Joint Task Assignment and Wireless Resource Allocation for Cooperative Mobile-Edge Computing

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Abstract—This paper studies a multi-user cooperative mobile-edge computing (MEC) system, in which a local mobile user can offload intensive computation tasks to multiple nearby edge devices serving as helpers for remote execution. We focus on the scenario where the local user has a number of independent tasks that can be executed in parallel but cannot be further partitioned. We consider a time division multiple access (TDMA) communication protocol, in which the local user can offload computation tasks to the helpers and download results from them over pre-scheduled time slots. Under this setup, we minimize the local user’s computation latency by optimizing the task assignment jointly with the time and power allocations, subject to individual energy constraints at the local user and the helpers. However, the joint task assignment and wireless resource allocation problem is a mixed-integer non-linear program (MINLP) that is hard to solve optimally. To tackle this challenge, we first relax it into a convex problem, and then propose an efficient suboptimal solution based on the optimal solution to the relaxed convex problem. Finally, numerical results show that our proposed joint design significantly reduces the local user’s computation latency, as compared against other benchmark schemes that design the task assignment separately from the offloading/downloading resource allocations and local execution.

I. INTRODUCTION

It is envisioned that by the year of 2020, around 50 billions of interconnected Internet of Things (IoT) devices will surge in wireless networks, featuring new applications such as video stream analysis, augmented reality, and autonomous driving. The unprecedented growth of such applications demands intensive and latency-critical computation at these IoT devices, which, however, is hardly affordable by conventional mobile computing systems. To address such new challenges, mobile-edge computing (MEC) has been identified as a promising solution by providing cloud-like computing functions at the network edge [1–5].

MEC has received growing research interests in both academia and industry. To maximally reap the benefit of MEC, it is critical to jointly manage the radio and computation resources for performance optimization [6]. For instance, [7] investigated an MEC system with orthogonal frequency division multiple access (OFDMA)-based computation offloading, in which the subcarrier allocation for offloading and the users’ central processing unit (CPU) frequencies for local computing were jointly optimized to minimize the energy consumption at mobile devices. [8] considered multi-user MEC systems with both time division multiple access (TDMA) and OFDMA-based offloading, in which the optimal resource allocation policies were developed by taking into account both wireless channel conditions and users’ local computation capabilities. Furthermore, a new multi-user MEC system was studied in [9] by exploiting multi-antenna non-orthogonal multiple access (NOMA)-based computation offloading. In addition, a wireless powered multi-user MEC system was developed for IoT systems in [10], where the users conducted computation offloading relying on the harvested energy from a multi-antenna access point (AP) integrated with MEC servers. In these prior works, the MEC servers are usually assumed to be of rich computation and energy resources, such that the computation time and/or the results downloading time are assumed negligible. This, however, may not be true in practice [11, 12], especially for scenarios where multiple lightweight edge devices such as cloudlets and smartphones are employed for cooperative mobile-edge computing.

On another front, in distributed computing systems, task assignment and task scheduling have been extensively studied to improve the computation quality of service (see, e.g., [13] and the references therein). For example, [14] studied the task assignment amongst multiple servers for parallel computation and [12] investigated the scheduling of sequential tasks with proper order. However, this line of research often assumed static channel and computation conditions but ignored their dynamics and heterogeneity, thus making it difficult to be directly applied to MEC. Recently, there are few works considering joint task scheduling and communications resource management. For instance, [12] jointly optimized the task scheduling and wireless power allocation in a single-user single-core MEC system, in which multiple independent computation tasks at the local user require to be sequentially executed at the MEC server.

