant number of Internet of Things devices. IoT is an abbreviation for the Internet of Things, which refers to low-power devices that are used to manage or aid the infrastructure of smart cities, such as traffic control, security aspects, surveillance, and pollution control. These real-time applications on these devices are generating a significant amount of data, which is being collected by these devices. On the other hand, the processing capabilities of these devices are insufficient to process the huge amount of data detected by these low-power sensors, which demand massive computation in a short amount of time. To overcome the limitations mentioned earlier, MEC emerges as a practical solution that allows these devices to offload their extensive computation. In comparison, MEC's performance can be increased by integrating it with the cutting-edge wireless communication technology called massive MIMO. Integration of massive MIMO and MEC will increase the performance of the MEC network and increase the spectral efficiency provided by massive MIMO. Specifically, massive MIMO's increased spectral and energy efficiencies can yield higher transmission rates and lower energy consumption for offloading in MEC. Moreover, the more significant number of users supported by massive MIMO can enable more parties to offload simultaneously, thus reducing queuing delays. Motivated by these facts, we aim to show the benefits of applying massive MIMO to MEC networks as given below:

- (1) A mathematical model is formulated for optimal allocation of resources like channel estimation time, transmission power, computational resources, and task offloading decision parameter to maximize the cumulative computation rate of the network with subject to latency and energy constraint
- (2) A fundamental trade-off between offloading and local computation is analyzed. It reveals that as the number of computational cycles requirement increases, devices start offloading their extensive task to maintain the quality of service requirements
- (3) Comparative analysis of partial offloading, binary offloading, edge computation, and local computation scheme is done. Results demonstrate that the partial offloading scheme outperforms the other by considering cumulative computational rate as a performance metric

The rest of the paper is organized as follows: Section 1 represents the mathematical model of massive MIMO-enabled mobile edge cloud, whereas algorithms and simula-

tions results are discussed in Section 3. Similarly, Section 4 concludes the work.

2. System Model

In this work, we consider the concept of massive MIMO-enabled MEC. As illustrated in Figure 1, an access point (AP) such as a base station equipped with K of antennas and a mobile edge cloud, also known as a MEC, is used to offer N number connected Internet of Things devices access to communication and computational resources. These IoT devices, such as sensor nodes, are deployed in smart cities to collect real-time data for the purpose of managing or assisting the smart city's existing infrastructure. Similarly, data generated by real-time applications is time-sensitive and must be processed in a minimal amount of time. In addition, Internet of Things devices have limited processing resources, which are insufficient to carry out operations that need large computations in a short period of time. As a result, IoT devices add latency to the system in which they are used. To overcome the constraint imposed by IoT devices' limited computational capability, the mobile edge cloud emerges as a practical solution capable of providing extensive computation to low-power IoT devices on-demand. IoT devices can offload computations that require massive amounts of computation in a short period of time.

Similarly, frame-based transmission is carried out over the same frequency band and flat fading channel. For ease of simplicity, we consider the case of perfect CSI, which means the channel is known at AP. Furthermore, for extensive computation, all users simultaneously transmit a portion of the computation task to the MEC located at the AP via space-division multiple access (SDMA) methods. Because of simultaneous transmission, AP uses the linear detector to detect each user information as represented by the matrix \mathcal{Q} between n -th user and K antennas. In addition, we take into consideration a partial offloading approach for the placement of the task at the MEC. In this particular scheme, the task is broken up into two portions. The remaining part of the work is sent to the MEC to be processed, while the first part of the task is computed locally.

