Delay Minimization in Sliced Multi-Cell Mobile Edge Computing (MEC) Systems

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Abstract—Here, we consider the problem of jointly optimizing users’ offloading decisions, communication and computing resource allocation in a sliced multi-cell mobile edge computing (MEC) network. We minimize the weighted sum of the gap between the observed delay at each slice and its corresponding delay requirement, where weights set the priority of each slice. Fractional form of the objective function, discrete subchannel allocation, considered partial offloading, and the interference incorporated in the rate function, make the considered problem a complex mixed integer non-linear programming problem. Thus, we decompose the original problem into two sub-problems: (i) offloading decision-making and (ii) joint computation resource, subchannel, and power allocation. We solve the first sub-problem optimally and for the second sub-problem, leveraging on novel tools from fractional programming and Augmented Lagrangian method, we propose an efficient algorithm whose computational complexity is proved to be polynomial. Using alternating optimization, we solve these two sub-problems iteratively until convergence is obtained. Simulation results demonstrate the efficacy of our proposed algorithm and its effectiveness compared to existing schemes.

Index Terms—Network slicing, partial offloading, interference, MEC, resource allocation.

I. INTRODUCTION

Network slicing is an indispensable technique to support heterogeneous services in fifth generation (5G) networks [1]. Using network slicing, multiple logical network slices can be created on a common physical infrastructure. Each slice can be tailored to a specific application with distinct Quality-of-Service (QoS) requirement. On another note, resource-intensive and latency sensitive services necessitate mobile edge computing (MEC) that brings computational resources to the Radio Access Network (RAN) edge. Thus, users would use both RAN and computation resources to offload and process their tasks at the MEC servers. On the other hand, in a sliced network, resources are restricted for each slice based on a service level agreement (SLA) with infrastructure provider (InP). Subsequently, joint optimization of RAN resources (e.g., subchannel and power) and computation resources (e.g., CPU cycles of MEC servers) with optimal computation offloading in a sliced network becomes imperative.

Recently, the problem of delay minimization in a multi-cell MEC network was solved through communication and computation resource allocations (RAs) without network slicing [2]–[4]. However, in all these works, the interference was either ignored [2], [3] or simplified [4]. Also, in [2], offloading decisions were not optimized, [3] did not consider RAN RA, and [4] considered a binary offloading scheme.

A handful of research studies considered RA in sliced cellular networks [1], [5]–[9]. In [1], the authors minimized a weighted combination of energy consumption and delay through subchannel and computation RA. This work considered two slices on a single base station (BS) with no interference. In [5], the authors minimized delay through computation RA, considering multiple BSs, and in [6], the authors maximized the offloaded workload that can be supported in a given time at each fog node through energy optimization and server allocation. However, in both [5] and [6], the inter-cell interference was ignored and offloading decisions and RAN RA were not considered. The authors in [7] optimized the traffic allocation in a multi-tier sliced architecture, while preventing over-provisioning. However RAN and computation RA were considered abstractly, i.e., neither subchannel, power, and computation RA were considered, nor offloading decisions were optimized. Similarly, in [8], an abstract view of ‘resource’ was adopted to minimize the weighted system delay, i.e., RAN and computation RA were not addressed.

Recently, using stochastic optimization, joint subchannel, power, and computation RA was considered in a multi-cell sliced network to minimize system energy consumption in [9], while ignoring offloading decisions. It should be noted that energy consumption can be modeled as a convex function of transmit power and subchannel allocation variables, and is different from delay, which at its simplest form, is a function of inverse of non-convex data rate. Also, when all users offload, as in [9], the delay can be easily restated in terms of the users’ data rate. However, with offloading decision optimization, such simplifications are not applicable.

To our best knowledge, the problem of delay minimization with joint offloading, computation, and communication RA in a cooperative multi-cell MEC network with or without slicing is not investigated in the literature. Our contributions are:

• We jointly optimize users’ offloading decisions, RAN and computing RA in a multi-cell MEC network to minimize the weighted sum of the difference between the delay observed at each slice and its corresponding desired delay. The fractional form of the objective function, discrete subchannel allocation, the partial offloading scheme, and the interference incorporated in the rate function, turns this problem into a mixed integer non-linear programming problem (MINLP) for which we proposed an efficient and novel algorithm.