In this paper, we study a multi-user cooperative MEC system, in which a local mobile user can offload a number of independent computation tasks to multiple nearby edge devices serving as helpers (such as smartphones, tablets, WiFi APs, and cellular base stations (BSs)) for remote execution. Assuming that the tasks can be executed in parallel but cannot be further partitioned, we consider a TDMA communication protocol, in which the local user offloads tasks and downloads
computation results over pre-scheduled time slots. The contributions of this paper are summarized as follows. 1) We formulate the latency-minimization problem that jointly optimizes computation tasks assignment and time/power allocations for both tasks offloading and results downloading, subject to individual energy constraints at all the user and helpers. 2) Since the formulated problem is a mixed-integer non-linear program (MINLP) that is hard to solve optimally in general, we propose an efficient algorithm to obtain a suboptimal solution based on the optimal solution to a relaxed (convex) problem. 3) Simulation results show striking performance gain achieved by the proposed design in comparison with other benchmark schemes that design the task assignment separately from the offloading/downloading resource allocations and local execution.

The remainder of this paper is organized as follows. The system model is presented in Section II. The joint computation task assignment and time allocations problem is formulated in Section III. In Section IV, an effective joint optimization algorithm is proposed. Simulation results are provided in Section V, with conclusion drawn in Section VI.

II. SYSTEM MODEL

We consider a multi-user cooperative MEC system that consists of one local mobile user, and \( K \) nearby wireless edge devices serving as helper-nodes, denoted by the set \( \mathcal{K} = \{1, \ldots, K\} \), all equipped with single antenna. For convenience, we define the local user as the \((K+1)\)-th node. Suppose that the local user has \( L \) independent tasks to be executed, denoted by the set \( \mathcal{L} = \{1, \ldots, L\} \), and the input (output) data length of each task \( l \in \mathcal{L} \) is denoted by \( T_l \) (\( R_l \)) in bits. In the considered MEC system, each task can be either computed locally, or offloaded to one of the \( K \) helpers for remote execution. Let \( \mathbf{\Pi} \in \mathbb{R}^{L \times (K+1)} \) denote the task assignment matrix, whose \((l, k)\)-th entry, denoted by \( \pi(l, k) \in \{0, 1\}, \) \( l \in \mathcal{L}, k \in \mathcal{K} \cup \{K+1\} \), is given by

\[
\pi(l, k) = \begin{cases} 1, & \text{if the } l\text{th task is assigned to the } k\text{th user,} \\ 0, & \text{otherwise.} \end{cases}
\]

Also, define \( \mathcal{L}^{(k)} = \{l \in \mathcal{L} : \pi(l, k) = 1\} \) as the set of tasks that are assigned to node \( k, k \in \mathcal{K} \cup \{K+1\} \). At last, denote by \( C_{l,k} \) (in cycles per bit) the number of CPU cycles required for computing one input bit of the \( l\)th task at the \( k\)th node, \( l \in \mathcal{L}, k \in \mathcal{K} \cup \{K+1\} \). Also denote the CPU frequency at the \( k\)th node as \( f_k \) (in cycles per second), \( k \in \mathcal{K} \cup \{K+1\} \).

A. Local Computing

The tasks in the set \( \mathcal{L}^{(K+1)} \) are executed locally. Hence, the local computation time is given by

\[
t^*_0 = \sum_{l=1}^{L} \pi(l, K+1) C_{l,0} T_l / f_0.
\]

The corresponding computation energy consumed by the local user is given by [2]

\[
E^*_0 = \kappa_0 \sum_{l=1}^{L} \pi(l, K+1) C_{l,0} T_l f_0^2,
\]

where \( \kappa_0 \) is a constant denoting the effective capacitance coefficient that is decided by the chip architecture of the local user.

B. Remote Computing at Helpers

On the other hand, the tasks in the set of \( \mathcal{L}^{(k)} \) requires to be offloaded to the \( k\)th node, \( k \in \mathcal{K} \), for remote execution. In this paper, we consider a three-phase TDMA communication protocol. As shown in Fig. 1, the local user first offloads the tasks in the set \( \mathcal{L}^{(k)} \) to the \( k\)th node, \( k \in \mathcal{K} \), via TDMA. Note that at each TDMA time slot, the local user merely offloads tasks to one helper. Then the helpers compute their assigned tasks and send the computation results back to the local user via TDMA. Similarly, at each time slot, there is merely one helper transmitting the results. In the following, we introduce the three-phase protocol in detail.