2.1. Task Offloading Model. Low-power Internet of Things devices are used in smart cities to collect huge amounts of raw data from real-time applications. These applications require considerable computation to be completed in a short amount of time. Latency is a problem that arises within the system as a result of the limited computational capacity of the components. As a result, quality of service (QoS) and quality of experience (QoE) are greatly compromised. Therefore, to meet the QoS and QoE requirements, these devices start offloading their tasks using a partial offloading scheme. Similarly, the number of bits offloaded by n -th to MEC located at AP in time t is represented as

$$\mathcal{R}_n^E = \text{Blog}_2(1 + \chi_n)t. \quad (1)$$

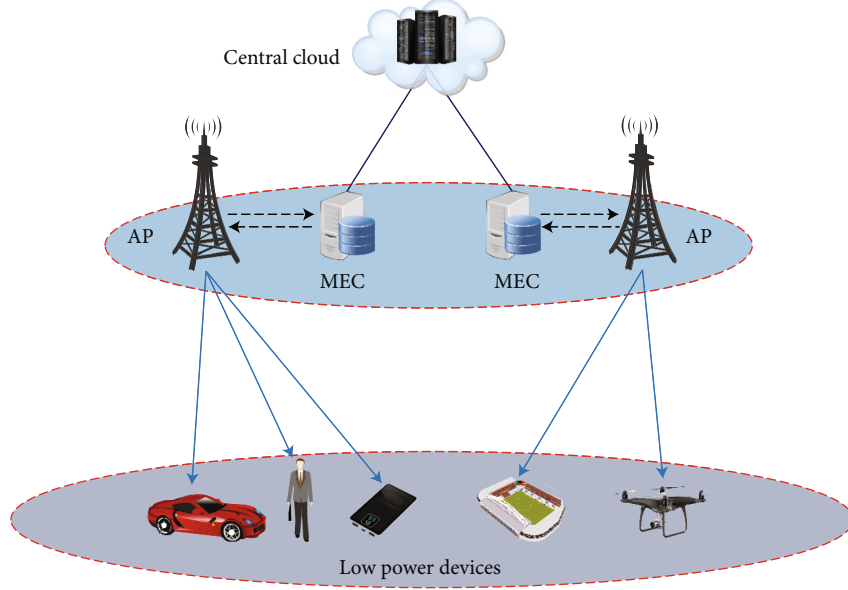


FIGURE 1: System model of mobile edge cloud system.

In Equation (1), B represents the system bandwidth, and χ_n represents the signal to interference plus noise ratio given by

$$\chi_n = \frac{\xi_n |q_n^H h_n|^2}{\Phi_n + |q_n^H q_n| \sigma^2}. \quad (2)$$

Similarly in (2), h_n represent the channel coefficient column matrix between n -th user and K number of antennas, ξ_n represents the uplink transmission power, and q_n represents the linear detector coefficient, whereas $\Phi_n = \sum_{i=1, i \neq n}^N \xi_i |q_n^H h_i|^2$ represents the interference imposed on n -th users from others and σ^2 represents the Gaussian noise factor. Simultaneously, energy consumption while offloading the number of bits to MEC for extensive computation is given by

$$\Psi_n^E = \xi_n t + \xi_r t. \quad (3)$$

In Equation (3), ξ_r signifies the constant circuit energy required for signal processing, which is static across all devices.

2.2. Local Computation. In conjunction with the computation that is taking place at MEC, a piece of the task is carried out locally by making use of the limited processing resources that are accessible on the devices. The number of cycles that must pass through the devices before one bit of data may be computed denoted by the notation \mathcal{E}_n . In order to complete the computation on a local scale, devices use the entire \mathcal{T} time frame. As a consequence of this, the following is how

the number of bits is determined locally:

$$\lambda^k = \frac{\Psi_n \mathcal{T}}{\mathcal{E}_n}. \quad (4)$$

In Equation (4), the symbol Ψ_n denotes the proportion of computational resources that the n -th device has designated to be used by itself in order to carry out the task locally. While simultaneously computing the task locally by the n -th user, the energy computation is expressed as follows:

$$\chi^k = \kappa_n \Psi_n^3 \mathcal{T}. \quad (5)$$

In Equation (5), κ_k represents the computational energy efficiency of the IoT devices.

