Fair Resource Allocation in an MEC-Enabled Ultra-Dense IoT Network with NOMA

Qun Wang, PhD student
Faculty advisor: Prof. Rose Q. Hu

Department of Electrical and Computer Engineering,
Utah State University, Logan, UT

April 8, 2019

[1]This work was supported by the National Science Foundation under the grants EECS-1308006, NeTS-1423348, and EARS-1547312, Intel Corporation.

Contents

UtahState University

Motivation and Objective

Challenges

- Ultra-dense Internet of Things (IoT) networks need massive IoT devices to perform computation-intensive and delay-sensitive tasks, it is challenging for IoT devices to execute those tasks due to their low computation capability and limited resource
- It is of crucial importance to design efficient resource allocation schemes for improving computation performance or for decreasing computation cost.
- Unfairness may occour when there exist massive IoT devices all with very limited computation capability.

Potential Solutions

- Mobile edge computing (MEC) can significantly improve the computation capability of IoT devices by deploying MEC servers in proximity to IoT users.
- An MEC-enabled ultra-dense IoT network with NOMA can effectively balance the computation efficiency and energy efficiency.

In order to achieve a better trade-off between computation efficiency and energy efficiency, we propose a new method for the resource allocation in an MEC-enabled ultra-dense IoT network with NOMA. Moreover, in order to address fairness among massive IoT users, we introduce fairness index into the utility function of the proposed scheme.

System Model

An MEC-enabled ultra-dense IoT network as shown is considered, N IoT devices that need to execute computation-intensive yet delay-sensitive tasks and one MEC server that can provide MEC service for those IoT devices.

- Partial computation offloading mode is supported, part of tasks for local computing and remaining part for offloading to the MEC server for computing.
- NOMA is applied so that multiple devices can offload their tasks simultaneously by using the same physical radio resource.
- Each IoT device can perform local computing and computation task offloading at the same time.

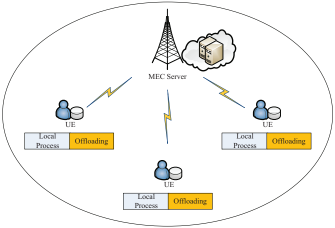

Figure 1: System Model

Data Offloading

Let $\mathcal{N} = \{1, 2, \dots, N\}$ denote the set of UEs. Let g_n and p_n represent the channel gain and the transmission power between the MEC server and UE n.

MEC server ranks the UEs by their channel quality, i.e., $g_1^2 \geq g_2^2 \geq \cdots \geq g_N^2$. All the N users can send the offloading data to the MEC simultaneously on the same radio resource.

Successive interference cancellation (SIC) technique is applied at the receiving side to decode the signal for each user, i.e., for decoding nth user's signal, the signals from user i, $1 \leq i \leq n-1$, are treated as interference and the signals from user m, $n \leq m \leq N$, are all removed from the composite received signal.

The offloading rate and power consumption for the nth user can be expressed as

$$r_n^{\text{off}} = B \log_2\left(1 + \frac{p_n g_n^2}{\sum_{i=1}^{n-1} p_i g_i^2 + \sigma^2}\right), \tag{1}$$

and

$$p_n^{\text{off}} = \zeta p_n + p_r, \tag{2}$$

where σ^2 is the power of the noise, B is the bandwidth. ζ is the amplifier coefficient, and p_r is the constant circuit power consumed for signal processing.

UtahState University

Local Computing

Let C_n be the number of computation cycles required to process one bit of data for UE n locally. Let f_n denote the computing speed of the processor (cycles per second).
The local computing rate of the nth UE can be expressed as

$$r_n^{local} = \frac{f_n}{C_n} \tag{3}$$

The power consumption of local computing is modeled as a function of processor speed f_n. It can be given as

$$p_n^{local} = \epsilon f_n^3, \tag{4}$$

where ϵ is the effective capacitance coefficient of the processor's chip.