1) Phase I: Task Offloading: First, the tasks are offloaded to the helpers via TDMA. For simplicity, in this paper we assume that the local user offloads the tasks to the helpers with a fixed order of \( 1, 2, \cdots, K \), as shown in Fig. 1.

Let \( h_k \) denote the channel power gain from the local user to the \( k\)th node for offloading, \( k \in \mathcal{K} \). The achievable rate from the local user to the \( k\)th node is given by (in bits/second)

\[
r^\text{off}_k = B \log_2 \left( 1 + \frac{p^\text{off}_k h_k}{\sigma_k^2} \right),
\]

where \( B \) in Hz denotes the available transmission bandwidth, \( p^\text{off}_k \) is the transmitting power at the local user for offloading tasks to the \( k\)th node, and \( \sigma_k^2 \) is the power of additive white Gaussian noise (AWGN) at the \( k\)th node. Then, the task offloading time for the \( k\)th node is given by

\[
t^\text{off}_k = \frac{\sum_{l=1}^{L} \pi(l, k) T_l}{r^\text{off}_k}.
\]

(1)

\[
\text{Fig. 1. The TDMA-based frame for the proposed protocol.}
\]
According to (3) and (4), \( p_k^{\text{off}} \) is expressed as
\[
p_k^{\text{off}} = \frac{1}{h_k} f \left( \sum_{l=1}^{L} \pi(l,k) T_l / t_k^{\text{off}} \right),
\]
where \( h_k = \bar{h}_k / \sigma_k^2 \) is the normalized channel power gain from the local user to the \( k \)th node, and \( f(x) = \frac{\sin(\pi x)}{\pi x} - 1 \). The total energy consumed by the local user for offloading all the tasks to the helpers is then expressed as:
\[
E_0^{\text{off}} = \sum_{k=1}^{K} \frac{1}{h_k} \left( \sum_{l=1}^{L} \pi(l,k) T_l / t_k^{\text{off}} \right) t_k^{\text{off}}.
\]

2) Phase II: Task Execution: After receiving the assigned tasks in \( \mathcal{L}^{(k)} \), the \( k \)th node proceeds with computing. Similar to (1), the computation time of the \( k \)th node is given by
\[
t_k^c = \sum_{l=1}^{L} \pi(l,k) C_{c,l} T_l / f_k.
\]
Its corresponding computational energy is thus given by
\[
E_k^{c} = \kappa_k \sum_{l=1}^{L} \pi(l,k) C_{c,l} T_l f_k^2,
\]
where \( \kappa_k \) is the corresponding capacitance constant of the \( k \)th node.

3) Phase III: Task Result Downloading: After computing all the assigned tasks, the helpers begin transmitting computation results back to the local user via TDMA. Similar to the task offloading, we assume that the helpers transmit their respective computation results in the order of \( 1, \ldots, K \). Let \( \bar{g}_k \) denote the channel power gain from node \( k \) to the local user for downloading. The achievable rate of downloading results from the \( k \)th node is then given by
\[
r_k^{dl} = B \log_2 \left( 1 + \frac{p_k^{dl} \bar{g}_k}{\sigma_0^2} \right),
\]
where \( p_k^{dl} \) denotes the transmitting power of the \( k \)th node, and \( \sigma_0^2 \) denotes the power of AWGN at the local user. The downloading time of the local user from the \( k \)th node is thus given by
\[
t_k^{dl} = \sum_{l=1}^{L} \pi(l,k) R_l / r_k^{dl},
\]
Accordingly, the transmitting power of the \( k \)th node is expressed as
\[
p_k^{dl} = \frac{1}{g_k} f \left( \sum_{l=1}^{L} \pi(l,k) R_l / t_k^{dl} \right),
\]
where \( g_k = \bar{g}_k / \sigma_k^2 \) denotes the normalized channel power gain from the \( k \)th node to the local user. The communication energy of the \( k \)th node for delivering its results to the local user is thus given by
\[
E_k^{dl} = \frac{1}{g_k} f \left( \sum_{l=1}^{L} \pi(l,k) R_l / t_k^{dl} \right) t_k^{dl}.
\]

