# AGORA: A Multi-Provider Edge Computing Resource Management and Pricing Framework

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***Abstract*—Multi-provider multi-user multi-access edge computing provides a recent market-driven networking paradigm facilitating the user data offloading process. In this paper we introduce the AGORA framework, which employs a sophisticated multi-leader multi-follower Stackelberg game that jointly optimizes the data offloading, computing resource allocation, and computing resource pricing, all facilitated through a non-cooperative game-theoretic approach. In order to support the aforementioned modeling and approach, a novel utility function that quantifies the users satisfaction, factoring in the computing service cost, and an innovative profit function for the MEC providers is introduced, emphasizing the market penetration and the computing service provision costs. Numerical results, obtained via modeling and simulation, demonstrate AGORA's remarkable adaptability, accommodating homogeneous and heterogeneous user computing demands, while simultaneously outperforming proportional fairness resource allocation approaches, and significantly enhancing the MEC providers' profitability and the users' satisfaction from the edge computing services.**

***Index Terms*—Multi-access Edge Computing, Network Economics, Game Theory, Resource Management.**

## I. Introduction

Multi-access edge computing (MEC) is an integral part of the vision of 5G/B5G systems and the Internet of Things (IoT), for real-time data processing, low-latency applications, and decentralized, interconnected ecosystems [1]. Extended research efforts have been devoted to the individual problems of optimal data offloading within MEC environments supported by multiple MEC providers and the optimal pricing policies to maximize the MEC providers' profit [2]. However, these efforts, though promising, remain fragmented, and consequently the joint optimization of the data offloading, computing resource allocation, and MEC services pricing yet remains highly unexplored [3]. In this paper, we introduce the AGORA framework[*], which enables all the users and MEC providers to determine their optimal data offloading strategies and their computing resource allocations and pricing, respectively, while optimizing their experienced MEC service and profit, respectively.

### A. Related Work

The problem of resource management and pricing of MEC resources has attracted the interest of the academic and industrial communities. An incentive mechanism for MEC systems is introduced in [4] via utilizing market-based pricing to encourage service provisioning by the MEC providers and incorporating a profit-maximizing multiround auction mechanism for resource trading. A trading model is proposed in [5] that addresses the resource allocation challenges in MEC systems with multiple MEC servers and users, utilizing evolutionary and non-cooperative game models. A multi-market trading framework for MEC systems is presented in [6] that utilizes double auctions within groups of users being served by the same MEC server, a market selection game, and a theory-based learning algorithm to enable MEC providers to participate in multiple auctions and optimize their strategies, resulting in significantly improved social welfare.

The maximization of the users' and/or the MEC providers' social welfare under optimal resource allocation and pricing strategies has been thoroughly explored in the existing literature. A sharing economy-inspired business model and a distributed pricing mechanism for MEC resource allocation is analyzed in [7], aiming at increasing resource efficiency and maximizing the overall social welfare of the users. A deep reinforcement learning and game theory-based approach to address the offloading decision problem in a software-defined networking-driven MEC system is studied in [8]. The authors aim to optimize the selection of MEC servers, the amount of offloaded data, and the pricing of computing services to maximize the overall profit of the MEC providers. An auction pricing-based MEC offloading strategy is proposed in [9] that maximizes the overall profit of the MEC providers by considering the users' devices' battery capacity and the users' task tolerable delay.

The theory of Stackelberg games has lately been adopted to deal with the resource allocation and pricing problem in MEC systems [10]. A nonlinear pricing strategy for the MEC

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[*]AGORA in Ancient Greek refers to a market.

provider is introduced in [11] via formulating a Stackelberg game among one MEC provider and the users, resulting in an optimized profit for the MEC provider and a minimum computing service cost for the users, via determining their optimal amount of offloaded data. A similar Stackelberg game-theoretic approach is discussed in [12] in order to maximize the profit of the MEC providers by incorporating energy conservation and latency reduction into the users' offloading strategies and determining optimal pricing policies. A multi-leader multi-follower Stackelberg game is introduced in [13] to optimize the amount of offloaded data from Unmanned Aerial Vehicles (UAVs) to multiple MEC providers, in order to ultimately achieve an optimal tradeoff between the MEC providers' profit and the UAVs' resource demand.

