

Multi-Agent Reinforcement Learning for Distributed Joint Communication and Computing Resource Allocation over Cell-Free Massive MIMO-enabled Mobile Edge Computing Network

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Abstract—To support the newly introduced multimedia services with ultra-low latency and extensive computation requirements, resource-constrained end user devices should utilize the ubiquitous computing resources available at network edge for augmenting on-board (local) processing with edge computing. In this regard, the capability of cell-free massive MIMO to provide reliable access links by guaranteeing uniform quality of service without cell edge can be exploited for seamless parallel processing. Taking this into account, we consider a cell-free massive MIMO-enabled mobile edge network to meet the stringent requirements of the advanced services. For the considered mobile edge network, we formulate a joint communication and computing resource allocation (JCCRA) problem with the objective of minimizing energy consumption of the users while meeting the tight delay constraints. We then propose a fully distributed cooperative solution approach based on multi-agent deep deterministic policy gradient (MADDPG) algorithm. The simulation results demonstrate that the performance of the proposed distributed approach has converged to that of a centralized deep deterministic policy gradient (DDPG)-based target benchmark, while alleviating the large overhead associated with the latter. Furthermore, it has been shown that our approach significantly outperforms heuristic baselines in terms of energy efficiency, roughly up to 5 times less total energy consumption.

Index Terms—Cell-free massive MIMO, joint communication and computing resource allocation (JCCRA), multi-agent reinforcement learning (MARL), deep deterministic policy gradient (DDPG), edge intelligence, mobile edge computing (MEC).

I. INTRODUCTION

THE past few years have seen a rapid increase in the computationally intensive applications such as face recognition, autonomous driving, traffic control, and so on [1-2]. One key aspect of the services is their tight delay requirement which poses a serious challenge to user equipment (UE) with limited battery power, computational and storage capabilities. To handle these bottlenecks at the UEs, computation offloading to powerful cloud computing platforms had been implemented for various services [3-5]. Recently, a paradigm that has brought computing resources to the edge of the network, dubbed as mobile edge computing (MEC), has been introduced to further reduce the experienced latency. As we move towards the next decade, however, the current cellular MEC systems cannot keep up with the diverse and yet, even more stringent requirements of the envisaged next generation advanced services, and the evolution of the existing ones. For instance, expected use cases of the sixth generation (6G)

communication network, such as multi-sensory extended reality (augmented, virtual, and mixed reality), and holographic displays, require extremely high data rate, improved coverage and spectral efficiency, deterministic ultra-low latency, and extensive computational capability [6-9].

To attain the requirements of the envisioned applications, however, a functionality of reliable *virtual bus* might be required for parallel and cooperative processing, i.e., to connect the users with ubiquitous computing resources at the edge, such as nearby mobile users (with idle or more powerful processors), and edge/cloud servers (with full-blown computing resources). In this regard, we consider a cell-free massive MIMO system, one of the potential network infrastructures for beyond-5G and 6G networks, for enabling a seamless computation offloading in a mobile edge network. Cell-free network can provide sufficiently fast and reliable access throughout the coverage of the network, virtually eliminating cell-edge users. This is accomplished by serving a relatively small number of users simultaneously from several geographically distributed access points (APs) that are connected to a central processing unit (CPU) [10-12]. In the mobile edge network under consideration, the CPU is equipped with an edge server of finite capacity to render computing services for resource-constrained users with time-critical and computationally intensive tasks. As opposed to the unreliable wireless links in cellular MEC systems, cell-free access links in our framework can play the key functionality of realizing virtual buses for parallel computing, i.e. allowing for instant access to the edge server in the CPU, irrespective of users' location, thus energy-efficient and consistently low latency computational task offloading can be provided.

In this paper, we formulate a joint communication and computing resource allocation (JCCRA) problem for the cell-free massive MIMO-enabled mobile edge network. Specifically, with the objective of minimizing energy consumption of all users subject to the ultra-low delay requirements, we intend to design joint allocation of local processor clock speed and uplink transmission power for each user. While solving the problem centrally at the CPU can allow for efficient joint resource allocation, global knowledge of the entire network state is required for decision making. For instance, information originating from users' side such as computing demands, maximum tolerable task execution deadlines, and channel conditions should be collected, processed and then

the allocation decisions need to be communicated back to the users within the tight delay tolerance, incurring prohibitively significant signaling and communication overheads. On the other hand, distributed approaches based on traditional optimization methods may lead to suboptimal performance. In general, applying conventional optimization methods or other heuristic algorithms to solve the JCCRA problem in a dynamic mobile edge network necessitates frequent re-evaluation of the optimal allocation strategy, following the non-deterministic task arrivals and stochastic wireless channel conditions. Furthermore, the algorithms must converge within the ultra-low delay tolerance. It is also important to note that the joint resource allocation decisions are inter-coupled among the users, which poses additional challenges. Consequently, the application of these methods to support time-critical and computation-intensive services is critically limited in practice. The JCCRA problem, therefore, calls for an adaptive and robust solution approaches with reasonable complexity and signaling overheads.

Recently, integrating the capabilities of artificial intelligence (AI) in the mobile edge network, referred to as edge intelligence, is considered as one of the key enablers to realize the highly delay-intolerant cloud services for advanced multimedia applications, e.g., extended reality (XR) [13]. More specifically, machine learning and reinforcement learning algorithms can be applied at different entities in the mobile edge network for efficient resource allocation strategies. Motivated by this trend, we propose a fully distributed solution approach based on cooperative multi-agent reinforcement learning (MARL) for the formulated JCCRA problem, wherein each user is implemented as a learning agent that makes joint resource allocation relying on local observations only. The agents are trained with the state-of-the-art multi-agent deep deterministic policy gradient (MADDPG) algorithm under the framework of centralized training and decentralized execution. Through continuous interactions with the mobile edge network, each agent tries to capture dynamics of the environment and makes use of the learned knowledge for an adaptive and robust joint resource allocation during the online execution phase. Our simulation results show that the proposed distributed JCCRA approach has achieved comparable performance with a centralized deep deterministic policy gradient (DDPG)-based target JCCRA scheme implemented at the CPU, without the need for central processing and resorting to large overhead. Moreover, a significant performance improvement in terms of providing energy-efficient and consistently low latency task offloading has been demonstrated as compared to conventional benchmarks. To the best of our knowledge, this is the very first attempt to solve JCCRA problem in a fully distributed fashion for mobile edge computing in a cell-free massive MIMO network. The fully distributed and intelligent JCCRA scheme coupled with a reliable performance of its cell-free architecture in our framework can be a promising means of handling the stringent requirements involved with the envisaged multimedia applications.

