Optimizing Computational and Communication Resources for MEC Network Empowered UAV-RIS Communications

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Abstract

With the technological evolution and new applications, user equipment (UEs) has become a vital part of our lives. However, limited computational capabilities and finite battery life bottleneck the performance of computationally demanding applications. A practical solution to enhance the quality of experience (QoE) is to offload the extensive computation to the mobile edge cloud (MEC). Moreover, the network’s performance can be further improved by deploying an unmanned aerial vehicle (UAV) integrated with intelligent reflective surfaces (IRS); an effective alternative to massive antenna systems to enhance the signal quality and suppress interference. In this work, the MEC network architecture is assisted by UAV-IRS to provide computational services to the UEs. To do so, a cost minimization problem in terms of computing time and hovering energy consumption is formulated. Furthermore, to achieve an efficient solution to a formulated challenging problem, the original optimization problem is decoupled into sub-problems using the block-coordinate decent method. Moreover, numerical results are compared to baseline schemes to determine the effectiveness of the proposed scheme. Simulation results demonstrate that the optimal allocation of local computational resources results in minimizing tasks’ computational time and hovering energy consumption.
Abstract—With the technological evolution and new applications, user equipment (UEs) has become a vital part of our lives. However, limited computational capabilities and finite battery life bottleneck the performance of computationally demanding applications. A practical solution to enhance the quality of experience (QoE) is to offload the extensive computation to the mobile edge cloud (MEC). Moreover, the network’s performance can be further improved by deploying an unmanned aerial vehicle (UAV) integrated with intelligent reflective surfaces (IRS); an effective alternative to massive antenna systems to enhance the signal quality and suppress interference. In this work, the MEC network architecture is assisted by UAV-IRS to provide computational services to the UEs. To do so, a cost minimization problem in terms of computing time and hovering energy consumption is formulated. Furthermore, to achieve an efficient solution to a formulated challenging problem, the original optimization problem is decoupled into sub-problems using the block-coordinate decent method. Moreover, numerical results are compared to baseline schemes to determine the effectiveness of the proposed scheme. Simulation results demonstrate that the optimal allocation of local computational resources results in minimizing tasks’ computational time and hovering energy consumption.

Index Terms—Intelligent reflective surfaces, unmanned aerial vehicle, mobile edge cloud, resource optimization.

I. INTRODUCTION

A. Background and Related work

With recent advancements in the 5G/6G wireless communication system, new applications such as augmented reality, online gaming, and videos that require extensive computation in a minimal amount of time have emerged [1], [2]. The user equipment (UEs), on the other hand, has limited computational resources and battery life that is not enough to handle the massive data generated from real-time applications, introducing latency into the system and severely compromising quality of service (QoS) [3], [4]. To address this, mobile edge clouds (MEC) emerge as a viable solution that provides on-demand extensive computation by allowing UEs to offload their extensive computation via a partial or binary offloading scheme [5], [6]. To that end, extensive research in literature has been conducted in which the MEC is located at a fixed point to provide services to the UEs [1], [3]–[5]. In contrast, practically fixed-located MEC fails to meet the required QoS in an emergency scenario or when the link between the UE and MEC is severely hampered due to blockage, such as in smart cities with high-raised buildings.

To tackle these limitations of fixed-located MEC, unmanned aerial vehicles (UAVs) aided MEC (UAV-MEC) has recently been emerged as an effective solution thanks to the deployment flexibility of the UAVs [7]. To benefit from the versatility of UAV deployment, authors in [8]–[10] consider the UAV-enabled MEC network, in which MECs are located at UAVs to provide computational resources to users in remote areas. The authors in [11] consider the UAV as a relay to assist the terrestrial communication network. However, besides providing computational resources to UEs, UAVs also face some limitations regarding battery life. In a UAV-MEC network, the hovering time or service providing time of the UAV mainly depends on the battery life. In contrast, energy consumed while computing the task at the UAV-MEC or while relaying the task results in rapid battery discharge; hence the quality of service is highly compromised.