• We decouple the original problem into two sub-problems: (i) offloading decision-making and (ii) joint computation resource, subchannel, and power allocation. We solve the first sub-problem optimally. For the second sub-problem, we propose an efficient algorithm with polynomial computational complexity, leveraging on tools from fractional programming and Augmented Lagrangian method (ALM). Using alternating optimization, we solve these two sub-problems iteratively until convergence. Complexity analysis is also presented.

• Simulation results demonstrate the efficacy of our pro-
poised algorithm compared to existing schemes and provide insights related to the impact of interference, slice prioritization, and cooperative MEC offloading, while demonstrating the convergence in a few iterations.

II. SYSTEM MODEL AND ASSUMPTIONS

We consider a MEC network with \(M\) edge points (or BSs) with co-located servers.\(^1\) The set of MEC servers is denoted as \(M = \{1, 2, \cdots, M\}\). The available spectrum at each cell is divided into \(N\) subchannels each with bandwidth \(B\). Network resources are sliced to accommodate \(K = \{1, 2, \cdots, K\}\) tenants each of which provide one specific type of service. Furthermore, the set of users for each tenant \(k\) is denoted by \(\mathcal{U}_k\) and the set of all users is \(\mathcal{U} = \{1, 2, \cdots, U\}\). Each tenant \(k\) has a SLA with InP in which the proportion of computation capacity, \(\beta_k\), and available bandwidth, \(\omega_k\), reserved for its users is determined. The task of each user with co-located servers \(u,j\) is represented by the tuple \((L_u,C_u)\), with \(L_u\) as the size of the task and \(C_u\) as the computational demand (CPU cycles) to process each bit.

To facilitate slice resource management, we consider a software-defined network (SDN) controller referred to as slice coordinator (SC). The SC keeps track of resource utilization in each slice and ensures that service providers (SPs) follow resource constraints in SLA and do not exceed their share of resources. This network architecture is given in Fig. 1.

We denote \(y_{u,j}\) as the proportion of the task of user \(u\) executed on the MEC server \(j\). Thus, we have \(\sum_{j \in \{M\}} y_{u,j} = 1, \forall u \in \mathcal{U}\), where index 0 denotes local computation.

1) Communication Model: We consider that if a user offloads its task, it first sends it to its assigned server denoted by \(m_u\), and then the remaining communication (possible handoffs between servers) would be done over the high speed backhaul links. Denoting \(\mathcal{U}_j\) as the set of users associated to server \(j\), the data rate of each user \(u\) over subchannel \(n\) is:

\[
r_{u,n} = B \log \left(1 + \frac{x_{u,n} p_{u,n} h_{u,m_u,n}}{\sigma^2 + I_{u,n}} \right)
\]

where \(p_{u,n}\), \(I_{u,n}\), and \(\sigma^2\) represent the transmit power of user \(u\) over subchannel \(n\), its inter-cell interference calculated as \(I_{u,n} = \sum_{j \in \{M\} \setminus m_u} \sum_{n' \in \mathcal{L}(j)} x_{u,n} p_{u,n} h_{u,j,n'}\), and receiver noise power, respectively. Also, \(h_{u,j,n}\) is the path-gain between user \(u\) and BS \(j\) over subchannel \(n\), and \(x_{u,n}\) denotes the binary subchannel allocation variable which is equal to one if subcarrier \(n\) is assigned to user \(u\), and zero otherwise.

Now, we can calculate the total data rate of each user \(u\) as

\[
R_u(X,Y) = \sum_{n \in N} r_{u,n},
\]

where \(N\), \(X\), \(Y\), denote the set of \(N\) subchannels, subchannel allocation matrix, and transmit power allocation matrix, respectively. Denoting \(Y\) as the matrix of offloading decisions, the communication delay of user \(u\) is:

\[
T_{u,m_u}^{\text{comm}}(X,Y) = \frac{\sum_{j \in M} y_{u,j} L_{u,j}}{R_u(X,Y)}.
\]


2) Computing Model: As a partial offloading scheme is adopted here, users’ task may be partly processed locally. Denoting the computation capability of local device for user \(u\) as \(f_u^L\) (CPU cycles per second), the local computation delay would be:

\[
T^L_u(Y) = \frac{y_{u,0} L_u C_u}{f_u^L}.
\]