The rest of the paper is organized as follows: In Section II, we review related works on JCCRA allocation in different MEC system models. In Section III, we discuss the system

Table I: Summary of important notations

Notation	Description
$\mathcal{M} = \{1, 2, \dots, M\}$	Set of access point (AP) indices
$\mathcal{K} = \{1, 2, \dots, K\}$	Set of user indices
\mathcal{C}_k	Cluster of APs to serve the k -th user
N_k	The number of APs in a cluster for user k
$AP_n^{(k)}$	The n -th AP in \mathcal{C}_k to serve the k -th user, $n = 1, 2, \dots, N_k$
Δt	Duration of a time step
t_k^d	Application deadline for user k
α_k	Proportion of local processor clock speed allocation for user k
η_k	Uplink transmit power control coefficient of user k
p_k^{\max} / p_k	Maximum / allocated uplink transmit power by user k
W	System bandwidth
R_k	Uplink rate of user k
N_{cpb}	The number of CPU cycles required to process a one-bit task
$\mathcal{T}_k / \mathcal{T}_k^{local} / \mathcal{T}_k^{offload}$	Incoming / locally computed / offloaded task size (in bits) by user k
f_k^{\max} / f_k^{local}	Maximum / allocated local processor clock speed (in Hz) by user k
f^{CPU}	Computing clock speed of the edge server in the CPU (in Hz)
f_k^{CPU}	Allocated computational resource at the CPU for user k
t_k^{tr} / t_k^{comp}	Transmission / computing delay experienced by user k
$t_k^{local} / t_k^{offload} / t_k$	Local execution / offloading / total delay experienced by user k
$E_k^{local} / E_k^{offload} / E_k$	Local / offloading / total energy consumption incurred by user k

model for the considered mobile edge network and then, present problem formulation for JCCRA. Section IV discusses the proposed distributed cooperative multi-agent reinforcement learning-based solution approach for the JCCRA problem. Simulation results are presented in Section V, followed by some concluding remarks in Section VI. For convenience, we summarized the key notations to be used throughout the paper in Table I.

II. RELATED WORK

Recently, several centralized schemes of computation offloading and resource allocation have been proposed for different MEC system models to minimize latency [14-15], energy consumption [16-18], or to balance delay-energy tradeoff [19-20]. Particularly, in [14] and [16], a joint computation offloading and resource allocation problem to minimize latency is studied in vehicular networks, and energy harvesting devices, respectively. Minimization of energy consumption with partial

offloading in a single-user MEC system is investigated in [16], which was later extended to a multi-user MEC system by jointly optimizing computation and communication resources [17]. Therein, to adjust the processor frequency, dynamic voltage scaling (DVS) technique was adopted. Similarly, energy-delay tradeoff is investigated in [19] for a binary offloading MEC system, in which the users decide to offload or not. Meanwhile, power-delay tradeoff for partial offloading MEC system based on Lyapunov optimization is studied in [20]. We note that the above centralized schemes are based on conventional optimization methods that need to gather information originating at the mobile devices, such as application requirements, task size, energy level of battery, offloading requests, and channel conditions of the users [21]. Therefore, their application to support computation-hungry time-sensitive services might be hindered due to communication and signaling overheads associated with collecting users' information and sharing the resource allocation decisions back to the users within the tight delay constraint. Moreover, the centralized algorithms are not scalable in the sense that their computational complexity increases with system size. It is even more challenging from a cell-free massive MIMO point of view as we have to deal with a large number of access points (APs) in a joint manner, in contrast to the above cell-centric MEC models, where a user is connected to only a single AP in each cell.

To relieve the signaling overhead and address scalability issues of the centralized resource allocation schemes, plethora of distributed approaches have been proposed. A design of distributed offloading decision is formulated as a multi-user offloading game among the users for mobile cloud computing [22], wireless-powered MEC networks [23], and MEC-empowered small-cell networks [24]. In [25], offloading decision and resource allocation problem is solved sequentially through decomposition technique within proximate clouds in a distributed fashion. However, the focus of the majority distributed JCCRA approaches is confined to the design of offloading decisions. In addition to this, due to the lack of global knowledge of the network environment, the algorithms are likely to converge to suboptimal solutions. It is worth mentioning that all these schemes are based on conventional optimization methods that are limited to quasi-static systems with deterministic task arrival and invariant channel conditions, failing to capture the randomness in practical systems. Consequently, in response to the dynamics in the environment, the JCCRA problem should be solved frequently, and the algorithms are expected to converge swiftly within the task execution deadline. Such approaches are, therefore, not suited for handling time-sensitive applications.

JCCRA in a dynamic mobile edge network with time-varying channel conditions and stochastic task arrivals require robust solutions that can not only adapt to the diversities in the network conditions and application-specific requirements (e.g., delay constraint), but also perform well with constrained radio and computational resources. In this regard, owing to their adaptability in dynamic settings, reinforcement learning-based frameworks have recently been proposed to solve joint resource allocation problems in various MEC

systems. For instance, a Q-learning based joint design of offloading decisions and resource allocation schemes have been proposed for a single-cell MEC to minimize energy consumption [26], and weighted sum cost of energy and task delay [27]. Furthermore, a deep Q-network (DQN) algorithm has been proposed to solve binary offloading decisions in different MEC system models [29-31]. In all of these works, however, the decisions are made by central entities which need to gather system-wide information; thus, the schemes are prone to the limitations of centralized resource allocations discussed above. Moreover, training a centralized super-agent can potentially be ineffective as the convergence of the training is not guaranteed. Furthermore, it is not a scalable approach since the performance degrades due to the linear input and output dimensions increase with the number of users in the system. [32] investigates a distributed JCCRA problem in a single-cell MEC system in which each user tries to minimize the individual cost, defined as a weighted sum of power and delay, in a non-cooperative fashion, possibly resulting in suboptimal performance. Moreover, the adopted computational model is not applicable to handle computation-intensive tasks, requiring extreme reliability and ultra-low hard deadline.