The recent development of intelligent reflecting surfaces (IRS) has emerged as a cost-effective and energy-efficient solution to address the above-mentioned challenges [12]. The IRS compromise of an array of reflecting elements and an IRS controller that help to adjust both the phase and amplitude of the arriving signal. To get the benefits of IRS, the authors of [13] compared the performance of data transmission between traditional decode and forward relaying and the IRS-supported scheme. The results demonstrated that IRS-supported data transmission could significantly improve network energy efficiency by re-configuring the propagation environment. Similarly, the authors of [14] believe that the UAV-IRS on internet of things (IoT) networks can enhance the freshness of the collected data from IoT devices by optimizing power, sub-carrier, and trajectory variables as well as the phase shift matrix elements. Following that, the energy consumption minimization problem of the UAV integrated with the IRS MEC network is discussed in [15].

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B. Contributions

In this work, we consider the UAV-IRS-assisted MEC network to minimize the cost of the network in terms of minimizing the task’s computational time and the UAV’s hovering energy consumption. The closely related work to ours was studied in [15], which minimizes the network’s energy consumption by optimizing the task segmentation, transmission power, trajectory, and IRS phase shift. It is noted that [15] considers the devices’ fixed energy consumption per second and fixed local computational resources which are in contrast to practical scenarios where the computation energy consumption at the UEs mainly depends on the local computational resources. In particular, we consider the cost minimization problem in terms of tasks’ computational time and hovering energy consumption by optimizing the computational resources of MEC and UEs, transmission power, task segmentation variable, beam-forming vector, phase-shift vector, and location of the UAV. A block coordinate descent (BCD) based iterative solution is proposed to overcome the exponential computational complexity of the joint optimization problem. Numerical results are compared with the baselines to reveal the effectiveness of the proposed schemes. Furthermore, we show that the proposed allocation of local computational resources results in minimal energy consumption and task completion time compared to the fixed solutions discussed in [15].

II. System Model

In this paper, we consider an up-link communication network in which N single-antenna low-power UEs are connected to an access point (AP) with M antennas and a mobile edge cloud (MEC); a practical solution that provides extensive computation. To assist the terrestrial MEC network in unfavorable environmental conditions, e.g., blockage due to high-raised buildings in smart cities, a UAV equipped with IRS constitutes K reflecting elements and is positioned in a 3D cartesian coordinate system. Furthermore, it is assumed that IRS elements are sufficiently spaced to avoid small-scale fading and that the AP has perfect channel state information for all links [16], [17]. Moreover, for clarity, the positions of the UAV, the UEs, and the AP in the 3D cartesian coordinate system are represented by $z = \{x_u, y_u, H\}$, $q = \{x_n, y_n, 0\}$, and $v = \{x_b, y_b, 0\}$, with the UAV flying at a fixed height of $H$, respectively.

A. Communication and Computational Model

Let $U_n = \{S_n, C_n\}$ represents the n-th UE task, whereas $S_n$ and $C_n$ represent the size (bits) and computational cycles requirements. Due to limited local resources, UEs offload a portion of their tasks to MEC. Therefore, the achievable data rate of n-th UE for offloading is represented as $R_n = B \log_2(1 + \gamma_n)$. Whereas $\gamma_n$ represents the signal to interference and noise ratio and mathematically can be expressed as follows:

$$\gamma_n = \frac{p_n^o \|w_n^H (h_n^b + G \Phi_h^o)\|^2}{\sum_{n' \neq n} p_{n'}^o \|w_{n'}^H (h_{n'}^b + G \Phi_h^{n'})\|^2 + \sigma^2 \|w_n^H\|^2}.$$  

In equation (1), $h_n^b \in \mathbb{C}^{K \times 1}$, $h_n^b \in \mathbb{C}^{M \times 1}$ and $G \in \mathbb{C}^{M \times K}$ represents corresponding the channel gain matrix between UE-UEV, UE-AP and UAV-AP respectively. Furthermore, $\Phi = \xi \text{diag} \{\phi_1, \phi_2, \ldots, \phi_K\}$ represents the reflecting coefficient matrix, where $\phi_k = e^{j \theta_k}$ such that $|\phi_k| = 1$, $\theta_k \in [0, 2\pi]$ and $\xi \in [0, 1]$ represents the phase shift of k-th element of IRS and the amplitude of the reflection coefficient, respectively. In this work we consider the IRS following the full reflection; accordingly, we set $\xi = 1$. Whereas $w_n$ represents the beam-forming vector at the AP. $p_n^o$ denotes the transmission power of the n-th UE such that $p_n^o \geq 0$ and $\sigma^2 \sim \mathcal{CN}(0, \sigma^2 I_M)$ is the additive white gaussian noise.