With \(F\) representing the matrix of all computation resource allocation variables, since the task of user \(u\) might be processed by servers other than its assigned server, the computation delay of user \(u\) is:

\[
T_u^{\text{comp}}(X,Y) = T_{u,m_u}^{\text{comm}}(X,Y) + \sum_{j \in \{M\} \setminus m_u} y_{u,j} T_{m_u,j}^{\text{ho}} + T_u^{\text{comp}}(F,Y),
\]

where \(T_{m_u,j}^{\text{ho}}\) denotes the hand-off delay, including the time for communicating with SC and the average round trip time for task transfer between \(m_u\) and \(j^{th}\) server. Moreover, \(T_u^{\text{comp}}\) denotes the offloading computation delay of user \(u\). If tasks’ fragments are processed sequentially (one after the other), \(T_u^{\text{comp}}\) would be the summation of delays of user \(u\) in each server \(j\) as in \(T^L_u\). In case of parallel processing, the computation delay of user would be equal to the delay in the slowest server. However, in order to retain a tractable form for our objective function, we consider an upper-bound and calculate the computation delay in both cases as follows:

\[
T_u^{\text{comp}}(F,Y) = \sum_{j \in M} y_{u,j} L_u C_u,
\]

where \(f_{u,j}\) represents the computation resource that is allocated to user \(u\) in server \(j\) (CPU cycles per second). Note that even when parallel computation of the tasks is possible, due to 1) positivity of computation delay and 2) the independence between \(f_{u,j}\) for different servers, this upper bound would not significantly affect the optimized value of computation resource allocation in the slowest server, as minimizing the sum translates into minimizing each component separately. Due to the typically small size of response, we ignore the downlink transmission delay. Thus, the total delay of each user \(u\) is:

\[
T_u(X,Y) = T^L_u(Y) + T_u^{\text{comp}}(X,F,Y).
\]

III. PROBLEM FORMULATION

In this section, we formulate the problem of minimizing the weighted sum of the difference between the delay observed at a given slice and its corresponding delay requirement (or weighted sum of the delay deviation at each slice), through...
jointly optimizing users’ offloading decisions, RAN and computing RA in a cooperative multi-cell MEC network. This problem offers SPs a valuable insight into the adequacy of their leased resources to meet the service quality requirement of their subscribers and the average delay they would experience under the existing SLA. Analysing the results obtained, SPs can better plan their future strategies to whether maintain their current SLA, invest more on leasing resources, or to modify their subscription policy to either increase or decrease the number of users they accept. Now, we formally state the optimization problem as follows:

\[
P^* = \min_{X,P,F,Y} \sum_{k \in K} \sum_{u \in U_k} \lambda_k (T_u(X,P,F,Y) - \bar{T}_k)
\]

Subject to:

\[
C_1: \sum_{u \in U_k} x_{u,n} \leq 1, \quad \forall n \in N, \forall j \in M,
\]
\[
C_2: x_{u,n} \in \{0,1\}, \quad \forall n \in N, \forall j \in M, \forall u \in U_j,
\]
\[
C_3: 0 \leq \sum_{n \in N} x_{u,n}p_{u,n} \leq P_{\max,u}, \quad \forall u \in U,
\]
\[
C_4: y_{u,0}L_uC_u \leq F_u^L, \quad \forall u \in U,
\]
\[
C_5: \sum_{u \in U} y_{u,j}L_uC_u \leq F_j^E, \quad \forall j \in M,
\]
\[
C_6: \sum_{u \in U_j} \sum_{n \in N} x_{u,n} \leq \alpha_k MN, \quad \forall k \in K,
\]
\[
C_7: \sum_{j \in M} f_{u,j} \leq \beta_k S_j^E, \quad \forall k \in K,
\]
\[
C_8: \sum_{j \in (M\cup 0)} y_{u,j} = 1, \quad \forall u \in U,
\]
\[
C_9: y_{u,j} \in [0,1], \quad \forall u \in U, \forall j \in M.
\]