Recently, there are few works on the cell-free massive MIMO-based MEC systems. In a MEC system with both CPU and APs equipped with computing servers, several performance analyses are presented in [33], while considering coverage radius of the APs and probabilities of offloading to the servers. From a massive access perspective, the issues of active user detection and channel estimations are discussed for a cell-free massive MIMO-based computing framework in [34]. In contrast to our work, both [33] and [34] do not deal with the JCCRA problem.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. User-centric Cell-free Massive MIMO: Overview

A cell-free massive MIMO system is considered as a potential beyond-5G and 6G network infrastructure as it provides a uniform user experience by eliminating the cell edge. It exploits joint signal processing from a large number of distributed access points (APs), which simultaneously serve a much smaller number of users using the same radio resources. To attain the tight requirements of the envisaged advanced services, the capability of cell-free access links to provide reliable performance without cell edge is essential to play the key functionality of virtual bus while offloading an intensive task for parallel computation at the edge server.

We consider a user-centric mobile edge network with M single-antenna access points (APs) and K single-antenna users, where $M \gg K$, entailing to the widely known model for cell-free massive MIMO system [10]. The APs are all connected to a central processing unit (CPU) via error-free backhaul links. Let $\mathcal{M} = \{1, 2, \dots, M\}$ and $\mathcal{K} = \{1, 2, \dots, K\}$ denote sets of AP and user indices, respectively. We assume that all APs and UEs are distributed uniformly throughout the network. Fig. 1 illustrates a system model for cell-free massive MIMO-enabled mobile edge network. Therein, the CPU is equipped with a computing server of finite computational

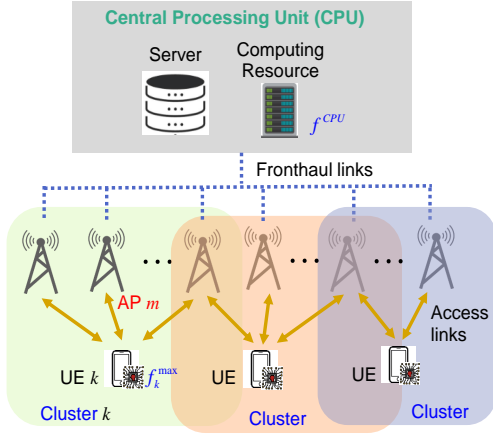


Fig. 1. User-centric cell-free massive MIMO-enabled mobile edge network: *Illustrative system model*

capability to provide computing resources for users with computationally intensive and latency stringent applications. Each user is also equipped with limited local processing capability.

Let the channel between m -th AP and k -th user is given as $g_{mk} = \beta_{mk}^{1/2} h_{mk}$ where β_{mk} is a large-scale channel gain coefficient and $h_{mk} \sim (0, 1)$ represents small-scale channel fading. Let τ_c denote a channel coherence period in which h_{mk} remains the same, while β_{mk} remains constant for a time interval which lapses multiple channel coherence times. The coherence period τ_c is divided into pilot transmission time of τ_p samples and uplink data transmission time of $(\tau_c - \tau_p)$ samples.

All users simultaneously transmit pilot sequences to the APs for uplink channel estimation. Let $\psi_k \in \mathbb{C}^{\tau_p \times 1}$ denote a pilot sequence of user k where $\|\psi_k\|^2 = 1$. We assume that pilot contamination can be ignored by picking pairwise orthogonal sequences $\psi_1, \psi_2, \dots, \psi_K$, i.e., $\tau_p = K$. Then, the received pilot vector at the m -th AP, $\mathbf{y}_m^p \in \mathbb{C}^{\tau_p \times 1}$, can be represented as follows:

$$\mathbf{y}_m^p = \sqrt{\tau_p} \sum_{k=1}^K \sqrt{p_k^p} g_{mk} \psi_k + \omega_m^p, \quad (1)$$

where p_k^p denotes the pilot transmit power, and ω_m^p denotes a τ_p -dimensional additive noise vector with independent and identically distributed entries of $\omega_m^p \sim \mathcal{CN}(0, \sigma_m^2)$. Based on the received vector \mathbf{y}_m^p , the least-square (LS) channel estimate \hat{g}_{mk} can be expressed as

$$\hat{g}_{mk} = \frac{1}{\sqrt{\tau_p p_k^p}} \psi_k^H \mathbf{y}_m^p. \quad (2)$$

The channel estimates are used to decode the uplink transmitted data of the users. After pilot transmission, the users transmit offloaded data to the APs. Let x_k denote the uplink transmission data of user k . Then, the received signal y_m^u at the m -th AP is given as

$$y_m^u = \sum_{k=1}^K \sqrt{p_k} g_{mk} x_k + \omega_m, \quad (3)$$

where p_k is the uplink data transmit power. Let $p_k = \eta_k p_k^{\max}$, where η_k , and p_k^{\max} represent power control coefficient and maximum uplink transmit power of UE k , respectively.