2.3. Problem Formulation. Within the scope of this work, we investigate the idea of massive MIMO-enabled MEC. This work was aimed at improving the device's computational rate by optimizing transmission power ξ , edge computational time t , local computational resources Ψ , and task segmentation y_n^E . Following that, mathematically, optimization problems can be formulated as follows:

$$\mathbf{P1} : \max_{t, \xi_n, \Psi_n, y_n^E} \sum_{n=1}^N \left(w_n^L \frac{y_n^L \xi \mathcal{T}}{\mathcal{E}_n} + w_n^E \frac{y_n^E t}{v} \text{B} \log_2(1 + \chi_n) \right) \quad (6a)$$

$$C_1 : y_n^L \kappa_k \Psi_n^3 \mathcal{T} + y_n^E (\xi_n t + p_r \tau) \leq \mathcal{E}_{\max}, \forall n \quad (6b)$$

$$C_2 : 0 \leq \Psi \leq \Psi_{\max}, \forall n \quad (6c)$$

$$C_3 : y_k \in (0, 1), \xi_n \geq 0, \forall n. \quad (6d)$$

The fundamental goal of this work is to maximize the computational rate of low-power devices that are connected


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1 input:  $N \leftarrow$  sensor nodes,  $\mathcal{C} \leftarrow$  cycles requirement,  $\mathcal{E}_{\max} \leftarrow$  Maximum battery life,  $\Psi \leftarrow$  Maximum computational capability of devices,  $[t^{\text{lower}}, \xi_n^{\text{lower}}, \Psi_n^{\text{lower}}, y_n^{\text{lower}}, \mathcal{F}_n^{\text{lower}}]$  lower bound of Decision variables,  $[t^{\text{upper}}, \xi_n^{\text{upper}}, \Psi_n^{\text{upper}}, y_n^{\text{upper}}, \mathcal{F}_n^{\text{upper}}]$  upper bound of Decision variables,
2 Initialization: Number of decision variables
3  $\mathfrak{A} \leftarrow 4N + 1$ , Generate Population.
4 Execution:
5 while error  $\leq \epsilon$ 
6   foreach  $p \in \text{Population}$  do
7      $\Omega \leftarrow$  solve (8)
8   end
9   // Sort  $\Omega$  in Descending order, and select best Population
10  // Base on best population, calculate mean  $\mathcal{M}$  and standard deviation  $\mathcal{SD}$ . foreach  $p \in \text{Population}$  do
11     $\Omega \leftarrow$  solve (8)
12  end
13 end
14

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ALGORITHM 1: Convex Optimization Algorithm.

to the MEC at the AP while simultaneously taking into consideration a number of constraints. In (6a), (6b), (6c), and (6d), the overhead at the MEC due to successive offloading is denoted by ν , whereas w_n^L and w_n^E are the weighting coefficients used to prioritize the users according to their quality of service requirements, such that $w_n^L + w_n^E = 1$. Simultaneously, y_n^L and y_n^E are chosen in such a way that $y_n^E = 1 - y_n^L$ indicates the part of the task that was executed either locally or at the MEC. Following that, constraint C_1 specifies that the task is computed locally or offloaded to MEC. In both cases, the energy consumption should be less than the maximum amount of power that the gadgets can draw from their batteries, as represented by E_{\max} .

3. Results and Discussion

3.1. Optimal Resource Allocation. The objective function specified in (6a), (6b), (6c), and (6d) is nonlinear and non-convex in nature due to logarithmic nature of rate equation. Following that, it is analytically challenging to solve and get the optimal results. To overcome this limitation, we introduce a slag variable \mathcal{F} and transform an optimization problem P1 as follows:

$$\text{P2 : } \max_{t, \xi_n, \Psi_n, y_n^E, \mathcal{F}_n} \sum_{n=1}^N \left(w_n^L \frac{y_n^L \xi \mathcal{F}}{\mathcal{C}_n} + w_n^E \frac{y_n^E t}{\nu} \mathcal{F}_n \right) \quad (7a)$$

$$C_1 : B \log_2 \left(1 + \frac{\xi_n |q_n^H h_n|^2}{\Phi_n + |q_n^H q_n| \sigma^2} \right) \geq \mathcal{F}_n, \forall n \quad (7b)$$

$$\text{s.t. Equations (6b) to (6d).} \quad (7c)$$

The objective function specified in (7a), (7b), and (7c) is convex by definition. Additionally, the constraint mentioned in (7b) is not convex in nature. To overcome this, we use the first-order approximation method and further transform the

objective function as follows:

$$\text{P3 : } \max_{t, \xi_n, \Psi_n, y_n^E, \mathcal{F}_n} \sum_{n=1}^N \left(w_n^L \frac{y_n^L \xi \mathcal{F}}{\mathcal{C}_n} + w_n^E \frac{y_n^E t}{\nu} \mathcal{F}_n \right) \quad (8a)$$

$$C_1 : \log(\mathfrak{F}_n) \geq \frac{\log(2) \mathcal{F}_n}{B} + \log(\Phi_n + |q_n^H q_n|), \forall n \quad (8b)$$

$$\text{s.t. Equations (6b) to (6d).} \quad (8c)$$

In Equation (8b), $\mathfrak{F}_n = \Phi_n + |q_n^H q_n| \sigma^2 + \xi_n |q_n^H h_n|^2$. Following that, the constraints and objection function of (8a), (8b), and (8c) is convex in nature and can be solve easily using the convex optimization Algorithm 1.

3.2. Discussion. In the concept of smart cities, these low-power devices are used to collect the real-time data used to make decisions for further action or planning. Data collected from real-time applications needs extensive computation that can be computed locally using device computational resources or placed as a whole in MEC for further processing. Figure 2 is a comparative study of the local computational scheme and the edge computational scheme through the use of varied amounts of computational cycles C_K from 10 K-cycles to 100 K-cycles. The computational rate is used as a performance metric, and this number refers to the number of bits that are computed in $T = 1$ seconds. The effectiveness of the model that has been proposed is evaluated using this metric. Simulations were carried out using Algorithm 1 by setting a number of devices $K = 50$. Results reveal that local computation, in which the whole task is computed locally using device computational resources, outperforms the edge computation scheme, where the whole task is to be placed on the MEC server for extensive computation. This behavior is because of successive offloading, and it leads to congestion at MEC and thus introduces overhead. As a result, it takes more time to compute the task. As a result, the computation rate is low using the edge computational scheme as compared to the local computation scheme. On

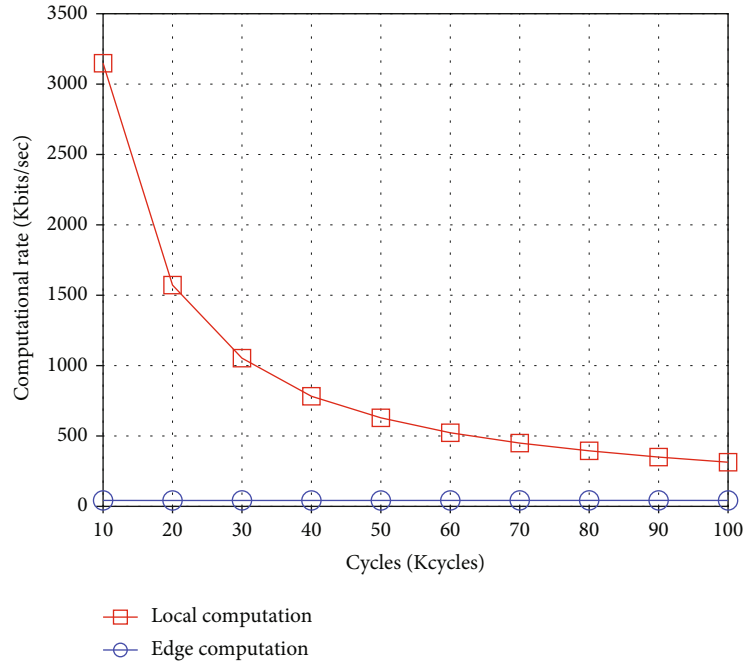


FIGURE 2: Comparison of local and edge computation scheme.