### B. Contributions and Outline

In this article we strive to treat the problem of joint optimization of the users' data offloading, the MEC providers' computing resource allocation, and the MEC services pricing, particularly when these decisions are expected to be autonomously and independently made by the users and the MEC providers in a distributed manner. Specifically, the AGORA framework is introduced, capturing not only the users' experienced utility from consuming computing resources to process their data, but also the MEC providers' profit. To realize this, while considering a multi-provider multi-user multi-access edge computing system, a novel utility function of the users' experienced satisfaction from consuming edge computing resources by multiple MEC providers is designed, accounting for the corresponding experienced service cost. Moreover, a new profit function for the MEC providers is designed to capture the benefits from serving multiple users, i.e., penetration to the market, and cost to provide the computing services.

Then, a multi-leader multi-follower Stacklberg game is introduced to determine the users' optimal data offloading strategies following the partial data offloading paradigm, the MEC providers' optimal computing resource allocation for each user, as well as the associated market computing prices set by each MEC provider. A non-cooperative game theoretic approach is followed to determine the Stackelberg equilibrium. The fundamental difference between the proposed AGORA framework compared to the existing literature is the consideration of a multi-variable approach reflecting both the users' and the MEC providers' perspectives.

Detailed numerical results are presented, obtained via modeling and simulation, in order to demonstrate the operational characteristics of the AGORA framework and capturing its adaptability in scenarios where the users have homogeneous and/or heterogeneous computing demand characteristics. A comparative evaluation is also performed demonstrating the MEC providers' profit and the users' satisfaction benefits compared to the proportional fairness resource allocation approach.

The rest of the paper is organized as follows. Section II presents the system model, while the AGORA framework is analyzed in Section III. Section IV presents the numerical evaluation and Section V concludes the paper.

## II. System Model

A multi-provider multi-user multi-access edge computing (MEC) system is considered, consisting of a set of MEC providers/servers $\mathcal{M} = \{1, ...., m, ...., M\}$ and a set of users $\mathcal{N} = \{1, ...., n, ...., N\}$, who can perform partial data offloading to multiple MEC servers. Each user is characterized by a computing task $A_n = (B_n, C_n, \phi_n, t_n, e_n)$, where $B_n$ [bits] denotes the user's total amount of data, $C_n$ [CPU-cycles] indicates the CPU-cycles needed to process the computing task, with $C_n = \phi_n B_n$, where $\phi_n$ $[\frac{CPU-cycles}{bits}]$ captures the computing task's computing intensity, and $t_n$ [sec], $e_n$ [J] denote the latency and energy constraints respectively, for user $n$. Each user can perform partial offloading to potentially all the servers, with $\mathbf{b_n} = [b_{n,1}, \dots, b_{n,m}, \dots, b_{n,M}]$ denoting the user's data offloading vector and $\sum_{\forall m \in \mathcal{M}} b_{n,m} \leq B_n$. Also, each user can process locally an amount of data $b_n, min$ on its device. Each MEC server is characterized by an overall computing capacity $F_m$ $[\frac{CPU-cycles}{sec}]$ and a price per computing resource unit $P_m$ $[\frac{\$}{\frac{CPU-cycles}{sec}}]$. Each MEC provider is assumed to have a maximum price limit $P_m^{Max}$, as defined by the market regulations. Each MEC server allocates part of its computing capacity to the users who offload data to this MEC server, where $\mathbf{f_m} = [f_{m,1}, \dots, f_{m,n}, \dots, f_{m,N}]$ $[\frac{CPU-cycles}{sec}]$ denotes the MEC server's $m$ computing capacity allocation vector, with $\sum_{\forall n \in \mathcal{N}} f_{m,n} \leq F_m$.

Each user experiences satisfaction by offloading and processing part of its total amount of data to the MEC servers, which is a concave and strictly increasing function with respect to the amount of offloaded data (first term of Eq. 1), given that the amount of data, which can offload to the MEC servers, is upper bounded. Also, each user experiences a cost imposed by the MEC servers to process its data, and its satisfaction is also impacted by the offloading strategies of the rest of the users within the examined multi-provider multi-user MEC system (second term of Eq. 1). The user's satisfaction is accordingly formulated as follows:

$$
\begin{aligned}
U_n(\mathbf{b_n}, \mathbf{b_{-n}}) =& \alpha_n \frac{\log(1 + \mu_n(\sum_{\forall m} b_{n,m} - b_{n,\min}))}{\sum_{\forall m} \sum_{n' \neq n} b_{n',m} + \gamma_n} \\
& - \beta_n \sum_{\forall m} [(\frac{P_m}{\sum_{n' \neq n} b_{n',m}}) \cdot b_{n,m}]
\end{aligned} \tag{1}
$$

where $\alpha_n = \frac{\sum_{\forall n' \neq n} B_{n'}}{\log(1+\mu_n(B_n - b^t_{n,\min}))}$, $\beta_n = \frac{1}{\max_{\forall m}\{P_m^{Max}\} B_n}$, and $\gamma_n$ are normalization parameters to guarantee that the impact of the user's pure satisfaction and experienced cost are of the same order of magnitude, resulting in a unitless user's utility function (Eq. 1).