In order to ensure scalability of cell-free massive MIMO system in terms of complexity for pilot detection and data processing, each UE is served by a limited number of APs, which forms a cluster. Let N_k denote a total number of APs in a cluster of user k . To this end, it is essential to form a cluster of APs serving each user in a user-centric manner. Let \mathcal{C}_k denote a cluster of the k -th user, i.e., $\mathcal{C}_k = \{AP_1^{(k)}, AP_2^{(k)}, \dots, AP_{N_k}^{(k)}\}$, where $AP_n^{(k)}$ denote the n -th AP in the cluster. For simplicity of exposition in the current discussion, assume that all users have the same size of cluster, given by C^{\max} , i.e., $N_k = C^{\max}$, $k = 1, 2, \dots, K$. In order to construct a cluster, we employ a greedy approach which orders the large-scale channel coefficients of user k with the respective APs in a descending order and then, includes all APs with the largest until $N_k = C^{\max}$. Thus, the transmitted data by user k is only decoded by the APs in \mathcal{C}_k . Then each AP $m \in \mathcal{C}_k$ transmits the quantity $\hat{g}_{mk}^* y_m^u$ to the CPU via a fronthaul link. The received soft estimates are combined at the CPU to decode the data transmitted by user k as follows:

$$\hat{x}_k = \sum_{m=1}^{N_k} \hat{g}_{mk}^* y_m^u. \quad (4)$$

Then, the uplink SINR γ_k for user k can be expressed as

$$\gamma_k = \frac{p_k \left\{ \left| \sum_{m \in \mathcal{C}_k} \hat{g}_{mk}^* g_{mk} \right|^2 \right\}}{\sum_{k' \neq k} p_{k'} \left\{ \left| \sum_{m \in \mathcal{C}_k} \hat{g}_{mk}^* g_{mk'} \right|^2 \right\} + \sigma_m^2 \left\{ \sum_{m \in \mathcal{C}_k} |\hat{g}_{mk}|^2 \right\}} \quad (5)$$

The uplink rate of user k is then given as $R_k(p_k) = W \log_2(1 + \gamma_k(p_k))$, where W is the system bandwidth. More specifically, we adopt the closed-form uplink spectral efficiency from [12].

B. Parallel Computation Model

Without loss of generality, we assume each user k has a computationally intensive task with $\mathcal{T}_k(t)$ bits at the beginning of every discrete time step $t = 1, 2, \dots$, whose duration is set to a coherence period, i.e., $\Delta t = \tau_c$. The task sizes in different time steps are independent and uniformly distributed over $[\mathcal{T}_{\min}, \mathcal{T}_{\max}]$, for every user $k \in \mathcal{K}$. Let t_k^d denote the maximum tolerable delay of user k to complete execution of the time-sensitive application. Furthermore, we assume the tasks are independent and fine grained, i.e., can be broken into arbitrary portions so that they can be computed at the user device and the edge server in parallel. At time step t , considering the delay constraint and energy consumption, the k -th user processes $\mathcal{T}_k^{\text{local}}(t)$ bits locally and offloads the remaining $\mathcal{T}_k^{\text{offload}}(t)$ bits to the edge server at the CPU. In the sequel, we describe the models adopted for local computation and computation offloading.

1) *Local computation*: Let us denote the maximum local computing clock speed of user k by f_k^{\max} (in cycle per second). Furthermore, let N_{cpb} denote the number of CPU cycles to process a one-bit task. Taking energy consumption and delay requirement of the application into account, the user decides the proportion $\alpha_k \in [0, 1]$ for achieving the local clock speed of $f_k^{local}(t) = \alpha_k(t) f_k^{\max}$, which in turn determines the size of locally computed task. The entire task $\mathcal{T}_k(t)$ is offloaded to the edge server if $\alpha_k(t) = 0$. Meanwhile, $\alpha_k(t) = 1$ if the whole local processing capability of f_k^{\max} is fully utilized while offloading the remaining task bits to the edge server. Note that conservative local processing may lead to high energy consumption, while aggressive computation offloading by all users may subject some users to service outage, since offloading all tasks cannot be supported with finite radio and computation resources. In general, α_k is one of the decision variables for efficient JCCRA, which is governed by the channel and computational constraints in the local and edge systems, subject to the energy consumption and delay requirement.

Given the application deadline t_k^d to process $\mathcal{T}_k(t)$ task bits subject to the local processing clock speed of $f_k^{local}(t)$, then the size of locally computed task can be expressed as $\mathcal{T}_k^{local}(t) = \min\left(\mathcal{T}_k(t), \frac{t_k^d f_k^{local}(t)}{N_{cpb}}\right)$ (in bits). Let $t_k^{local}(t)$ denote the time taken for local execution at time step t , which is given as

$$t_k^{local}(t) = \min\left(\frac{\mathcal{T}_k^{local}(t) N_{cpb}}{f_k^{local}(t)}, t_k^d\right). \quad (6)$$

Then, the energy consumed for the local execution is expressed as

$$E_k^{local}(t) = \varsigma \mathcal{T}_k^{local}(t) N_{cpb} (f_k^{local}(t))^2, \quad (7)$$

where ς corresponds to the effective switched capacitance depending on the chip architecture.

2) *Computation offloading*: The k -th user offloads the remaining task bits $\mathcal{T}_k^{offload}(t) = \max(0, \mathcal{T}_k(t) - \mathcal{T}_k^{local}(t))$ to the edge server at the CPU for parallel computation. While offloading the computational task to the edge server, the experienced latency can be broken down into transmission delay for offloaded data, processing delay in edge server, and transmission delay for retrieving the result. Since the retrieved data size after computation in the server is much smaller as compared to the offloaded data size, we ignore the retrieving delay in our formulation. Let $t_k^{tr}(t)$ and $t_k^{comp}(t)$ denote the transmission delay and computing delay, respectively, for the k -th user. To offload $\mathcal{T}_k^{offload}(t)$ data bits to the edge server, the transmission delay $t_k^{tr}(t)$ is given as

$$t_k^{tr}(t) = \frac{\mathcal{T}_k^{offload}(t)}{R_k(\eta_k, t)}, \quad (8)$$

where $R_k(\eta_k, t)$ is the uplink rate of user k with a power control factor of η_k at time step t , which is expressed according to the discussion in the previous subsection. It should be noted that power control plays a critical role as we must consider co-channel interference among the different clusters while offloading computation. To that end, η_k is another variable to

consider for efficient utilization of limited radio and computing resources.