Utility Function

Combining data offloading and local computing, the total computation rate R_n for UE n can be expressed as $R_n = r_n^{off} + r_n^{local}$. The total power consumption P_n of UE n is $P_n = p_n^{off} + p_n^{local}$.
In order to consider the computation rate fairness among users, the following utility $U_\alpha(R_n)$ is defined, where α is the fairness index.

$$U_\alpha(R_n) = \begin{cases} \dfrac{R_n^{1-\alpha}}{1-\alpha} & \text{if } \alpha \geq 0,\ \ \alpha \neq 1, \\ \ln(R_n) & \alpha = 1. \end{cases} \tag{5}$$

When $\alpha = 0$, the utility function is the sum computation rate for all UEs; when $\alpha = 1$, the utility function is the sum logarithmic function of UE rates, which normally provides proportional fairness; when $\alpha = \infty$, the utility function is the minimum rate among all UEs, which corresponds to the max-min fairness.

Problem Formulation

The optimization problem aims to minimize the total power consumption as well as maximize the achievable data rate utility. The problem is formulated as

$$\begin{aligned}
\mathbf{P_1}: \quad & \max_{f_n, p_n} \ \Phi_{SE} \sum_{n \in \mathcal{N}} U_\alpha(R_n) - \Phi_{EE} \sum_{n \in \mathcal{N}} P_n && \text{(6a)} \\
& s.t. \ \ C1: \ p_n \geq 0, \quad \forall n \in \mathcal{N}, && \text{(6b)} \\
& \qquad C2: \ R_n \geq R_n^{th}, \quad \forall n \in \mathcal{N}, && \text{(6c)} \\
& \qquad C3: \ P_n \leq P_n^{th}, \quad \forall n \in \mathcal{N}, && \text{(6d)} \\
& \qquad C4: \ f_n^{min} \leq f_n \leq f_n^{max}, \quad \forall n \in \mathcal{N}. && \text{(6e)}
\end{aligned}$$

$\mathbf{P_1}$ is a resource allocation problem that optimizes the offloading power p_n, local computing chip frequency f_n. Φ_{SE} and Φ_{EE} are the weighting factors that can be used to prioritize different computation service requirements of UEs.

Proportional Fairness $\alpha = 1$

When $\alpha = 1$, the system utility is the sum logarithmic function of UE's computation rate. In this case, the proportional fairness can be achieved. The original problem $\mathbf{P_1}$ under this case can be expressed as

$$\begin{aligned}\mathbf{P_2}: \quad & \max_{f_n, p_n} \Phi_{SE} \sum_{n \in \mathcal{N}} \ln\Big(B \log_2\Big(1 + \frac{p_n g_n^2}{\sum_{i=1}^{n-1} p_i g_i^2 + \sigma^2}\Big) + \frac{f_n}{C_n}\Big) - \Phi_{EE} \sum_{n \in \mathcal{N}} (\zeta p_n + p_r + \epsilon f_n^3) \\ & s.t. \quad C1 - C4. \end{aligned} \tag{7}$$

$\mathbf{P_2}$ is a non-convex optimization problem.

Let $\mathbf{a} = [a_1, \cdots, a_N]^T$, $\mathbf{P_2}$ can be transformed into

$$\mathbf{P_3} : \max_{f_n, \rho_n, a_n} \Phi_{SE} \sum_{n \in \mathcal{N}} a_n - \Phi_{EE} \sum_{n \in \mathcal{N}} (\zeta \exp(\rho_n) + p_r + \epsilon f_n^3)$$

$$s.t. \quad a_n \geq \ln(R_n^{th}), \quad \forall n \in \mathcal{N}, \tag{8a}$$

$$\zeta \exp(\rho_n) + p_r + \epsilon f_n^3 \leq P_n^{th}, \ \forall n \in \mathcal{N}, \tag{8b}$$

$$f_n^{min} \leq f_n \leq f_n^{max}, \quad \forall n \in \mathcal{N}, \tag{8c}$$

$$\ln(2^{\frac{\exp(a_n) - \frac{f_n}{C_n}}{B}} - 1) + \ln(\sum_{i=1}^{n-1} \frac{g_i^2}{g_n^2} e^{\rho_i - \rho_n} + \frac{\sigma^2}{g_n^2} e^{-\rho_n}) \leq 0, \quad \forall n \in \mathcal{N}. \tag{8d}$$

The objective function is jointly concave with respect to a_n and ρ_n due to the subtraction of a linear term and convex term. However, the first part of the last constraint (8d) is non-convex. Thus, the problem is non-convex.