Focusing on the MEC providers' utility (for simplicity of notation in our analysis, we consider that a MEC provider is equivalent to a MEC server $m$), a MEC provider experiences a revenue while considering the market penetration of the other MEC providers in terms of serving the users (first term of Eq. 2), and a cost associated with maintaining its computing infrastructure (second term of Eq. 2), and its energy consumption to process the users' offloaded data (third term of Eq. 2). Thus, the MEC server's utility function is formulated as follows.

$$U_m(\mathbf{f_m}, \mathbf{f_{-m}}, P_m, \mathbf{P_{-m}}) = \delta_m \frac{\frac{P_m}{\sum\limits_{\forall n} b_{n,m}} \sum\limits_{\forall n} f_{m,n}^{x_m}}{[\sum\limits_{\forall m}(\frac{P_m}{\sum\limits_{\forall n} b_{n,m}}) \sum\limits_{\forall n} \sum\limits_{\forall m \neq m'} f_{m',n}]^r} - \epsilon_m \sum_{\forall n} f_{m,n}^2 - \zeta_m \sum_{\forall n} f_{m,n} \tag{2}$$

In order to rationalize and balance the impact of three different terms on shaping the MEC server's utility, the following normalization factors $\delta_m = \frac{[\sum\limits_{\forall m} P_m^{Max} \sum\limits_{\forall m \neq m'} F_{m'}]^r}{P_m^{Max} F_m}$, $\epsilon_m = \frac{1}{{F_m}^2}$, $\zeta_m = \frac{1}{F_m}$, $0 < x_m < 1$, and $r > 1$ are introduced, while ensuring that the MEC server's utility is dimensionless.

## III. AGORA Framework

In this section, we present the AGORA framework, which leverages a complex multi-leader multi-follower Stackelberg game to optimize data offloading strategies, computing resource allocation, and market pricing within the MEC system, following a non-cooperative game-theoretic approach to find the Stackelberg equilibrium.

### A. Users' Optimal Data Offloading

Each user aims at maximizing its utility (Eq. 3a), while considering the data offloading feasibility constraints (Eq. 3b - 3c), the allocated computing capacity from a MEC server (Eq.3d), and its latency (Eq.3e) and energy (Eq.3f) constraints. Thus, the corresponding optimization problem of each user's utility function is formulated as follows:

$$\max_{\mathbf{b_n}} U_n(\mathbf{b_n}, \mathbf{b_{-n}}) \tag{3a}$$

$$\text{s.t. } b_{n,min} \leq \sum_{\forall m} b_{n,m} \leq B_n \tag{3b}$$

$$b_{n,m} \geq 0, \forall m \in \mathcal{M} \tag{3c}$$

$$\frac{\phi_n b_{n,m}}{1\text{sec}} \leq f_{m,n}, \forall m \in \mathcal{M} \tag{3d}$$

$$\sum_{\forall m} \frac{b_{n,m}}{R_{n,m}} + \sum_{\forall m} \frac{\phi_n b_{n,m}}{f_{m,n}} + \frac{\phi_n (B_n - \sum\limits_{\forall m} b_{n,m})}{lc_n} \leq t_n \tag{3e}$$

$$\sum_{\forall m} \frac{b_{n,m} P_{n,m}}{R_{n,m}} + \phi_n (B_n - \sum_{\forall m} b_{n,m}) le_n \leq e_n \tag{3f}$$

where $R_{n,m} = W \log(1 + \frac{P_{n,m} g_{n,m}}{\sum\limits_{\forall n' \in \mathcal{N}_m} P_{n',m} g_{n',m} + \sigma_0^2})$ is the user's $n$ data rate offloading its data to the MEC server $m$, with $\sigma_0^2$ denoting the background noise, $P_{n,m}$ [W] is the user's transmission power, and $g_{n,m}$ is its channel gain. The three terms in the latency constraint (3e) capture the user's experienced delay, consisting of the data transmission delay, and the data processing delay at the MEC servers, and locally on the user's device, respectively, where $lc_n$ [$\frac{CPU-Cycles}{sec}$] denotes the local computing capability of user $n$. The two terms in (3f) represent the user's energy consumption due to the data offloading and the local data processing, respectively, with $le_n$ [$\frac{Joules}{Sec}$] denoting the user's local energy consumption rate.