Let f_k^{CPU} (in cycle per second) denote the computing clock speed of the edge server in the CPU which is shared among the users in proportion to the offloaded task size so that each user can experience uniform computation delay. In other words, the allocated computational resource at the CPU for user k , denoted as $f_k^{CPU}(t)$, can be expressed as

$$f_k^{CPU}(t) = \frac{\mathcal{T}_k^{offload}(t)}{\sum_{k=1}^K \mathcal{T}_k^{offload}(t)} f_k^{CPU}. \quad (9)$$

Then the computing time $t_k^{comp}(t)$ required to execute bits $\mathcal{T}_k^{offload}(t)$ is given as

$$t_k^{comp}(t) = \frac{\mathcal{T}_k^{offload}(t) N_{cpb}}{f_k^{CPU}(t)}. \quad (10)$$

Therefore, the total edge-computing delay for executing $\mathcal{T}_k^{offload}(t)$ bits is given as the sum of the delays for uplink transmission and computation at the CPU, i.e., $t_k^{offload}(t) = t_k^{comp}(t) + t_k^{tr}(t)$. The corresponding energy consumption is given as

$$E_k^{offload}(t) = p_k(t) t_k^{tr}(t), \quad (11)$$

where the transmission power $p_k(t)$ is expressed as $p_k(t) = \eta_k(t) p_k^{\max}$, and p_k^{\max} corresponds to the maximum uplink transmission power of UE k .

According to the communication and parallel computation models discussed above, the overall experienced latency $t_k(t)$ by user k , to execute $\mathcal{T}_k(t)$ bits locally and at the edge is given by

$$t_k(t) = \max(t_k^{local}(t), t_k^{offload}(t)). \quad (12)$$

The corresponding energy consumption $E_k(t)$ of user k , can be expressed as

$$E_k(t) = E_k^{local}(t) + E_k^{offload}(t). \quad (13)$$

C. JCCRA Problem Formulation

We now present JCCRA problem formulation in our framework. Specifically, our objective is to minimize the total energy consumption of all users while meeting the respective user-specific delay requirements by jointly optimizing the local processor speed $f_k^{local}(t) = \alpha_k(t) f_k^{\max}$, and uplink transmission power $p_k(t) = \eta_k(t) p_k^{\max}$, for every user $k \in \mathcal{K}$ at each time step t , without the assumption of any prior knowledge of future realizations of the incoming task size and channel conditions of the users. The JCCRA problem to jointly determine $(\alpha_k(t), \eta_k(t))$, $\forall k \in \mathcal{K}$ can mathematically be formulated by (14), shown at the top of the next page. Therein, the first constraint ensures that the task execution delay $t_k(t)$ should not exceed the user-specific delay requirement t_k^d .

The JCCRA problem in (14) is a stochastic optimization problem in which the objective function and the first condition involve constantly changing random variables, following the dynamics caused by the random incoming task size at each user, and wireless channel conditions. Hence, the time-varying

$$\begin{aligned}
& \min_{\{\alpha_k(t), \eta_k(t) | \forall k\}} \sum_{k=1}^K E_k(t) = \sum_{k=1}^K \varsigma \min \left(\mathcal{T}_k(t), \frac{t_k^d \alpha_k(t) f_k^{\max}}{N_{cpb}} \right) N_{cpb} \{\alpha_k(t) f_k^{\max}\}^2 + \eta_k(t) p_k^{\max} \frac{\max \left(0, \mathcal{T}_k(t) - \min \left(\mathcal{T}_k(t), \frac{t_k^d \alpha_k(t) f_k^{\max}}{N_{cpb}} \right) \right)}{R_k(\eta_k(t))} \\
& \text{subject to} \quad \max \left(\min \left(\frac{\min \left(\mathcal{T}_k(t), \frac{t_k^d \alpha_k(t) f_k^{\max}}{N_{cpb}} \right) N_{cpb}}{\alpha_k(t) f_k^{\max}}, t_k^d \right), \mathcal{T}_k^{offload}(t) \left[\frac{N_{cpb}}{f_k^{CPU}(t)} + \frac{1}{R_k(\eta_k, t)} \right] \right) \leq t_k^d, \forall k \\
& \quad 0 \leq \alpha_k(t) \leq 1, \forall k \\
& \quad 0 \leq \eta_k(t) \leq 1, \forall k
\end{aligned} \tag{14}$$

optimization variables $(\alpha_k(t), \eta_k(t)), \forall k \in \mathcal{K}$, should be determined frequently, i.e., at every step t , and rapidly within the ultra-low deadline. Further, the joint resource allocation decisions are inter-coupled among the users, which poses additional challenge. It is, therefore, challenging to solve the problem using conventional optimization algorithms. Moreover, from the cell-free massive MIMO perspective, solving the JCCRA problem centrally at the CPU might allow for efficient management of the available radio and computing resources due to globally processing of network-wide information. However, the associated signaling and communication overheads are forbiddingly significant, especially given the ultra-low delay constraints. Thus, to cope up with the dynamics in the mobile edge network and derive a flexible and efficient joint resource allocation for every user, we propose a fully distributed JCCRA based on cooperative multi-agent reinforcement learning. We note that this is the very first attempt to solve JCCRA problem in a fully distributed manner for a cell-free massive MIMO-enabled mobile edge computing network. While alleviating the large overheads associated with the centralized implementation, the proposed distributed approach enables users to entertain energy-efficient and consistently low end-to-end delay computational task offloading.

IV. THE PROPOSED MULTI-AGENT REINFORCEMENT LEARNING-BASED DISTRIBUTED JCCRA

In this section, we present a fully distributed JCCRA solution approach based on cooperative multi-agent reinforcement learning framework, in which each user device is implemented as an agent for joint resource allocation relying on local observation only. In particular, the agents learn to map their local observation into JCCRA actions that minimize the total energy consumption while meeting the respective application deadlines. As opposed to the centralized schemes, such a distributed approach significantly alleviates signaling and communication overhead while making resource allocation decisions.