In order to tackle it, the SCA method is applied. By introducing the auxiliary variables x_n, we have $\exp(a_n) - \frac{f_n}{Cn} \leq \exp(x_n)$ and $\exp(x_n) \leq B\log_2(1 + \frac{\exp(\rho_n)g_n^2}{\sum_{i=1}^{n-1}\exp(\rho_i)g_i^2 + \sigma^2})$. By using the SCA technique, the first-order Taylor expansion is used to approximate the right part. Thus, $\mathbf{P_3}$ can be solved by iteratively solving the following approximate problem, given as

$$\mathbf{P_4}: \max_{f_n,\rho_n,a_n,x_n} \Phi_{SE}\sum_{n\in\mathcal{N}} a_n - \Phi_{EE}\sum_{n\in\mathcal{N}}(\zeta\exp(\rho_n) + p_r + \epsilon f_n^3) \tag{9a}$$

$$s.t. \quad a_n \geq \ln(R_n^{th}), \ \forall n \in \mathcal{N}, \tag{9b}$$

$$\zeta\exp(\rho_n) + p_r + \epsilon f_n^3 \leq P_n^{th}, \ \forall n \in \mathcal{N}, \tag{9c}$$

$$f_n^{min} \leq f_n \leq f_n^{max}, \forall n \in \mathcal{N}, \tag{9d}$$

$$\exp(a_n) - \frac{f_n}{Cn} \leq \exp(\overline{x}_n^k) + \exp(\overline{x}_n^k)(x_n - \overline{x}_n^k), \tag{9e}$$

$$\exp(x_n) \leq B\log_2(1 + \frac{\exp(\rho_n)g_n^2}{\sum_{i=1}^{n-1}\exp(\rho_i)g_i^2 + \sigma^2}), \tag{9f}$$

where $\overline{x}_n^k, n \in \mathcal{N}$ are the given local points at the kth iteration. The above problem is convex and can be readily solved by using the existing convex optimization tool.

Max-Min Fairness $\alpha = \infty$

In this case, the objective of the system is to maximize the minimum computation rate among all the users. The original optimization problem $\mathbf{P_1}$ becomes

$$\mathbf{P_5}: \quad \max_{f_n, p_n} \Phi_{SE} \min_{n \in \mathcal{N}} B \log_2\Big(1 + \frac{p_n g_n^2}{\sum_{i=1}^{n-1} p_i g_i^2 + \sigma^2}\Big) + \frac{f_n}{C_n} - \Phi_{EE} \sum_{n \in \mathcal{N}} \zeta p_n + p_r + \epsilon f_n^3 \tag{10}$$

$$s.t. \quad C1 - C4.$$

It is difficult to directly solve the max-min problem $\mathbf{P_5}$. By introducing a new variable l, auxiliary variables $\rho_n = \log(p_n)$, the auxiliary variable z_n,

$$\exp(z_n) \leq B \log_2(1 + \frac{\exp(\rho_n) g_n^2}{\sum_{i=1}^{n-1} \exp(\rho_i) g_i^2 + \sigma^2}), \tag{11}$$

and apply the SCA method to solve the problem $\mathbf{P_6}$ by iteratively solving the approximate problem, given as

$$\mathbf{P_6}: \max_{f_n, \rho_n, l, z_n} -\Phi_{EE} \sum_{n \in \mathcal{N}} (\zeta \exp(\rho_n) + p_r + \epsilon f_n^3) + \Phi_{SE} * l \tag{12a}$$