Since TDMA is used in both Phase I and Phase III, each helper has to wait until it is scheduled. Specifically, the first scheduled helper, i.e., node 1, can transmit its computation result to the local user only when the following two conditions are satisfied: first, its computation has been completed; and second, task offloading from the local user to all the \( K \) helpers are completed such that the wireless channels begin available for data downloading, as shown in Fig. 1. As a result, node 1 starts transmitting its results after a period of waiting time given by
\[
I_1 = \max \{ t_1^{off} + t_1^{dl}, \sum_{k=1}^{K} t_k^{off} \},
\]
where \( t_1^{off} \) is the task execution time at node 1 (c.f. (7)).

Moreover, for each of the other \( K-1 \) helpers, it can transmit the computation results to the local user only when: first, its computation has been completed; second, the \((k-1)\)th node scheduled preceding to it has finished transmitting. Consequently, denoting the waiting time for node \( k \) \( (k \geq 2) \) to start transmission as \( I_k, I_k \) expressed as
\[
I_k = \max \{ \sum_{j=1}^{k-1} t_j^{off} + t_k^{dl}, I_{k-1} + t_{k-1}^{dl} \}.
\]

Accordingly, the completion time for all the results to finish being downloaded is expressed as
\[
T = I_K + t_K^{dl}.
\]

To summarize, taking both local computing and remote execution into account, the total latency for all of the \( L \) tasks to be executed is given as
\[
T^{\text{total}} = \max \{ t_0, T \}.
\]

III. PROBLEM FORMULATION

In this paper, we aim at minimizing the total latency, i.e., \( T^{\text{total}} \), by optimizing the task assignment strategy, i.e., \( \pi(l,k) \)'s, the transmission time for task offloading and result downloading, i.e., \( t_k^{off} \)'s and \( t_k^{dl} \)'s (equivalent to transmitting power as shown in (5) and (11)), subject to the individual energy constraints for both the local user and the \( K \) helpers as well as the task assignment constraints. Specifically, we are interested in the following problem:

(P1) : Minimize \( T^{\text{total}} \)
\[
\Pi(t_k^{off}, t_k^{dl})
\]
Subject to
\[
E_0 + E_0^{off} \leq E_0,
\]
\[
E_k + E_k^{off} \leq E_k, \forall k \in \mathcal{K},
\]
\[
\sum_{k=1}^{K+1} \pi(l,k) = 1, \forall l \in \mathcal{L},
\]
\[
\pi(l,k) \in \{0,1\}, \forall l \in \mathcal{L}, k \in \mathcal{K} \cup \{K + 1\},
\]
\[
t_k^{off} \geq 0, t_k^{dl} \geq 0 \forall k \in \mathcal{K}.
\]
The constraints given by (17a) and (17b) represent the total energy constraints for the local user and the $k$th node, respectively; (17c) guarantees that each task must be assigned to one node; and finally (17d) ensures that each task cannot be partitioned.

IV. PROPOSED JOINT TASK ASSIGNMENT AND TIME ALLOCATIONS

The challenges in solving problem (P1) lie in two folds. First, the objective function (c.f. (15)) is a complicated function involving multiple max functions due to recursive feature of $I_k$ (c.f. (14)), for $k \geq 2$. Second, the task assignment variables are constrained to be binary (c.f.(17d)). Hence, in this section we first simplify the objective function leveraging the structure of the optimal solution. Then for the equivalently transformed problem, we propose a suboptimal solution to deal with the binary constraints.

A. Problem Reformulation

First, the following lemma is required to simplify the objective function of (P1).

**Lemma 4.1:** The function $h(y, t) = f \left( \frac{y}{t} \right)$ monotonically decreases over $t > 0$.

**Proof:** The monotonicity of the above function can be obtained by evaluating the first-order partial derivative of $h(x, t)$ with respect to (w.r.t.) $t$, and using the fact that $(1 - x)e^x - 1 < 0$, for $x > 0$. Then problem (P1) can be recast into an equivalent problem as stated in the following proposition.