A. Distributed DRL Formulation for JCCRA

The DRL agents sequentially interact with the mobile edge network in discrete-time steps to learn optimal joint resource allocation policies. Let \mathcal{O}_k , and \mathcal{S} denote the local observation space of agent $k \in \mathcal{K}$, and the complete environment state space, respectively. As shown in Fig. 2, at time step t , each agent relies on local observation of the environment state $o_k(t) : \mathcal{S} \mapsto \mathcal{O}_k$ to determine an action $a_k(t) \in \mathcal{A}_k$,

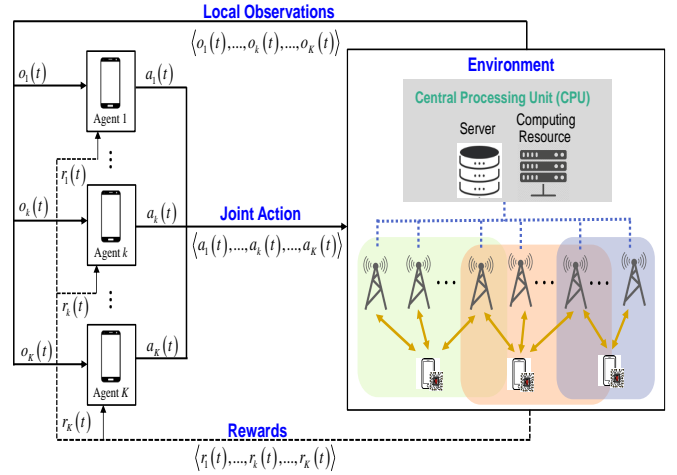


Fig. 2. Multi-agent reinforcement learning framework: *Illustration*

from its action space \mathcal{A}_k according to the current JCCRA policy μ_k . The shared environment collects the joint action of the agents $a(t) = (a_1(t), \dots, a_K(t))$, and emits the next observations $o_k(t+1) \in \mathcal{O}_k$ and real-valued scalar rewards $r_k(t) : \mathcal{S} \times \mathcal{A}_k \mapsto \mathbb{R}$ for all $k \in \mathcal{K}$. The goal of the agents is, therefore, to constantly improve their respective policy until it converges to the optimal JCCRA policy μ_k^* that maximizes the expected long-term discounted cumulative reward, defined as $J_k(\mu_k) = \mathbb{E} \left[\sum_{t=1}^T \varepsilon^{t-1} r_k(t) \right]$, where $\varepsilon \in [0, 1]$ is the discount factor and T is the total number of total time steps (horizon). The optimal JCCRA policy μ_k^* is then given as

$$\mu_k^* = \arg \max_{\mu_k} J_k(\mu_k). \tag{15}$$

In the sequel, we define the *local observation*, *action*, and *reward* of each agent $k \in \mathcal{K}$ for JCCRA at a given time t .

1) *Local observation*: As discussed in the previous section, the compute-intensive tasks are subjected to user-specific application deadline. Specifically, at time step t , the maximum delay tolerance of the k -th agent to execute incoming task of $\mathcal{T}_k(t)$ bits is given by t_k^d . Meanwhile, we assume the agent has a rate assignment result from the previous time step, which is given as uplink data rate $R_k(t-1)$. At the beginning of each time step t , the local observation of agent k is defined as

$$o_k(t) \triangleq [\mathcal{T}_k(t), t_k^d, R_k(t-1)]. \tag{16}$$

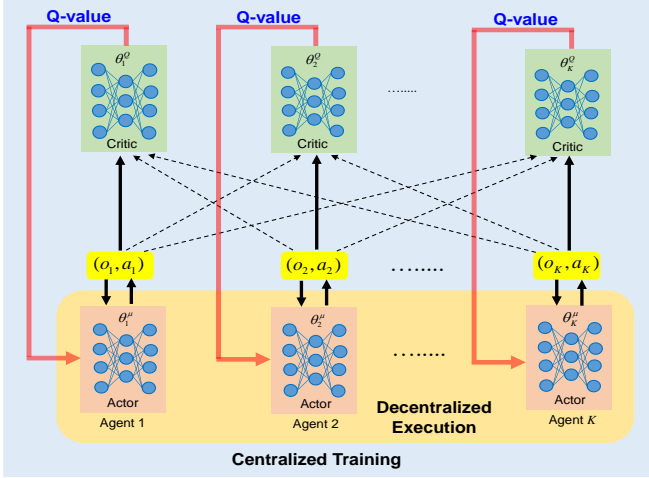


Fig. 3. Centralized training and decentralized execution framework in MADDPG algorithm

Note that the local observation is only a partial view of the environment, i.e., it does not include information about the other agents.

2) *Action*: Based on the local observation of the environment, each agent k jointly determines how much local computing resources and uplink transmit power must be allocated to execute $\mathcal{T}_k(t)$ within t_k^d . Accordingly, the action of the k -th agent at time step t can be expressed as

$$a_k(t) \triangleq [\alpha_k(t), \eta_k(t)], \quad (17)$$

where $\alpha_k(t) \in [0, 1]$, and $\eta_k(t) \in [0, 1]$ are continuous values that govern the local processor clock speed $f_k^{local}(t) = \alpha_k(t) f_k^{\max}$, and uplink transmit power $p_k = \eta_k p_k^{\max}$, respectively.

3) *Reward*: The agents must learn a cooperative JCCRA policies that minimize the total energy consumption of all users while meeting the respective delay constraints. The immediate reward, therefore, should encapsulate both aspects of the design objective. Accordingly, to encourage the agents to maximize the common goal and enforce cooperation among them, we define the joint reward as

$$r_k(t) = - \sum_{k=1}^K \xi_k E_k(t), \quad \forall k \in \mathcal{K}, \quad (18)$$

where $\xi_k = 1$ if $t_k(t) \leq t_k^d$, otherwise $\xi_k = 10$ to punish potentially selfish behavior of the agents that lead to failure in meeting the delay constraint.