The optimization problem (3a)–(3f) can be formulated as a non-cooperative game $G = [\mathcal{N}, \{B_n\}_{\forall n \in \mathcal{N}}, \{U_n\}_{\forall n \in \mathcal{N}}]$, where $\mathcal{N}$ is the set of players, i.e., users, $B_n$ is their strategy set in terms of the total amount of data, and $U_n$ denotes their payoff function (Eq. 2).

*Theorem 1:* The non-cooperative game $G$ is a concave $n$-person game and admits at least one Pure Nash Equilibrium (PNE).

*Proof:* The strategy set $\{B_n\}_{\forall n \in N}$ is by definition a convex and compact set. Also, the utility function $\{U_n\}_{\forall n \in N}$ is continuous, and we need to show that it is concave with respect to $\mathbf{b_n}, \forall n \in \mathcal{N}$. We set: $f(\mathbf{b_n}, \mathbf{b_{-n}}) = \alpha_n \log(1 + \mu_n(\sum\limits_{\forall m} b_{n,m} - b_{n,\min}))$ and $g(\mathbf{b_n}, \mathbf{b_{-n}}) = \beta_n \sum\limits_{\forall m}[(\frac{P_m}{\sum\limits_{n' \neq n} b_{n',m}}) b_{n,m}]$, and $A = \sum\limits_{\forall m} \sum\limits_{n' \neq n} b_{n',m} + \gamma_n$. We have: $f' = \frac{\alpha_n \mu_n}{1 + \mu_n(\sum\limits_{\forall m} b_{n,m} - b_{n,min})} > 0$, $f'' = -\frac{\alpha_n \mu_n^2}{[1 + \mu_n(\sum\limits_{\forall m} b_{n,m} - b_{n,min})]^2} < 0$, $g' = \beta_n(\frac{P_m}{\sum\limits_{\forall n' \neq n} b_{n',m}}) > 0$, and $g'' = 0$. Thus, we have: $\frac{\partial^2 U_n}{\partial b_{n,m}^2} = \frac{f''}{A} < 0$, $\frac{\partial^2 U_n}{\partial b_{n',m} \partial b_{n,m}} = \frac{\partial^2 U_n}{\partial b_{n,m} \partial b_{n',m}} = -\frac{f'}{A^2} + \frac{\beta_n P_m}{b_{n',m}^2}$, and $\frac{\partial^2 U_n}{\partial b_{n,m'} \partial b_{n,m}} = \frac{\partial^2 U_n}{\partial b_{n,m} \partial b_{n,m'}} = \frac{\alpha_n \mu_n^2}{A[1 + \mu_n(\sum\limits_{\forall m} b_{n,m} - b_{n,min})]^2}$. From the above analysis, we conclude that the Hessian matrix of $U_n$ is negative definite, and the utility function $U_n$ is concave. Therefore, we conclude that the non-cooperative game $G$ is a concave $n$-person game. Given that the non-cooperative game $G$ is a concave $n$-person game, then based on Theorem 1 in [14], there exists at least one PNE. ■

*Theorem 2:* The PNE $\mathbf{b}^* = [\mathbf{b_1^*}, \ldots, \mathbf{b_n^*}, \ldots, \mathbf{b_N^*}]$ is unique.

*Proof:* Based on [14], [15], we need to show that $\sigma(\mathbf{b}, \boldsymbol{\lambda}) = \sum\limits_{\forall n} \lambda_n U_n(\mathbf{b})$ is diagonally strictly concave (DSC) for some $\boldsymbol{\lambda} > \mathbf{0}$. Thus, we need to prove: (i) $U_n$ is strictly concave in $\mathbf{b}_n$, (ii) $U_n$ is convex in $\mathbf{b_{-n}}$, and (iii) $\sigma(\mathbf{b}, \boldsymbol{\lambda})$ is concave in $\mathbf{b}$. The first condition holds true based on Theorem 1. The second condition also holds true, given that $\frac{\partial^2 U_n}{b_{n',m}^2} = \frac{2f}{A^3} - \frac{2\beta_n P_m b_{n,m}}{b_{n',m}^3} > 0$, given that $\beta_n$ takes very small values. Finally, by following a similar analysis as in the proof of Theorem 1 and by appropriately choosing $\boldsymbol{\lambda} > \mathbf{0}$, we derive that $\sigma(\mathbf{b}, \boldsymbol{\lambda})$ is concave in $\mathbf{b}$. Thus, we conclude that the PNE $\mathbf{b}^* = [\mathbf{b_1^*}, \ldots, \mathbf{b_n^*}, \ldots, \mathbf{b_N^*}]$ is unique. ■

### B. MEC Providers' Optimal Computing Resource Allocation and Pricing

Focusing on the MEC server's resource allocation and pricing, each MEC server aims at maximizing its utility function (Eq. 4a), considering its computing capacity feasibility constraints (Eq. 4b-4c), and the pricing bounds captured by the maximum computing capacity pricing $P_m^{Max}$ (Eq. 4d), and the computing demand from the users (Eq. 4e). Thus, the corresponding optimization problem of each MEC server's utility function is defined as follows.