**Proposition 4.1:** Problem (P1) is equivalent to the following problem:

(P1-Eqv): \[
\text{Minimize } I_1 + \sum_{k=1}^{K} t_{k}^{dl}
\]

Subject to

\[
\begin{align*}
\sum_{k=1}^{K} t_{k}^{off} & \leq I_1, \\
n & \leq \sum_{k=1}^{K} t_{k}^{dl}, \\
\sum_{j=1}^{K} \pi(k, j) & \leq I_1 + \sum_{k=1}^{K} t_{k}^{dl}, \\
\sum_{j=1}^{K} \pi(k, j) & \leq I_1 + \sum_{k=1}^{K} t_{k}^{dl},
\end{align*}
\]

$\forall k \in K \setminus \{1\}$, (17a) – (17e),

where the constraints given by (18a) and (18b) determine the waiting time of node 1 (c.f. (13)); (18c) follows by substituting (1) for $t_0^l$ (c.f. (26)); and (18d) are obtained by replacing $t_k^c$’s, $k \geq 2$, with (7) (c.f. (22)).

**Proof:** There are two possible cases for the optimal $I_k$’s given by (14): case 1) $\sum_{j=1}^{k} t_{j}^{off} + t_{k}^{c} > I_{k-1} + t_{k-1}^{dl}$; and case 2) $\sum_{j=1}^{k} t_{j}^{off} + t_{k}^{c} \leq I_{k-1} + t_{k-1}^{dl}$. In line with Lemma 4.1, the total transmitting energy of the $k$th node, i.e., $E_{k}^{dl}$’s (c.f. (12)), monotonically decreases over $t_{k}^{dl}$’s. Hence, if the first case occurs, node $k - 1$ ($k \geq 2$) can slow down its downloading, e.g., extending $t_{k-1}^{dl}$, until $I_{k-1} + t_{k-1}^{dl} = \sum_{j=1}^{k} t_{j}^{off} + t_{k}^{c}$, such that $I_k$ remains unchanged but the transmitting energy of node $k - 1$ gets reduced. As such, without loss of optimality, the two cases can be merged into one as

$I_k = I_{k-1} + t_{k-1}^{dl}$, $\forall k \in K \setminus \{1\}$,

subject to the computation deadline constraints given by

$t_{k}^{c} \leq I_{k-1} + t_{k-1}^{dl} - \sum_{j=1}^{k} t_{j}^{off}$, $\forall k \in K \setminus \{1\}$.

Since it follows from (19) that

$I_k = I_1 + \sum_{k=1}^{K} t_{k}^{dl}$, (21)

(20) reduces to

$t_{k}^{c} \leq I_1 + \sum_{j=1}^{k-1} t_{j}^{dl} - \sum_{j=1}^{k} t_{j}^{off}$, $\forall k \in K \setminus \{1\}$. (22)

Furthermore, substituting (21) for $I_k$ in (15), $T$ is simplified as

$T = I_1 + \sum_{k=1}^{K} t_{k}^{dl}$. (23)

Then, plugging (23) into (16), the total latency given by (16) turns out to be

$T_{\text{total}} = \max \{t_0^l, I_1 + \sum_{k=1}^{K} t_{k}^{dl}\}$. (24)

On the other hand, it can be similarly verified that when the optimal $T_{\text{total}}$ given by (24) yields $t_0^l > I_1 + \sum_{k=1}^{K} t_{k}^{dl}$, it is always possible for one of the $K$ helpers to slow down its transmission with its communication energy saved such that $I_1 + \sum_{k=1}^{K} t_{k}^{dl} = t_0^l$. Therefore, without loss of optimality, $T_{\text{total}}$ can be further reduced to

$T_{\text{total}} = I_1 + \sum_{k=1}^{K} t_{k}^{dl}$, (25)

which is the objective function of Problem (P1-Eqv), and subject to

$t_0^l \leq I_1 + \sum_{k=1}^{K} t_{k}^{dl}$. (26)