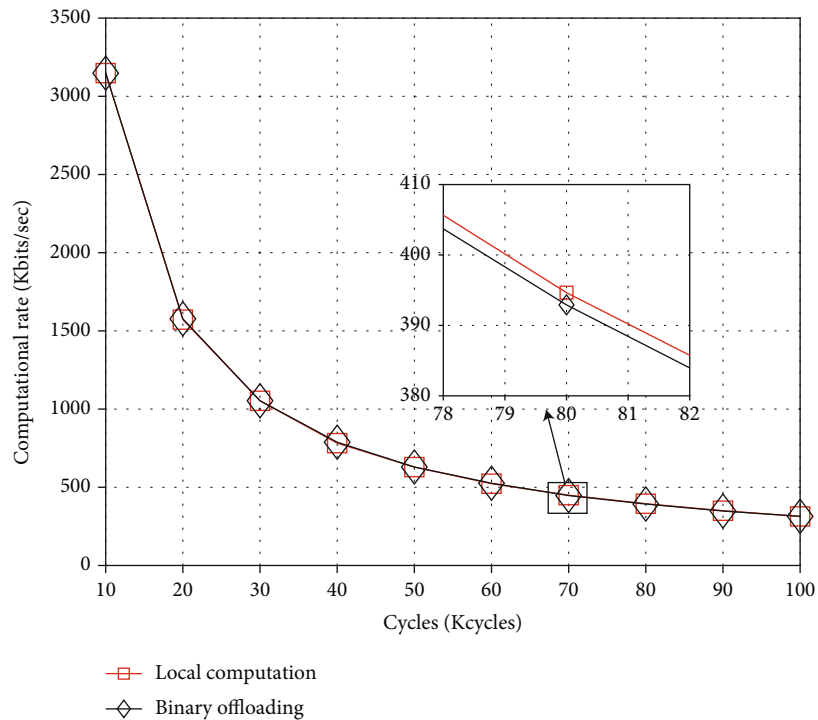


FIGURE 3: Comparison of local computation and binary offloading scheme.

the other hand, as the computational cycle requirements increase, the performance of the local computational scheme is going to decrease because of the finite computational capability of the devices. Thus, the quality of service requirements is highly compromised.

As is evident from the above discussion, successive offloading results in congestion at the MEC servers; thus, it

introduces overhead. In order to prevent congestion, MEC gives devices the ability to offload their computation by utilizing a binary offloading method. In a binary offloading strategy, some devices offload their tasks to MEC, where the rest compute locally using their finite computational resources. Figure 3 shows a comparative analysis of the binary offloading method and the local computation by

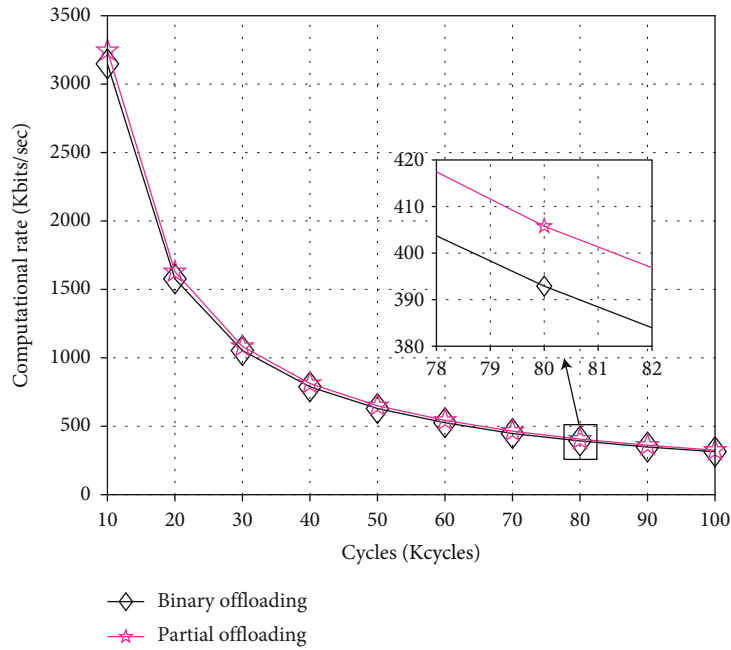


FIGURE 4: Comparison of binary and partial offloading scheme.