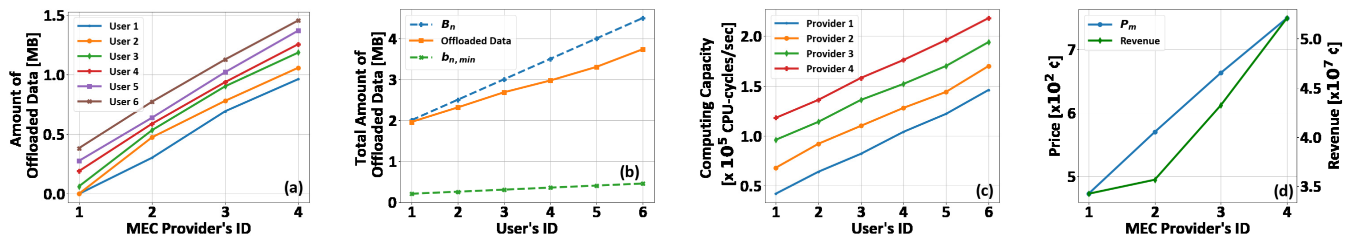


Fig. 1: Pure Operation and Performance

$$\max_{\{\mathbf{f_m}, P_m\}} U_m(\mathbf{f_m}, \mathbf{f_{-m}}, P_m, \mathbf{P_{-m}}) \quad (4a)$$

$$\text{s.t.} \sum_{\forall n} f_{m,n} \leq F_m \quad (4b)$$

$$f_{m,n} \geq 0, \forall n \in \mathcal{N} \quad (4c)$$

$$\frac{P_m}{\sum_{\forall n} b_{n,m}} \leq P_m^{Max} \quad (4d)$$

$$f_{m,n} \leq \frac{\phi_n b_{n,m}}{1\text{sec}}, \forall n \in \mathcal{N} \quad (4e)$$

The above optimization problem can be captured as a multi-nature multi-variable non-cooperative game, given the involvement of both the computing capacity of the MEC servers and its corresponding price. The non-cooperative game among the MEC servers is formulated as $\mathcal{G} = [\mathcal{M}, \{F_m, P_m\}_{\forall m \in \mathcal{M}}, \{U_m\}_{\forall m \in \mathcal{M}}]$, where $\mathcal{M}$ is the set of players, i.e., MEC servers, $\{F_m, P_m\}$ denotes the multi-nature multi-variable strategy set, and $U_m$ is the MEC server's utility function.

*Theorem 3:* The non-cooperative game $\mathcal{G}$ is a concave $n$-person game and admits at least one PNE.

*Proof:* The multi-nature multi-variable strategy set $\{F_m, P_m\}, \forall m \in \mathcal{M}$ is a convex and compact set, and the utility function $U_m$ is continuous in $\{F_m, P_m\}$. We set: $B = \sum_{\forall n} f_{m,n}^{x_m}$, $C = \sum_{\forall n} \sum_{\forall m \neq m'} f_{m',n}$, $D = \sum_{\forall m} (\frac{P_m}{\sum_{\forall n} b_{n,m}}) \sum_{\forall n} \sum_{\forall m \neq m'} f_{m',n}$, and $E = \sum_{\forall n} b_{n,m}$, and we have $\frac{\partial^2 U_m}{\partial f_{m,n}^2} = \frac{\delta_m P_m x_m (x_m - 1) f_{m,n}^{x_m - 2}}{E D^r} - 2\epsilon_m < 0$ and $\frac{\partial^2 U_m}{\partial P_m^2} = \frac{\delta_m B r C}{E^2 D^r} [\frac{P_m C D^{-2}(1-r)}{E} - 2D^{-1}] < 0$. Thus, the utility function $U_m$ is concave in $\{\mathbf{f_m}, P_m\}$, and $\mathcal{G}$ is a concave $n$-person game and admits at least one PNE [14]. ■

*Theorem 4:* The PNE $\{\mathbf{f}^*, \mathbf{P}^*\} = [\mathbf{f_1^*}, \dots, \mathbf{f_m^*}, \dots, \mathbf{f_M^*}, P_1^*, \dots, P_m^*, \dots, P_M^*]$ is unique.