It is also worthy of noting that to guarantee the feasibility of problem (P1) or (P1-Eqv), it is sufficient to have $E_0^l > \sum_{k=1}^{L} (\kappa_k C_0 T_k f_{0}^2 + \ln 2 \sum_{k=1}^{K} \frac{1}{\nu_k})$ and $E_k > \sum_{k=1}^{L} (\kappa_k C_k T_k f_{k}^2 + \ln 2 \frac{1}{\nu_k})$, $\forall k \in K$, which are assumed to be true throughout the paper, and thus we only focus on the feasible cases.
B. Suboptimal Solution to (P1)

Problem (P1-Eqv) is an MINLP and is in general NP-hard. Note that under given \( \Pi \), (P1-Eqv) proves to be convex, since it is shown that \( E_{l,i}^{off} \) (c.f. (6)) and \( E_{l,i}^{dl} \) (c.f. (12)) are convex functions over \( \pi_{l,k}^{off} \)'s and \( \pi_{l,k}^{dl} \)'s, respectively. However, although the optimal solution to (P1-Eqv) can be obtained by exhaustive search, it is computationally too expensive (as many as \( (K+1)^L \) times of search) to implement in practice. Therefore, in this subsection we propose a suboptimal solution to (P1-Eqv) (or (P1)) by jointly optimizing the task assignment and the transmission time/power.

We first replace the binary constraints given by (17d) with the continuous ones given by

\[
\pi(l, k) \in [0, 1], \quad \forall l \in L, \quad \forall k \in K \cup \{K + 1\},
\]

which results in a relaxed problem denoted by (P1-Eqv-R). Since (P1-Eqv-R) proves to be jointly convex w.r.t. \( \Pi \), \( \{t_{l,k}^{off}, t_{l,k}^{dl}\} \), and \( I_l \), it can be efficiently solved by some off-the-shelf convex optimization tools such as CVX [15].

Next, denoting the optimal task assignment matrix \( \Pi \) to (P1-Eqv-R) as \( \Pi^* \), we propose to round off \( \pi_{l,k}^* \)'s to \( \hat{\pi}_{l,k} \)'s as follows such that (17c) and (17d) for (P1-Eqv) are satisfied.

\[
\hat{\pi}(l, k) = \begin{cases} 1, & \text{if } k = \hat{k}_l, \\ 0, & \text{otherwise}, \end{cases} \quad \forall l \in L,
\]

where \( \hat{k}_l = \arg \max_{k \in K \cup \{K + 1\}} \pi_{l,k}^*, \forall l \in L \). As shown earlier, given \( \hat{\pi}_{l,k} \)'s as (28), (P1-Eqv) turns out to be jointly convex w.r.t. \( \{t_{l,k}^{off}, t_{l,k}^{dl}\} \) and \( I_l \), and thus can again be efficiently solved by convex optimization tools to obtain optimal transmission time/power under given task assignment. The proposed algorithm for solving (P1) is summarized in Algorithm 1.

**Algorithm 1** Proposed Algorithm for Solving (P1)

1. Solve (P1-Eqv-R) using CVX;
2. Obtain the optimal task assignment matrix \( \Pi^* \);
3. Round off \( \pi_{l,k}^* \)'s in accordance with (28) yielding \( \hat{\Pi} \);
4. Solve (P1-Eqv) given \( \hat{\Pi} \) to obtain \( \{t_{l,k}^{off}, t_{l,k}^{dl}\} \) and \( \hat{I}_l \).