We note that the decision variables, i.e., α_k and η_k , for the JCCRA, are continuous-valued. However, a direct extension of single-agent reinforcement learning methods for continuous action spaces, such as deep deterministic policy gradient (DDPG) algorithm [35], i.e., training each agent independently, faces several problems when applied to learn coordinated policies. Learning in a multi-agent setup is more challenging and complex than in single-agent case, since the environment is no longer stationary from the agent's perspective as the other agents update their policies concurrently. In other words, the agents face a moving target problem,

Algorithm 1: MADDPG Algorithm for JCCRA

```

1 for each agent  $k \in \mathcal{K}$  do
2   Initialize replay buffer  $\mathcal{D}_k$ .
3   Initialize the actor network  $\mu_k(o_k|\theta_k^\mu)$  and critic
   network  $Q_k(s_k, a|\theta_k^Q)$  with weights  $\theta_k^\mu$  and  $\theta_k^Q$ ,
   respectively.
4   Initialize the target networks,  $\mu'_k$  and  $Q'_k$  with
   weights  $\theta_k^{\mu'}$  and  $\theta_k^{Q'}$ , respectively.
5 end
6 for each episode  $e = 1, 2, \dots$  do
7   for each agent  $k \in \mathcal{K}$  do
8     Initialize random process  $\mathcal{N}_k$  for exploration.
9     Generate initial local observation from the
     environment simulator.
10  end
11  for each step  $t = 1, 2, \dots$  do
12    for each agent  $k \in \mathcal{K}$  do
13      Select action
14       $a_k(t) = \mu_k(o_k(t)|\theta_k^\mu) + \mathcal{N}_k(t)$ 
15    end
16    Execute joint action  $a(t) = (a_1(t), \dots, a_K(t))$ 
17    for each agent  $k \in \mathcal{K}$  do
18      Collect reward  $r_k(t)$  and observe
19       $s_k(t+1)$ .
20      Store the transition
21       $(s_k(t), a(t), r_k(t), s_k(t+1))$  into  $\mathcal{D}_k$ .
22      Sample random minibatch of  $B$  transitions
23       $(s_k^i, a^i, r_k^i, s_k^{i+1})$  from  $\mathcal{D}_k$ .
24      Update the critic network by minimizing
      the loss given by (19).
25      Update the actor policy using the sampled
      policy gradient given by (20).
26      Update the target networks according to
      (21).
27    end
28  end
29 end

```

which may lead to learning instability. Moreover, the non-stationarity of the environment compounded on agents' partial observations of the dynamic environment can cause shadowed equilibria, a phenomenon in which agents' local optimal actions result in globally sub-optimal joint action [36]. In the next subsection, we discuss a multi-agent version of DDPG algorithm, referred to as multi-agent deep deterministic policy gradient (MADDPG) [37], based on the centralized training and decentralized execution framework, to train all agents for JCCRA decision making.

B. MADDPG Algorithm for Distributed JCCRA

Similar to its single agent counterpart, MADDPG is an actor-critic policy gradient algorithm. However, in the course of the offline training phase, the multi-agents are trained at a central unit which presents an opportunity for sharing extra information so as to ease the training process. As depicted in

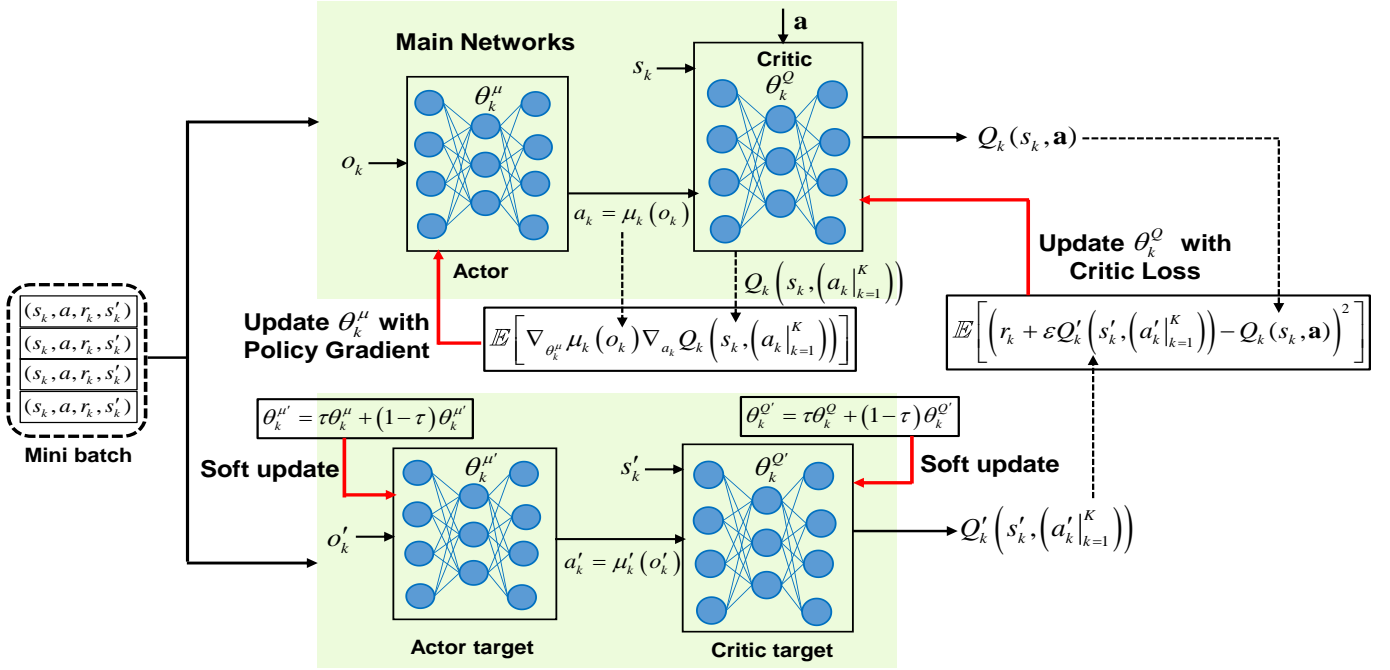


Fig. 4. Illustration of the training procedure in MADDPG algorithm for the k -th agent

Fig. 3, in addition to the local observations of the environment, the agents are provided with additional information (shown as dotted lines), such as observations and actions of the other agents. Specifically, agent k has now access to the joint action $a(t) = (a_1(t), \dots, a_K(t))$, and full observation of the environment state $s_k(t) = (o_k(t), o_{-k}(t))$, where $o_{-k}(t)$ is the local observations of other agents at time step t . The additional information, in particular the actions taken by other agents, can enable the multi-agents to overcome the challenges posed by the non-stationarity of the environment, thereby successfully capturing the dynamics of the mobile edge network. The extra information endowed to the agents during the centralized training phase, however, is discarded during the execution phase, meaning that the agents fully rely on their local observations to make JCCRA decisions in a fully distributed manner.