*Proof:* Similarly to the proof of Theorem 2, we need to show that $h(\boldsymbol{\kappa}, \mathbf{f}, \mathbf{P}) = \sum_{\forall m} \kappa_m U_m(\mathbf{f}, \mathbf{P})$ is DSC for some $\boldsymbol{\kappa} > \mathbf{0}$. $U_m$ is strictly concave in $\{F_m, P_m\}$ based on Theorem 3. We set: $F = \sum_{\forall m} (\frac{P_m}{\sum_{\forall n} b_{n,m}})$ and we have: $\frac{\partial^2 U_m}{\partial f_{m',n}^2} = \frac{P_m \delta_m B r F^2 (r+1)}{E D^{r+2}} > 0$, $\frac{\partial^2 U_m}{\partial P_m'^2} = \frac{P_m \delta_m B r C^2 (r+1) D^{-r-2}}{E^3} > 0$, $\frac{\partial^2 U_m}{\partial f_{m',n} \partial f_{m,n}} = \frac{\partial^2 U_m}{\partial f_{m,n} \partial f_{m',n}} = \frac{-r P_m \delta_m x_m f_{m,n}^{x_m - 1} F}{E D^{r+1}}$, and $\frac{\partial U_m}{\partial P'_m \partial P_m} = \frac{\partial U_m}{\partial P_m \partial P'_m} = \frac{\delta_m B C r}{E^2 D^{r+2}} [\frac{C P_m}{E} - D + \frac{r C P_m}{E}]$, thus, $U_m$ is convex in $\{\mathbf{f_{-m}}, \mathbf{P_{-m}}\}$. After applying a similar analysis as in the proof of Theorem 2 and selecting an appropriate positive value for $\boldsymbol{\kappa}$, we derive that $h(\boldsymbol{\kappa}, \mathbf{f}, \mathbf{P})$ is concave in $\{\mathbf{f}, \mathbf{P}\}$, and the PNE $\{\mathbf{f}^*, \mathbf{P}^*\}$ is unique. ■

Based on Theorems 1 – 4, we can design a best response dynamics algorithm to derive the Stackelberg equilibrium of the overall AGORA framework [16].

## IV. Numerical Evaluation

In this section, the performance evaluation of the proposed AGORA framework is demonstrated via modeling and simulation. The assessment starts with an evaluation of the pure performance of the AGORA framework (Section IV-A), followed by a scalability analysis, taking into consideration both homogeneous and heterogeneous characteristics of users' computing demands, in order to demonstrate the framework's efficiency and robustness in large-scale scenarios (Section IV-B). Subsequently, a comparative evaluation is performed to demonstrate the advantages of the AGORA framework over conventional proportional fairness resource allocation approaches (Section IV-C). It is noted that, unless otherwise explicitly stated, we consider the following set of simulation environment parameters throughout our evaluation: $N = 6$, $M = 4$, $B_n = [2000, 2500, 3000, 3500, 4000, 4500][Kbytes]$, $b_{n,min} = 10\% * B_n$, $\phi_n = 100[CPU - cycles/bits]$, $t_n = 0.2$ $[sec]$, $e_n = 0.01[J]$ $\forall n \in \mathcal{N}$, $F_m = [5, 5.5, 6, 6.5] * 10^6 [CPU - cycles/sec]$, $P_m^{Max} = [1.0, 1.7, 2.4, 3.1]$, $x_m = [0.7, 0.75, 0.8, 0.85, 0.9, 0.95]$, $\mu_n = [0.7, 0.75, 0.8, 0.85, 0.9, 0.95]$, $\gamma_n = 14$, $\forall n \in \mathcal{N}$, $\sigma_0^2 = 10^{-22}$, $lc_n = 0.5 * 10^9 [CPU - cycles/sec]$, $le_n = 10^{-9}[Joules/sec]$, $W = 5[MHz]$, $r = 1.2$, $P_{n,m} = [0.04, 0.0324, 0.03, 0.025][W]$ and $g_{n,m} = [0.0025, 0.003, 0.0035, 0.004] * 10^{-5}$, $\forall n \in \mathcal{N}$.