In the above optimization problem, \( \bar{T}_k \) denotes the desired delay threshold of each slice \( k \) and \( \lambda_k \) is the weighting factor whose value is defined in SLA and handles the precedence of slices over each other. Furthermore, constraint \( C_1 \) indicates that each subchannel can be allocated to at most one user in each cell and \( C_2 \) shows the binary nature of the subchannel allocation variable. In constraint \( C_3 \), users’ transmit power is restricted between zero and a maximum threshold denoted by \( P_{\max,u} \). In constraints \( C_4 \) and \( C_5 \), the limitation of local and edge computation resources are specified for each user and server, respectively, with \( F_u^L \) and \( F_j^E \) denoting the total computation capacity of user \( u \) and server \( j \) (both in CPU cycles per second), in that order. Constraints \( C_6 \) and \( C_7 \) ensure that resource consumption at each slice follows SLA. That is, \( C_6 \) limits the spectrum usage for each slice. Since there are \( M \) cells in the system and each cell has access to \( N \) subchannels, then in total we have \( NM \) subchannels, from which only \( \alpha_k \) percent can be used by users of slice \( k \). Similar to communication resources, the proportion of the total computation capacity \( S_j^E \) (\( S_j^E = \sum_{j \in M} F_j^E \)) that is allocated to each slice \( k \) is limited to \( \beta_k \) as given in constraint \( C_7 \). Constraints \( C_8 \) and \( C_9 \) clarify the partial offloading decision scheme adopted in this work.

As the result of interference included in the rate function, the binary subchannel allocation variables, and the objective function which is in the form of summation of ratios, optimization problem (7) is MINLP and thus difficult to tackle. In what follows we present our resource allocation algorithm.

IV. PROPOSED RESOURCE ALLOCATION FRAMEWORK

To tackle the difficulties of solving problem (7), we first take advantage of the problem structure and decompose it into the following two subproblems:

\[
P_1: \min_Y \sum_{k \in K} \sum_{u \in U_k} \lambda_k (T_u(Y) - \bar{T}_k)
\]
Subject to: \( C_4, C_5, C_8, C_9 \).

\[
P_2: \min_X \sum_{k \in K} \sum_{u \in U_k} \lambda_k (T_u(X,F,Y) - \bar{T}_k)
\]
Subject to: \( C_1 - C_3, C_6, C_7 \).

In problem (9), both the objective function and constraint set are affine with respect to the variable \( Y \). As such, it can be solved using standard optimization tools such as CVX toolbox.

The first challenge in (9) is the multiplication of subchannel and power allocation variables in (1) as well as in constraint \( C_3 \). To tackle this challenge, we first replace all \( x_{u,n}p_{u,n} \) terms with \( p_{u,n} \) and then add the following constraint to (9):

\[
C_{3,1}: 0 \leq p_{u,n} \leq x_{u,n}P_{\max,u}
\]

By using the above modification, users’ transmit power would be automatically set to zero over subchannels they do not own. By adding this constraint, data rate function \( R_u(X,P) \) would become a function of transmit power only \( (R_u(P)) \). This step solves the variable multiplication issue, however discrete subchannel allocation variable is still challenging. To deal with this issue we replace \( C_2 \) with the following two constraints:

\[
C_{2,1}: 0 \leq x_{u,n} \leq 1, \quad C_{2,2}: x_{u,n} - x_{u,n}^2 \leq 0
\]

Remark 2: Although we relax \( x_{u,n} \) to a continuous variable in \( C_{2,1} \), since the only two values in \([0,1]\) that fit \( C_{2,2} \) are 0 and 1, the binary nature of this variable would be preserved.

The fractional form of users’ delay, \( T_u \), is the next issue we focus on. After offloading decision is obtained through solving subproblem \( P_1 \), edge computation delay, \( T_u^{\text{comp}}(F,Y) \), in the objective function of \( P_2 \) would turn into a convex function and hand-off delay would be a constant. This leaves us with the summation of users’ transmission delay, whose non-convexity can be easily proved.

Lemma 1. Using tools from fractional programming, problem (9) can be restated as:

\[
\min_{X,P,F} T(P,F) = \sum_{k \in K} \sum_{u \in U_k} \lambda_k \left[ y_{u,j}L_u \frac{1}{2R_u(P)} \right] + \sum_{j \in M} y_{u,j}T_u^{\text{comp}}(F,Y) - \bar{T}_k
\]
Subject to: \( C_1 - C_3, C_6, C_7 \).

Proof. An optimization problem with the form \( \min_{x \in X} \sum_{i=1}^{l} \frac{B_i(x)}{A_i(x)} \), can be restated equivalently as \( \min_{x \in X, t \in R^+} \sum_{i=1}^{l} t_iB_i(x)^2 + \sum_{i=1}^{l} \frac{1}{4t_i} A_i(x)^2 \)
where \( t_i = \frac{1}{2B_i(X_i)A_i(X_i)} \). Using (13) and by setting \( B_i = 1 \) and \( A_i = R_u(P) \), we restate problem (9) as given in Lemma 1.