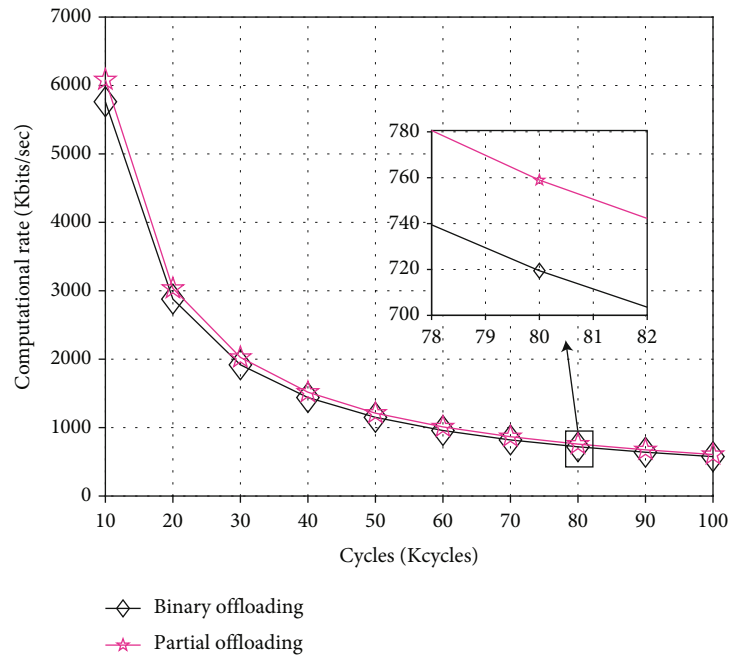


FIGURE 5: Comparison of binary and partial offloading scheme with multiple users.

taking the computational rate into consideration as a performance parameter across numerous needs for the computational cycle. Results reveal that, for the low number of computational cycles required, the performance of both schemes is the same. On the other hand, as the number of computational cycle requirements increases, the binary offloading scheme starts performing better than the local computation scheme. This trend is because, in the local computation scheme, the finite computational capability of

the devices is not enough to handle a large number of computational cycle requirements. Therefore, as a result, to maintain the quality of service requirements, they started offloading their whole task to the MEC server located at the AP for extensive computation. To overcome the latency constraint, binary offloading is an effective solution that allows some of the devices to start offloading their extensive computation; thus, the commutative computation rate of the network increases.

In the binary offloading scheme, some devices are offloading their task to MEC, whereas the rest of the devices are computing their task locally using finite computational resources. In contrast, a second offloading technique known as the partial offloading scheme delegates a portion of the work to MEC from each of the devices. In the partial offloading technique, the work is divided into two halves; one component is computed locally, and the other portion is offloaded to MEC for additional processing. Both portions of the task are computed in parallel. Figure 4 represents the comparative analysis of the partial and binary offloading scheme. An extensive simulation was carried out, and average results were produced. The results reveal that the partial offloading scheme's performance is much better than the binary offloading scheme, even for the small number of computational cycle requirements. This trend is because, in the binary offloading scheme, the task as a whole is offloaded to MEC; thus, it requires more computational energy and time, whereas in the partial offloading scheme, only a portion of the task is offloaded, and as compared to the whole task, it also consumes less energy and requires minimal time. This tremendous effect can be seen more effectively by increasing the number of users from 50 to 100, as shown in Figure 5. The effectiveness of this proposed model can be utilized in the future generation communication system, where a large number of devices are used to collect data for making a future decisions like in smart cities to manage traffic, and pollution control, make better use of infrastructure, and keep citizens safe and clean.

4. Conclusion

In this work, we considered the massive MIMO-enabled mobile edge cloud to provide the computational resources to the low-power devices to maintain the quality of service requirements. This work is aimed at maximizing the computational rate by optimal allocation of computational resources, computational and channel estimation time, and transmission powers. A comparative analysis of the local computation scheme, edge computational scheme, binary offloading scheme, and partial offloading scheme were carried out in order to validate the proposed system. The results of these analyses revealed the fundamental trade-off that exists between offloading and local computations. The findings demonstrate that the limited computing capabilities of devices are insufficient to manage substantial computation when the required number of computational cycles grows. In contrast, a partial offloading strategy performs significantly better than the other offloading strategies used for comparison in the scenario described above.

Data Availability

This article does not meet the criteria for data sharing since no data sets were generated or analyzed.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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