$$s.t. \;\; l \geq R_n^{th}, \; \forall n \in \mathcal{N}, \tag{12b}$$

$$\zeta \exp(\rho_n) + p_r + \epsilon f_n^3 \leq P_n^{th}, \; \forall n \in \mathcal{N}, \tag{12c}$$

$$f_n^{min} \leq f_n \leq f_n^{max}, \forall n \in \mathcal{N}, \tag{12d}$$

$$l \leq \exp(\overline{z}_n^k) + \exp(\overline{z}_n^k)(z_n - \overline{z}_n^k) + \frac{f_n}{C_n}, \tag{12e}$$

$$\exp(z_n) \leq B \log_2(1 + \frac{\exp(\rho_n) g_n^2}{\sum_{i=1}^{n-1} \exp(\rho_i) g_i^2 + \sigma^2}), \tag{12f}$$

where $\overline{z}_n^k, n \in \mathcal{N}$ are the given local points at the kth iteration.

Utah State University

Algorithm 1: The SCA iterative algorithm for $\mathbf{P_4}$ and $\mathbf{P_6}$

1) **Input settings:**
   the error tolerance $\xi > 0$, $R_n^{th} > 0$ and $P_n^{th} > 0$,
   the maximum iteration number K.
2) **Initialization:**
   $k = 0$, $f_n(0)$, $\rho_n(0)$,$a_n(0)$ $\overline{x}_n^0$;
3) **Optimization:**
   $\trianglerighteq$ **for k=1:K**
   solve $\mathrm{P_4/P_6}$ by using the interior-point method;
   obtain the solution $\{f_n^{k*}, \rho_n^{k*}, a_n^{k*}, x_n^{k*}\}$ and the system efficiency H_k^*;
   if $\|H_k^* - H_{k-1}^*\| \leq \xi$;
   the maximum system efficiency H^* is obtained;
   break;
   else
   update $\overline{x}_n^{k+1} = x_n^{k*}$ and $k = k + 1$.
   end
   $\trianglerighteq$ **end**
4) **Output:**
   $\{f_n^*, \rho_n^*\}$ and system efficiency H^*

Utah State University

Fairness with $\alpha = 0$

In this case, the tradeoff between the weighted sum computation rate and the power consumption cost is considered. The original problem $\mathbf{P_1}$ can be expressed as

$$\begin{aligned} \mathbf{P_7}: \quad & \max_{f_n, p_n} \Phi_{SE} \sum_{n \in \mathcal{N}} (B \log_2(1 + \frac{p_n g_n^2}{\sum_{i=1}^{n-1} p_i g_i^2 + \sigma^2}) + \frac{f_n}{C_n}) - \Phi_{EE} \sum_{n \in \mathcal{N}} (\zeta p_n + p_r + \epsilon f_n^3) \\ & s.t. \quad C1 - C4. \end{aligned} \tag{13}$$

The problem (13) is NP-hard. In order to solve it, we apply a SCALE method, by introduce the equation:

$$a \log z + b \leq \log_2(1 + z). \tag{14}$$

That is tight at $z = z_0$ when the approximation constants are given as

$$a = \frac{z_0}{1 + z_0}, \tag{15a}$$

$$b = \log_2(1 + z_0) - \frac{z_0}{1 + z_0} \log_2(z_0). \tag{15b}$$

UtahState University

By applying the SCALE method to the problem (13), and the logarithmic change of variables $\rho_n = \log(p_n)$, we can obtain the following problem as

$$\begin{aligned}
\mathbf{P_8} \quad & \max_{f_n,\rho_n} \Phi_{SE} \sum_{n\in\mathcal{N}} (B\overline{R}_n(\rho_n; a_n, b_n) + \frac{f_n}{C_n}) - \Phi_{EE} \sum_{n\in\mathcal{N}} (\zeta \exp(\rho_n) + p_r + \epsilon f_n^3), && \text{(16a)}\\
s.t. \quad & B\overline{R}_n(\rho_n; a_n, b_n) + \frac{f_n}{C_n} \geq R_n^{th}, \forall n \in \mathcal{N}, && \text{(16b)}\\
& \zeta \exp(\rho_n) + p_r + \epsilon f_n^3 \leq P_n^{th}, \forall n \in \mathcal{N}, && \text{(16c)}\\
& f_n^{min} \leq f_n \leq f_n^{max}, \forall n \in \mathcal{N}, && \text{(16d)}\\
& && \text{(16e)}
\end{aligned}$$