**Output** the suboptimal solution to (P1) as \( \hat{\Pi}, \{t_{l,k}^{off}, t_{l,k}^{dl}\}, \) and \( \hat{I}_l \).

V. Simulation Results

In this section, we verify the effectiveness of the proposed joint task assignment and TDMA resource allocation against other baseline schemes. First, we provide two heuristic schemes: 1) ‘heuristic-1’ assigns each task as per the channel gains only, i.e., \( k = \arg \max_{k \in K} \{1/h_{l,k}/g_k\}, \forall l \in L; \) and 2) ‘heuristic-2’ assigns each task as per the computational time for executing this task, i.e., \( k_l = \arg \min_{k \in K} C(l, k)T_l/f_k, \forall l \in L \). In addition, ‘random selection’ solves (P1-Eqv) by randomly choosing a feasible \( \Pi \). Moreover, since the theoretically optimal task assignment must be found by exhaustive search, we provide a near-optimal ‘random search’ scheme that runs ‘random selection’ for 1000 times and selects the best solution. At last, in ‘local execution’, the local user executes all the computation tasks locally.

The input data length \( T_l \) is assumed to be uniformly distributed between 0 and \( 10^4 \), denoted by \( T_l \sim U[0, 10^4] \), \( \forall l \in L \). Similarly, we set \( R_l \sim U[0, 10^4] \) and \( C_{l,k} \sim U[0, 10^3] \), \( \forall l \in L, k \in K \). The \( K \) helpers are located within a radius uniformly distributed within 0.5km away from the local user. The wireless channel model consists of both large-scale pathloss, and small-scale Rayleigh fading with an average channel power gain of 1. The other parameters are set as follows unless otherwise specified: \( B = 312.5 \text{ KHz} \), \( \sigma^2 = -144 \text{ dB} \), \( \kappa = 10^{-28} \), \( K = 5 \), \( L = 10 \), \( f_0 = 1 \text{ GHz} \), \( f_k = 2 \text{ GHz} \), and \( E_k = E_0 = -20 \text{ dB}, \forall k \in K \).

Fig. 2 shows the total latency versus the energy constraints with \( E_k = E_0, \forall k \in K \).

Fig. 2 shows the total latency versus the energy constraints. It is observed that our proposed joint task assignment and time allocations outperforms all other schemes in most cases and keeps a negligible gap with the near-optimal ‘random search’ under large energy constraints. It is also seen that ‘heuristic-2’ only outperforms ‘random selection’ when \( E_0 \) is larger than \(-8.5 \text{ dB} \), since in the low-energy case, assigning tasks as per only computational resources may occur too much energy for computation and thus less for communications.

Fig. 3 compares the system latency versus the helpers’
It is seen that the total latency reduces with the helpers’ frequency, which is intuitive. Moreover, both ‘heuristic-2’ and the proposed scheme tend to be lower-bounded when \( f_k \)’s continues increasing, since under the same energy constraint, large \( f_k \)’s leads to significant computation energy expenditure, and thus the latency of the system is eventually bottlenecked by communications time. Furthermore, as ‘heuristic-1’ only selects the helper with the best channel condition, all the tasks are then performed on this single helper, whose frequency thus needs to be sufficiently larger than the local frequency \( f_0 \) to surpass ‘local execution’. It is also worth noting that the performance of ‘heuristic-1’ is not evaluated further when \( f_k \)’s is larger than 2GHz, simply because operating with such high frequency violates its energy constraint.

The impact of the total number of computation tasks on the latency is shown in Fig. 4. With the number of tasks increasing, longer delay is expected for all schemes with the proposed design achieving the best performance, especially when \( L \) becomes large. Unlike in Fig. 3, ‘heuristic-1’ always outperforms ‘local execution’, since the communication-aware task assignment selects the helper with potentially short communications time to offload the tasks, while exploiting its high CPU frequency.

VI. Conclusion

In this paper, we investigated joint task assignment as well as time and/or power allocations for a multi-user cooperative MEC system employing TDMA-based communications. We considered a practical task model where the local user has multiple independent computation tasks that can be executed in parallel. Under this setup, we aimed at minimizing the computation latency subject to individual energy constraints at the local user and the helpers. The latency minimization problem was formulated as an MINLP, which is difficult to be solved optimally. We proposed a low-complexity suboptimal scheme by first relaxing the integer variables (for task assignment) as continuous ones, then solving the relaxed problem, and finally constructing a suboptimal solution to the original problem based on the optimal solution to the relaxed problem. Finally, the effectiveness of the proposed scheme was verified by numerical results.

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