### *A. Pure Operation and Performance*

In this section, we examine the operational performance of the AGORA framework, aiming to demonstrate how various system attributes impact its function and overall effectiveness. It is noted that, as presented above, the higher the user and the MEC provider ID, the higher the total amount of data and the computing capacity, respectively. Fig. 1a illustrates the amounts of user-offloaded data to the MEC providers, revealing that as the MEC provider IDs increase, so does the data volume due to enhanced computing capabilities. Similarly, users with higher IDs are characterized by a larger total amount of data and consequently, they offload more data to each MEC provider compared to lower ID users. Fig. 1b shows the portion of total available data $B_n$ offloaded by each user independently of the provider, with users engaged in more intensive computing tasks forwarding a larger amount of data.

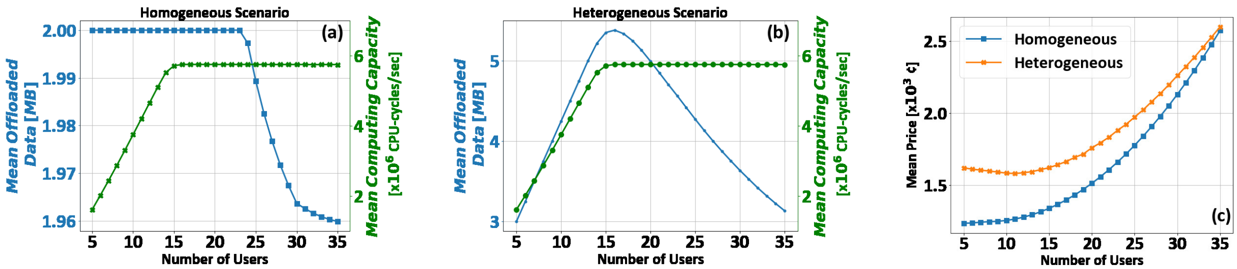


Fig. 2: Scalability Analysis.

This rate, however, decreases with higher user IDs, as the users with more data must offload a smaller portion to meet their latency and energy constraints, as they are constrained by their communication characteristics.

Fig. 1c illustrates the computing supply from the MEC providers to the users, with higher ID providers possessing greater computing capabilities to meet user demands. The users follow a corresponding trend, offloading more data to providers with higher computing capabilities. Fig. 1d shows the price of the computing resources, i.e., $P_m$ factor, announced by each provider and their resulting revenue. Providers with higher IDs, attracting a greater users' demand, announce a higher price, leading to increased revenue.

### B. Scalability Analysis

In this section, we perform a scalability analysis to show the efficiency and robustness of the proposed framework. Specifically, we increase the number of users, considering two scenarios: (i) a Homogeneous Scenario, where all users have computing tasks of the same size (i.e., 2 Mbits), and (ii) a Heterogeneous Scenario, where each new introduced user has a larger computing task size, increased by 0.5 Mbits, compared to the baseline scenario presented in Section IV.

Fig. 2a-2b present the mean user-offloaded data and the mean computing supply of the MEC providers in the two scalability scenarios. In both scenarios, as the number of users in the market grows, the provider supply increases to meet the rising demand. This trend continues until the providers reach their maximum supply capacity, after which they offer their entire computing capability, regardless of the number of users. However, the two scenarios differ in terms of user-offloaded data size. In the homogeneous scenario, all users offload the same amount of data until the providers reach their capacity because all users are identical. In contrast, in the heterogeneous scenario, the mean offloaded data increases as the users possess a larger total amount of data. After the MEC providers reach their computing capacity, the mean offloaded data decreases in both scenarios since more users must share the same computing supply, which cannot be further increased. In the homogeneous scenario, the decrease in data occurs with a slight delay due to the AGORA framework's design, which ensures that the MEC providers offer slightly more computing supply than the user demand, allowing continued data offloading. This behavior is not observed in the heterogeneous scenario as new users have significantly more data.

Fig. 2c presents the price $P_m$ of the computing resources announced by each MEC provider as the number of users increases in both scalability scenarios. In both cases, the presence of more users drives an increase in the MEC providers' price, reflecting the increased demand. It is noted that in the heterogeneous scenario, the price is even higher than the homogeneous one due to the introduction of new users with more complex computing tasks, resulting in greater demand.

### C. Comparative Evaluation

In this section, we perform a comparative evaluation of the AGORA framework against alternative approaches to highlight its advantages. We explore three distinct comparative scenarios, motivated by the key attributes of the AGORA framework: (i) Proportional Offloading: the users offload all their available data to providers in proportion to their computing capability, with the MEC providers optimizing their utility to determine the price and computing supply; (ii) Proportional Supply: the users determine their offloaded data based on the AGORA framework, while the MEC providers supply computing resource to the users proportionally to their total data, and set their price by maximizing their utility; (iii) Fixed Price: All the MEC providers have the same constant price $P_m$, chosen as the mean value of the optimal price as derived by the AGORA framework for fairness, while all other system parameters are determined as in the AGORA framework.