Due to the presence of interference, \( R_u(P) \) is still a non-convex function of transmit power.

**Lemma 2.** We can obtain an equal but convex representation of communication delay function by restating the rate as:

\[
\hat{r}_{u,n}(P, z_{u,n}) = \log_2 \left( 1 + 2z_{u,n}\sqrt{h_{u,m,u,n}}p_{u,n} - z_{u,n}^2(I_{u,n} + \sigma^2) \right),
\]

(14)

**Proof.** As mathematically proven in (11) and since in Lemma 1, we set \( A_i = R_u(P) \), and \( R_u(P) = \sum_{n \in N} r_{u,n} \), \( r_{u,n} \) can be equally restated as (14). This modification, not only makes \( r_{u,n} \) a concave function of \( P \), \( \frac{1}{P} \) would also become a convex function.

In (14), \( z_{u,n} \) is a slack variable that will be updated iteratively. Using Lemma 2, we convexify the complex non-convex function \( T_{\text{comm}}(P) \), also we redefine \( R_u(P) = \sum_{n \in N} \hat{r}_{u,n}(P, z_{u,n}) \). For optimizing \( P, X, \) and \( F \) we adopt ALM. For a given \( z_{u,n} \), the augmented Lagrangian function is given in (15).

In the augmented Lagrangian function, \( \Psi \) is a positive constant that plays the role of an adjustable penalty coefficient and \( \Gamma \) is the vector of all Lagrangian multipliers \( \Theta, \Delta, \Phi, \), \( \xi \), and \( \Xi \). Solving problem (9) or, equivalently (12) can be done in three steps. In the first step, we consider Lagrangian multipliers to be fixed and minimize \( L(X, P, F, \Psi) \) given in (15).

In the second step, Lagrangian multipliers would be updated as:

\[
\theta_{u+1}^{t+1} = \left[ \theta_u + \Psi \left( \sum_{n \in N} p_{u,n} - P_{\text{max},u} \right) \right]^+,
\]

(16)

\[
\delta_{k+1}^{t+1} = \left[ \delta_k + \Psi \left( \sum_{u \in U_k} \sum_{j \in M} f_{u,j} - \beta_k E^{\Phi} \right) \right]^+,
\]

(17)

\[
\phi_{n+1}^{t+1} = \left[ \phi_{n}^{t} + \Psi \left( \sum_{u \in \mathcal{U}} x_{u,n} - 1 \right) \right]^+.
\]

(18)

\[
\xi_{u,n+1}^{t+1} = \left[ \sum_{n \in N} \sum_{j \in M} \xi_{u,n,j}^{t} + \Psi \left( \sum_{n \in N} \sum_{j \in M} x_{u,n} - x_{2,u,n}^2 \right) \right]^+.
\]

(19)

\[
\Xi_{u,n+1}^{t+1} = \left[ \sum_{u \in \mathcal{U}} \sum_{n \in N} \Xi_{u,n}^{t} + \Psi \left( \sum_{u \in \mathcal{U}} \sum_{n \in N} p_{u,n} - x_{2,u,n}P_{\text{max},u} \right) \right]^+.
\]

(20)

The third step is executed after a solution is obtained for (15). In this last step, using the values obtained for \( P \) and \( X \), we update slack variable \( z_{u,n} \) as \( z_{u,n} = \sqrt{p_{u,n}h_{u,m,u,n}} \).

Our proposed algorithm is given in **Algorithm 1**.

**Algorithm 1 Proposed Algorithm**

1: Obtain the solution of problem (9) and initialize \( Z \).
2: Repeat
3: Initialize \( \Gamma = [\Theta, \Delta, \Phi, \xi, \Xi] \) with small numbers.
4: Repeat
5: Solve problem (13) considering \( \Gamma \) to be fixed,
6: Update \( \Gamma \) using (16), (17), (18), (19), and (20).
7: Until convergence.
8: Set \( z_{u,n} = \frac{\sqrt{p_{u,n}h_{u,m,u,n}}}{I_{u,n} + \sigma^2} \) for all users and subchannels.
9: Until Convergence.

**V. Computation Complexity Analysis**

Our proposed algorithm is divided into two sub-problems, i.e., (i) offloading decision optimization and (ii) joint computation and RAN RA. For the first sub-problem, we use interior point method in CVX whose complexity is in the order of \( O(\log(C\epsilon^2/k)) \), where \( C \), \( k \), \( \epsilon \), and \( k \) denote the total number of constraints, the initial point for interior point method, the stopping criterion, and a representation of the accuracy of the method, respectively. For the second sub-problem based on ALM the order of complexity at each iteration is \( O(KM) \) which is polynomial.