where

$$z_n = \frac{\exp(\rho_n) g_n^2}{\sum_{i=1}^{n-1} \exp(\rho_i) g_i^2 + \sigma^2}, \tag{17a}$$

$$a_n = \frac{z_n}{1+z_n}, \qquad b_n = \log_2(1+z_n) - \frac{z_n}{1+z_n} \log_2(z_n), \tag{17b}$$

and

$$\overline{R}_n(\rho_n; a_n, b_n) = a_n[\log_2(g_n^2) + \ln 2\rho_n - \log(\sum_{i=1}^{n-1} \exp(\rho_i) g_i^2 + \sigma^2)] + b_n. \tag{18}$$

The problem (16a) is a standard concave maximization problem.

Algorithm 2: The SCALE iterative algorithm for $\mathbf{P_8}$

1) **Input settings:**

   the error tolerance $\xi > 0$, $R_n^{th} > 0$ and $P_n^{th} > 0$, $a_n^1 = 1, b_n^1 = 0$, the maximum iteration number K.

2) **Initialization:**

   $k = 0$, $f_n(0)$, $\rho_n(0)$, $a_n(0)$ and $b_n(0)$;

3) **Optimization:**

   ⊵ **for k=1:K**

   solve $\mathbf{P_9}$ by using the interior-point method;

   obtain the solution $\{f_n^*, \rho_n^*\}$ and the rate approximation $\overline{R}_n^{k*}$;

   if $\|\overline{R}_n^{k*} - \overline{R}_n^{k-1*}\| \leq \xi$;

   the maximum system efficiency H^* is obtained;

   break;

   else

   update a_n^{k+1}, b_n^{k+1} by (21) and $k = k + 1$.

   end

   ⊵ **end**

4) **Output:**

   $\{f_n^*, \rho_n^*\}$ and system efficiency H^*

NUMERICAL RESULTS

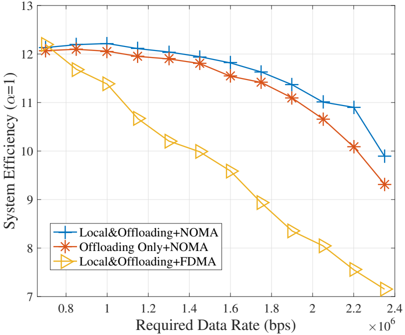

Figure 2: System Efficiency for $\alpha = 1$ ($\Phi_{SE} = 0.3$, $\Phi_{EE} = 0.7$).

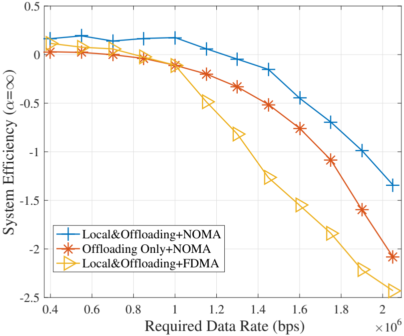

Figure 3: System Efficiency for $\alpha = \infty$ ($\Phi_{SE} = 10^{-6}$, $\Phi_{EE} = 0.5$).

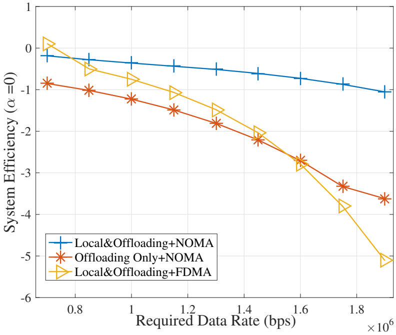

Figure 4: System Efficiency for $\alpha = 0$ ($\Phi_{SE} = 0.3$, $\Phi_{EE} = 0.7$).

UtahState University

Thank You !