Following that, time and energy consume to offloading the portion of task to MEC can be represented as follows:

$$t_n^o = \frac{(1 - \beta_n) S_n}{R_n}, \quad E_n = \rho_n^o t_n^o.$$  

In Equation (2), $\beta_n \in [0, 1]$ represents the portion of the task computed locally. Following that, after receiving the computation task at AP, MEC allocate the computational resources $f_n^E$ to perform the extensive computation. Furthermore, the maximum $f_{E \max}$ computational resources at the MEC shared among all the UE such that:

$$\sum_{n=1}^{N} f_n^E \leq f_{E \max}.$$  

Similarly the time consume while computing the task at the MEC can be expressed as:

$$t_n^E = \frac{(1 - \beta_n) C_n}{f_n^E f_{E \max}}.$$  

Furthermore, we assume that, AP compromise of infinite and continuous and power supply, therefore, energy consume while computing the task at MEC is not considered in this work. Moreover, Communication from the UE-AP is carried out via UAV hovering at the point $z$ to perform the passive signal reflection. Therefore the energy consumption of the UAV is represented as $E_u^H = P^h t^h$, $P^h$ and $t^h$ represents the constant hovering power depends upon the UAV hardware and hovering time respectively. The hovering time of the UAV mainly depends on the offloading time $t_n^o$, computational edge time $t_n^E$, and the time taken by the MEC to send the results back to the user in the downlink phase. Generally the time taken by the MEC in downlink phase is very small and thus can be neglected. Therefore the total hovering time of the UAV is represented as $t^h = t_n^o + t_n^E$.

$^1$The IRS phase shift is configured by the AP and fed back to the IRS controller via a dedicated control link.
Similarly in the case of local computation, time and energy consume while computing the task using local computation resources expressed as:
\[
t_n^i = \frac{\beta_n C_n}{f_n^{E} f_n^{max}}, \quad E_n^i = \epsilon_n \left( f_n^{E} f_n^{max} \right)^2 \beta_n C_n.
\]
In Equation (5), \( f_n^{E} \) and \( \epsilon_n \) represent the maximum computation resources and computational energy efficiency \( n \)-th UE.

B. Problem Formulation

We aim to minimize the network cost in terms of tasks’ computational time and hovering energy of the UAV by jointly optimizing the computational resources of MEC \( f_n^{E} \) and UEs \( f_n^{p} \), transmission power \( p_n^{c} \), task segmentation variable \( \beta_n \), beam-forming vector \( w_n \), phase-shift vector \( \theta_n \) and location of UAV \( z \). Mathematically, the joint optimization problem can be formulated as follows:

\[
\mathcal{P}_1 : \min_{\beta_n, f_n, p_n, z} \omega_1 E_n^H + \omega_2 \sum_{n=1}^{N} \left( t_n^i + p_n^o + t_n^E \right)
\]

s.t. \[
\sum_{n=1}^{N} f_n^{E} \leq f_n^{E} f_n^{max}, \quad(6b) \]

\[
\gamma_n \geq \gamma_n^\text{min}, \quad p_n^o \geq 0, \forall n, \quad(6c) \]

\[
E_n^i + E_n^o + P_n^{p} \leq E_n^{\text{max}}, \forall n, \quad(6d) \]

\[
d_n^i = \|z - v_n\|^2 \leq d_{n,u}^{\text{max}}, \quad(6e) \]

\[
d_n^o = \|z - q_n\|^2 \leq d_{n,u}^{\text{max}}, \forall n, \quad(6f) \]

\[
|\phi_k| = 1, \forall k, \quad(6g) \]

\[
0 \leq \left\{ f_n, f_n^{E}, \beta_n \right\} \leq 1, \forall n. \quad(6h) \]

In (6a), \( \omega_1 \) and \( \omega_2 \) represent the weighting coefficients used to prioritize the time and hovering energy of the UAV. Constraint in (6b) ensures the sum of computation resources at MEC should be less than the maximum available resources. Constraint (6c) specifies that SINR constraints. Constraint (6d) makes sure the total energy consumption of UE should not exceed the maximum threshold \( E_n^{\text{max}} \), where \( P_n \) represents the constant energy consumption of the UEs. Constraints (6e) and (6f) guarantee the communication link quality and that the distance between the UAV-AP and UE-UAV cannot exceed the maximum allowable communication distance \( d_{n,u}^{\text{max}} \) and \( d_{n,u}^{\text{max}} \), respectively. Finally, constraint (6g) represents the unit modulus constraint of IRS and (6h) represent the decision variables’ bounds.