**VI. Simulation Results and Discussions**

We consider a network with two cells each having 6 users and 16 available subchannels, unless stated otherwise. Similar to [8], we consider three slices/services as: elastic services with flexible latency constraints, inelastic services that require ultra-low latency, and background services with low latency requirement. The weighting parameter \( \lambda \) is set to [3, 2, 1] for inelastic, elastic, and background services, with 50ms, 100ms, and 5s desired delay threshold, respectively. The value of \( L_u \) is 1 MB and the CPU cycle, \( C_u \), is randomly chosen from \([1500, 2000, 2500]\). As a convex problem, initial point does not effect the solution of (8), however, to avoid increasing the complexity, the initial point of the problem (9) is obtained by checking various values and selecting the best values that minimizes our objective function.

Fig. 2 depicts the effect of number of users in each cell on the sum of weighted delay deviation at each slice. We have compared our algorithm with 1) Joint Offloading and Computation RA (JOCRA): where only offloading and computing RA is considered (with interference and server cooperation, this scenario is in fact an improvement on [5]), 2) Joint Offloading, Subchannel, Power RA (JSPRA): in which only RAN RA is addressed and computation resource is equally allocated to users, and 3) our proposed scheme without server cooperation. We can clearly observe the significance of joint computation and RAN RA in the delay that users experience. In fact, if we ignore computation RA we would have 58\% and if we overlook communication RA we will have 62\% increase in network delay deviation on average. In Fig. 1, the impact of cooperation among cells is also illustrated. At first, when number of users is not too high, there is almost no need for cooperation. However, as the number of users increases, we observe that the effect of cooperation becomes noteworthy (i.e., 9% reduction on average). The positive delay deviation occur when network becomes infeasible (i.e., insufficient resources in at least one slice) and satisfying the QoS of high priority services takes precedence in the network. Thus, we can preserve the QoS of slices by increasing their weight (\( \lambda_i \)) for prioritization of the slice or the quota of reserved resources (\( \beta \) and \( \alpha \)) to avoid infeasibility. However, such modifications are often a function of the cost SPs are willing to pay.
\[
\min L(X, P, F, Z, \Gamma) = T(X, P, F, Z) + \frac{1}{2\Psi} \left[ \left( \sum_{u \in U} \theta_u + \Psi \left( \sum_{n \in N} p_{u,n} - p_{\text{max},u} \right) \right) \right] - \sum_{u \in U} \theta_u^2 \\
+ \left( \sum_{k \in K} \delta_k + \Psi \left( \sum_{u \in U} \sum_{j \in M} f_{u,j} - \beta_k E^k \right) \right) + \sum_{k \in K} \delta_k^2 + \left( \sum_{n \in N} \sum_{j \in M} \phi_{n,j} + \Psi \left( \sum_{u \in U} x_{u,n} - 1 \right) \right) \\
+ \sum_{n \in N} \sum_{j \in M} \xi_{n,j}^2 - \sum_{u \in U} \sum_{n \in N} \xi_{n,u}^2 - \sum_{u \in U} x_{u,n}^2 \right]^{2}.
\]

In Fig. 3, we examine how increasing the number of cells impacts the delay of users. We again compare our proposed algorithm with JOCRA and JSPRA. As the number of users per cell remains constant here, we depict the average delay deviation per user. Increasing the number of cells notably increases the delay of users, however this increase is more significant when communication RA is overlooked. Because, while the average amount of resources available for users remains almost the same (since the number of users in each cell is constant), more cells means intensified interference in the network. To deal with the negative effect of this intensified interference, precise RAN RA becomes imperative.

The convergence of our proposed algorithm and the importance of slice resource management is numerically demonstrated in Fig. 4. Here, we observe that: i) our algorithm converges to its final solution after a few iterations, and ii) careful resource reservation plays a significant role in the QoS users of each slice achieve.

**VII. CONCLUSION**

In this work we propose a framework to minimize the delay in cooperative MEC network by optimizing both RAN and computation resources and offloading decisions, using tools from fractional programming, convexification of rate function, and ALM. The problem of routing between edge servers is a venue for future works, especially with wireless backhauling.

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