Fig. 3 - 4 present a comparison of various system parameters between the AGORA framework and the three alternative scenarios. Specifically, in Fig. 3a, we observe the total size of user-offloaded data to all the MEC providers. In the Proportional Offloading and Proportional Supply scenarios, the users offload all their data to the providers. However, the Fixed Price scenario results in providers offering slightly lower computing supply and the users offloading a smaller portion of their data compared to the AGORA framework. Fig. 3b illustrates the total computing supply of each provider to all the users. In the Proportional Supply scenario, the providers allocate their entire available computing capacity among the users. The AGORA framework achieves the highest computing supply among the other two scenarios. The Fixed Price scenario leads to slightly lower computing supply, while in the Proportional Offloading scenario, the lower computing supply by the providers corresponds to a reduction in the computing resource price. Fig. 3c presents the computing resource price $P_m$ of each provider. In the Fixed Price scenario, the price

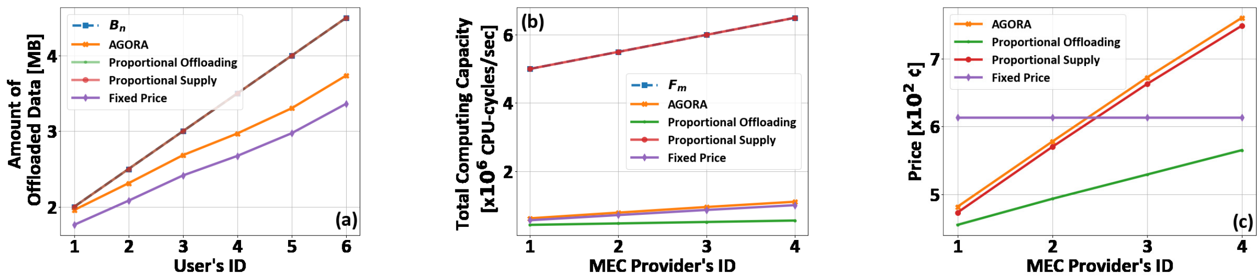


Fig. 3: Comparative Evaluation.

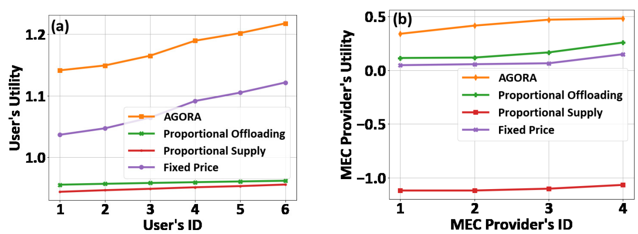


Fig. 4: Users' and MEC Providers' Utility.

remains constant for all the providers. The AGORA framework achieves the most favorable pricing for the MEC providers. In the Proportional Supply scenario, the providers' computing supply is not concurrently optimized with their pricing, leading to a slight reduction in the price, while in the Proportional Offloading case, the lower providers' computing supply results in corresponding reductions in the price.

Finally, Figs. 4a and 4b depict the utilities of each user and MEC provider. The AGORA framework benefits both the users and the MEC providers in terms of utility by concurrently adjusting the market parameters, including offloaded data, computing supply, and computing resource price. In the Proportional Supply scenario, the allocation of all the computing capacity by the MEC providers, exceeding the user demand, burdens both the users and the providers. Comparing the remaining scenarios, the Proportional Offloading scenario allows the users to offload their total amount of data, benefiting the providers, but the users are compelled to send data that could be processed locally, making it challenging to meet their latency and energy consumption constraints.

## V. Conclusion

In this paper, we introduce the AGORA framework applicable in multi-provider multi-user multi-access edge computing, featuring novel users' utility and providers' profit functions, and a complex multi-nature multi-variable multi-leader multi-follower Stackelberg game. The latter approach involves multiple variables to determine the most efficient data offloading strategies by the users to multiple MEC servers, the allocation of computing resources by the MEC providers to each user, and the associated market computing prices set by each MEC provider. A non-cooperative game theoretic approach is followed to determine the Stackelberg equilibrium. The corresponding numerical results demonstrate the benefits obtained by the joint optimization of the data offloading, computing resource allocation, and MEC services pricing, offered by the AGORA framework. Our current and future work involves the adoption and implementation of advanced machine learning algorithms to improve real-time decision-making within the AGORA framework and compare their performance against the proposed game-theoretic approach.

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