III. PROPOSED SOLUTION

The optimization problem \( \mathcal{P}_1 \) mentioned in (6) is non-convex due to the joint optimization of the beam-forming vectors and computation resources at MEC, the phase shift control and the placement variable at the UAV-IRS, the task allocation and transmission power at the UEs. To overcome this difficulty, we decouple the original optimization problem into sub-problems and solve them iteratively.

A. Optimal Placement of UAV

Optimal placement of UAV can be carried out by taking into account the location of AP and UEs in the 2D cartesian coordinate system. Similarly, according to the constraints (6e) and (6f), the UAV should be placed at a point such that the distance between the UAV-AP and UE-UAV cannot exceed the maximum allowable communication distances. Generally, the system consists of \( N \) UEs and one AP. For the ease of simplicity, we represent \( N + 1 \) elements are distributed uni-formally whose location in the 2D cartesian coordinate system is represented as \( q_n = (q, v) \). Mathematically, the sub-problem for optimal 2D placement can be formulated as:

\[
\mathcal{P}_2 : \min_{z} \sum_{n=1}^{N+1} \|z - q_n\|^2
\]

s.t. Equation (6e) and (6f). (7b)

The main aim (7) is to place the UAV at a point that has a minimum distance from the AP and UEs. Furthermore, the optimization problem is linear and can be solved efficiently using linear programming (LP).

B. Task Segmentation

In the concept of MEC, task segmentation \( \beta_n \) is an important parameter that can be calculated by analyzing the monotonic relation between the local computation time \( t_n^i \) and UAV hovering time \( t^h \). As noted form (5), as the value of \( \beta_n \) varies from its minimal value toward maximum values, the local computational time of the UEs increases. In contrast, it shows the inverse relationship with the hovering time of the UAV. Therefore, a point occurs due to the inverse relation of both edge and local computation time across task segmentation variables that satisfies \( t_n^i = t^h \). Furthermore, by taking into account the mathematical expression of both the computation times, we can have

\[
\frac{\beta_n C_n}{f_n^{E} f_n^{max}} = \left( 1 - \beta_n \right) C_n + \frac{\left( 1 - \beta_n \right) S_n}{R_n}.
\]

After some mathematical operation, task segmentation variable can be expressed as:

\[
\beta_n = \frac{f_n^{E} f_n^{max} \left( R_n C_n + f_n^{E} f_n^{max} S_n \right)}{C_n R_n f_n^{E} f_n^{max} + C_n R_n f_n^{E} f_n^{max}}.
\]

According to (9), the value of \( \beta_n \) is primarily determined by local computational resources, edge computational resources, and data rate \( R_n \), which is the function of transmission power \( p_n^{c} \), IRS phase shift \( \theta_k \), and beam forming vector \( w_n \). Therefore, optimal values of these decision variables result in the optimal value of the task segmentation variable \( \beta_n \).

C. Beam-forming at AP

According to (1), the value of SINR is primarily determined by the receiving beamforming vector \( w_n \) for given values of \( p_n^{c} \) and \( \theta_k \). Following that, the
optimal beam-forming vector that balances the noise and interference at the AP computed by employing the minimum mean square error (MMSE) technique [18], whose mathematical form can be expressed as follows:

\[ w_n = \left( \sigma^2 + \sum_{a',a \neq a'}^N p_{n,a,a'}^\phi \right)^{-1} g_n, \tag{10} \]

where \( g_n = h_n^h + G\Phi h_n^u \) given in (10).

**D. Phase Shift Optimization**

In this subsection, we optimize the phase shift matrix of IRS. For the given values of system parameters, the sub-problem for phase shift optimization can be formulated as:

\[
P_{\phi_k}^a : \max_{\phi_k} \sum_{n=1}^N \log_2 \left( 1 + \gamma_n \right) \tag{11a}
\]

subject to

\[
\gamma_n \geq \gamma_n^\text{min}, p_{n,a}^\phi \geq 0, \forall n, \tag{11b}
\]

\[
|\phi_k| = 1, \forall k, \tag{11c}
\]

where the problem in \( P_{\phi_k}^a \) is non-convex optimization and it is challenging to obtain the optimal solution. Thus, we first transform the problem \( P_{\phi_k}^a \) and then adopt DC programming to obtain an efficient solution. For simplicity, we rearrange the diagonal matrix \( \Phi \) which is used in \( \| w_n^H (h_n^h + G\Phi h_n^u) \|^2 \) of the SINR in (1). By doing this, we convert it into a vector \( v \in \mathbb{C}^K \times 1 \), where \( v_k = \phi_k^H, \forall k \in K \). It can be observed that vector \( v \) contains all the information of \( \Phi \). Now we define an auxiliary vector \( h_{n,k} \) such that \( h_{n,k} = w_n^H b_n^h + w_n^H G \cdot h_k \), where \( \cdot \) is the Hadamard product. It can be proved that \( \| w_n \left( h_n^h + G\Phi h_n^u \right) \|^2 = \| v^H h_{n,k} \|^2 \). Based on the above modifications, the problem \( P_{\phi_k}^a \) can be updated as:

\[
P_{\phi_k}^a : \max_v \sum_{n=1}^N \log_2 \left( 1 + \frac{p_n^\phi \| v^H h_{n,k} \|^2}{\sum_{n \neq n'}^N p_{n,a}^\phi \| v^H h_{n,k} \|^2 + \sigma^2 \| v_n \|^2} \right), \tag{12a}
\]

subject to

\[
p_n^\phi \| v^H h_{n,k} \|^2 \geq \gamma_n^\text{min} (\Pi), \forall n, \tag{12b}
\]

\[
|v_k| = 1, \forall k, \tag{12c}
\]

where \( \Pi = \sum_{n \neq n'}^N p_{n,a}^\phi \| v^H h_{n,k} \|^2 + \sigma^2 \| v_n \|^2 \).

Next, the term \( p_n^\phi \| v^H h_{n,k} \|^2 \) can be further expressed as:

\[
p_n^\phi \| v^H h_{n,k} \|^2 = \sum_{n \neq n'}^N p_{n,a}^\phi \| v^H h_{n,k} \|^2 + \sigma^2 \| v_n \|^2.
\]

We will define two auxiliary matrices \( H_{n,k} \) and \( V \) such that \( H_{n,k} = p_n^\phi h_n^h h_{n,k}^H \) and \( V = v^H v \). It is worth mentioning that both matrices are positive semi-definite. Therefore, the problems \( P_{\phi_k}^a \) can be reformulated as:

\[
P_{\phi_k}^a : \max_{v \in \text{dom} v} \sum_{n=1}^N \log_2 \left( 1 + \frac{\text{Tr}(Vh_{n,k})}{\sum_{n \neq n'}^N \text{Tr}(Vh_{n,k}) + \Omega} \right), \tag{14a}
\]

subject to

\[
\text{Tr}(Vh_{n,k}) \geq \gamma_n^\text{min} \left( \sum_{n',n \neq n'}^N \text{Tr}(Vh_{n,k} + \Omega) \right), \forall n, \tag{14b}
\]

\[
\text{dom}(V) = 1, \quad V \succeq 0, \tag{14c}
\]

\[
\text{rank}(V) = 1, \tag{14d}
\]

where \( \Omega = \sigma^2 \| v_n \|^2 \) and \( \text{diag}(\cdot) \) represent the diagonal elements of matrix \( V \). Thus, \( \text{diag}(V) = v_k^2 = 1 \) and \( |v_k| = 1 \). We can see that the problem in \( P_{\phi_k}^a \) is still non-convex due to the objective function and constraint in (14d).

Firstly, the rank-one constraint in (14d) can be efficiently replaced by a convex positive semi-definite constraint such as \( V - \overline{vv}^H \succeq 0 \), where \( \overline{v} \in \mathbb{C}^K \times 1 \). Next, \( V - \overline{vv}^H \succeq 0 \) can be efficiently replaced by its convex Schur complement as:

\[
\begin{bmatrix}
V \\
\overline{v}^H
\end{bmatrix} \succeq 0, \tag{15}
\]

Secondly, we study the objective function (14a) and can be efficiently reformulated as:

\[
\sum_{n=1}^N \log_2 \left( \text{Tr}(Vh_{n,k}) + \Omega \right) - \sum_{n=1}^N \log_2 \left( \text{Tr}(Vh_{n,k}) + \Omega \right).
\]

We can see that (16) has a form of a DC function and can be efficiently solved using DC programming, which requires the derivative with respect to \( V \). Since \( V \) is a complex matrix, we calculate its derivative for both real and imaginary parts as:

\[
\frac{\partial}{\partial \Omega} \sum_{n=1}^N \log_2 \left( \text{Tr}(Vh_{n,k}) + \Omega \right) = \frac{1}{\ln 2} \sum_{n=1}^N \frac{\text{Tr}(Vh_{n,k})}{\text{Tr}(Vh_{n,k}) + \Omega}, \tag{17}
\]

\[
\frac{\partial}{\partial \Omega} \sum_{n=1}^N \log_2 \left( \text{Tr}(Vh_{n,k}) + \Omega \right) = -\frac{i}{\ln 2} \sum_{n=1}^N \frac{\text{Tr}(Vh_{n,k})}{\text{Tr}(Vh_{n,k}) + \Omega}.
\]

where \( \Re \) and \( \Im \) show the real and imaginary parts of the complex variables. Using the DC programming, problem in \( P_{\phi_k}^a \) in the \( i \)-th iteration can be expressed as:

\[
P_{\phi_k}^a : \max_{v \in \text{dom} v} \psi_1(V) - \psi_2(V^{(i-1)}) \sum_{k'=1}^{K} \frac{\Re}{\Omega} \left( V(k,k') - V(k,k')^{(i-1)} \right) \times \frac{\partial \psi_2}{\partial \Omega} \left( V(k,k')^{(i-1)} \right) - \sum_{k'=1}^{K} \frac{\Re}{\Omega} \left( V(k,k') - V(k,k')^{(i-1)} \right) \times \frac{\partial \psi_2}{\partial \Omega} \left( V(k,k')^{(i-1)} \right), \tag{19a}
\]

subject to

\[
\text{dom}(V) = 1 \quad (14b) - (14c), (15), \tag{19}
\]

where \( \psi_1 = \sum_{n=1}^N \log_2 \left( \text{Tr}(Vh_{n,k}) + \Omega \right) \) and \( \psi_2 = \sum_{n=1}^N \log_2 \left( \text{Tr}(Vh_{n,k}) + \Omega \right) \).
It is observed that (19) is a semi-definite programming and also a convex problem. Thus, it can be efficiently solved by using the interior point method, having a computational complexity of \(O((N + K^2)^{3.5})\).

Next, the important thing here is to convert the global solution to a feasible solution to the problem in \(P_3\). To do this, we can use Gaussian randomization, where the solution is considered as the mean of a multivariate Gaussian random vector. In particular, we generate \(J\) trials such that \(\varepsilon_j \sim (v^*, V^* - \overline{v}V^*H)\), where \(j \in J\). Note that \(\varepsilon_j\) cannot be guaranteed to be feasible. Therefore, we employ a re-scaling factor to achieve a feasible vector such as \(v\varepsilon_1, v\varepsilon_2, \ldots, v\varepsilon_J\). Now let us assume that \(v\varepsilon_j\) is the trail that maximizes the objective. Then we compare it with the previous \(v\) and choose the better one.

E. Optimal Resource Allocation and Power Control

This subsection demonstrates the optimal computational resources and power allocation problem to minimize the cost of the network in terms of tasks’ computational time and the UAV’s hovering energy. Given \(\theta_k\), \(\beta_n\) and \(w_n\), the original optimization problem \(P_1\) can be simplified as:

\[
P_4 : \min_{f^E, f^I, p^o} \omega_1 E_u^H + \omega_2 \sum_{n=1}^N (t_n^I + t_n^c + t_n^E) \tag{20a}
\]

subject to Equations (6b) to (6d) and (6h) \(\tag{20b}\)

The optimization problem mentioned in (20) is non-linear and convex and can be solved using a convex optimization toolbox such as CVX.

F. Iterative Convergence

Iteratively solving sub-problems until convergence minimizes (6) objective function. Steps include: 1) Solve (7) to find \(z\); 2) Calculate \(w\) from (10); 3) Iteratively solve and Gaussian randomize (19) to find \(\phi_k\); 4) Solve (20) and (9) to find the value of he value of \(f^E, f^I, p^o\) and \(\beta_n\). It is important to note that convergence occurs when objective functions stay constant or change by epsilon each iteration.

IV. RESULTS AND DISCUSSION

In this section, the effectiveness of the proposed scheme is demonstrated numerically. Extensive simulations were performed using the simulation parameters as given in [15]. Following that, we assume that UEs are distributed in the 150m x 150m area, whereas an AP integrated with MEC and \(M=16\) antennas is located at the point \(v = \{0, 0, 0\}\). To assist the MEC network, the UAV integrated with IRS constitutes \(K=30\) reflecting elements flies at a fixed height of \(H=80\) meters. The maximum computational resources of the UEs and MEC are set to \(f_n^m = 1 \times 10^5\) and \(f_E^m = 1 \times 10^8\) cycles per second, respectively. Whereas the rest of the simulation parameters are given as \(\gamma_{n}^{1n} = 20\) dB, \(B = 10\) MHz, \(d_{n,b}^{max} = d_{n,w}^{max} = 100\) m, \(\sigma^2 = -110\) dBm, \(p_n = 1000\) W. In addition, we compare the proposed algorithm with following baseline schemes: 1) **Fully Off-loading** that assumes the UEs offload their tasks as a whole to the MEC; 2) **Fixed Computation** in which UEs compute their tasks using fixed computational resources [15].

In Figure 1, a comparison of the proposed scheme is
carried out with all off-loading and fixed computation schemes by considering the computational time of the task as a performance parameter. Results reveal the effectiveness of the proposed schemes as compared to others. Furthermore, results demonstrate that, for the small number of UEs, the performance gap between a fully off-loading scheme is 13.35ms. Whereas, with the increment in UEs, task computational time for the edge computational scheme increases dramatically. This is because computing resources at the MEC are shared between all the UEs. Similarly, the percentage of computing resources shared among the UEs decreases with the increase of UEs in the system.

Following that, by using computational energy consumption (J) as a performance metric, this trend can be seen more explicitly in Figure 2. Results illustrate that the proposed scheme, which implies partial off-loading, divides the task into two portions; one portion is computed locally. In contrast, the other portion is off-loaded, resulting in minimal computational energy consumption compared to others. Furthermore, Figure 1 shows that the performance of the proposed and fixed computations in terms of tasks’ computational time is the same for a small number of UEs. This is because task computational time decreases as the number of computational resources at the UEs increases. Simultaneously, more energy is required for extensive local computation, severely compromising the energy efficiency requirements for the 5-th generation communication system as shown in Figure 2. Thus, the proposed model in which computational resources are allocated optimally emerges as a viable solution for minimizing the tasks’ computational time and energy consumption on the network.

Following that, tasks’ computational time also significantly impacts the hovering time of the UAVs. Figure 3 reveals that the fully off-loading scheme, where all the tasks are off-loaded to MEC for the computation, leads to more hovering time for UAV than other schemes. This is because, as the number of bits increases, more time is required for the off-loading, and the computational time at MEC also increases. In contrast, a fixed computational scheme computes a significant portion of the task locally, resulting in a minimum hovering time, whereas the proposed scheme, which employs optimal task segmentation, outperforms all other schemes.

V. CONCLUSION

In this work, we studied the up-link UAV-IRS assisted MEC network to provide computational resources to the remote UEs with the aim of minimizing the task’s computational time and the hovering energy consumption of the UAVs. To achieve the desired objective, a joint optimization of communication and computational resources has been formulated. To tackle the joint problem’s exponential complexity, we decoupled the original problem into sub-problems which are solved iteratively. The benefits of the proposed design have been demonstrated via numerical results and comparison with baseline schemes.

REFERENCES