The MADDPG agent k employs two main deep neural networks: actor network with parameters θ_k^μ to approximate a joint resource allocation policy $\mu_k(o_k|\theta_k^\mu)$ and a critic network, parametrized by θ_k^Q , to approximate a state-value function $Q_k(s_k, a|\theta_k^Q)$, along with their respective time-delayed copies, $\theta_k^{\mu'}$ and $\theta_k^{Q'}$ which serve as targets. At time step t , the actor deterministically maps local observation $o_k(t)$ to a specific continuous action $\mu_k(o_k(t)|\theta_k^\mu)$ and then, a random noise process \mathcal{N}_k is added to generate an exploratory policy such that $a_k(t) = \mu_k(o_k(t)|\theta_k^\mu) + \mathcal{N}_k(t)$. The environment, which is shared among the agents, collects the joint action $a(t) = \{a_k(t), \forall k \in \mathcal{K}\}$ and returns the immediate reward $r_k(t)$ and the next observation $o_k(t+1)$ to the respective agents. To make use of the experience in later decision-making steps, i.e., to improve sample efficiency, and stability of the training, the agent's transition along with the extra information

$e_k(t) = (s_k(t), a(t), r_k(t), s_k(t+1))$ is saved in the replay buffer \mathcal{D}_k of the agent k .

To train the main networks, mini batch of B samples $(s_k^i, a^i, r_k^i, s_k^{i+1})_{i=1}^B$, is randomly drawn from the replay buffer \mathcal{D}_k , denoting a sample index by i . The critic network is updated to minimize the following loss function:

$$\mathcal{L}_k(\theta_k^Q) = \frac{1}{B} \sum_i (y_k^i - Q_k(s_k^i, a^i|\theta_k^Q))^2, \quad (19)$$

where y_k^i is the target value expressed as $y_k^i = r_k^i + \epsilon Q'_k(s_k^{i+1}, a_{i+1}|\theta_k^{Q'})|_{a_{i+1}=\{\mu'_k(o_k^{i+1}), \forall k \in \mathcal{K}\}}$, with a discount factor ϵ . More specifically, the parameters of the critic network, θ_k^Q , are adjusted by following the gradient of (19) such that $\theta_k^Q \leftarrow \theta_k^Q - \beta_Q \nabla_{\theta_k^Q} \mathcal{L}_k(\theta_k^Q)$, with a learning rate of β_Q for the critic network. On the other hand, the policy network updates its parameters to maximize the expected long-term discounted reward $J(\mu_k|\theta_k^\mu)$ according to $\theta_k^\mu \leftarrow \theta_k^\mu - \beta_\mu \nabla_{\theta_k^\mu} J(\mu_k|\theta_k^\mu)$, where $\nabla_{\theta_k^\mu} J(\mu_k|\theta_k^\mu)$ is the deterministic policy gradient expressed as

$$\nabla_{\theta_k^\mu} J(\mu_k|\theta_k^\mu) \approx \frac{1}{B} \left[\sum_i \nabla_{a_k} Q_k(s_k^i, a_i|\theta_k^Q) \times \nabla_{\theta_k^\mu} \mu_k(o_k^i|\theta_k^\mu) \right] \Bigg|_{a_i=\{\mu_k(o_k^i), \forall k \in \mathcal{K}\}}, \quad (20)$$

and β_μ is the learning rate of the actor network. The target parameters in both actor and critic networks are updated with soft updates as follows:

$$\begin{aligned} \theta_k^{\mu'} &\leftarrow \tau \theta_k^\mu + (1-\tau) \theta_k^{\mu'} \\ \theta_k^{Q'} &\leftarrow \tau \theta_k^Q + (1-\tau) \theta_k^{Q'}, \end{aligned} \quad (21)$$

where τ is a constant close to zero.

Fig. 4 depicts the interactions of the four networks while training the k -th MADDPG agent. The learning agents are trained with MADDPG algorithm for several episodes, each consisting of many time steps, to derive effective joint resource allocation. The details of the MADDPG algorithm are summarized in Algorithm 1.

V. PERFORMANCE ANALYSIS

A. Simulation Setup

We start by uniformly distributing $M = 100$ APs and $K = 10$ active users over an area of 1km^2 . The APs are connected to the CPU via ideal fronthaul links. Unless stated otherwise, 30% of the entire APs are clustered to serve each user, i.e., $N_k = 0.3M$, $k = 1, 2, \dots, 10$. The system bandwidth is set to 5 MHz, which is shared among all users without channelization. A channel coefficient of the small-scale fading between the k -th user and m -th AP is set as $h_{mk} \sim (0, 1)$, which is independent across all APs and users. Furthermore, a channel gain of large-scale fading between the k -th user and m -th AP is given as

$$\beta_{mk} = 10^{\frac{PL_{mk}}{10}} 10^{\frac{\sigma_{sh} z_{mk}}{10}}, \quad (22)$$

where σ_{sh} represents the standard deviation of the shadow fading, and $z_{mk} \sim \mathcal{N}(0, 1)$. According to the three-slope model [38], with fixed distance of d_0 , and d_1 , the path loss PL_{mk} between the k -th user and m -th AP with a distance of d_{mk} apart at the carrier frequency of f is given as

$$PL_{mk} = \begin{cases} -L - 35\log_{10}(d_{mk}) & \text{if } d_{mk} > d_1 \\ -L - 10\log_{10}(d_{mk}^2 d_1^{1.5}) & \text{if } d_0 < d_{mk} \leq d_1, \\ -L - 10\log_{10}(d_0^2 d_1^{1.5}) & \text{if } d_{mk} \leq d_0 \end{cases} \quad (23)$$

where

$$L = 46.3 + 33.9\log_{10}(f) - 13.82\log_{10}(h_{AP}) - (1.1\log_{10}(f) - 0.7)h_u + 1.56\log_{10}(f) - 0.8, \quad (24)$$

with h_{AP} and h_u to denote the antenna height (in meters) of AP and user, respectively. Further, there is no shadowing unless $d_{mk} > d_1$. The values of d_0 , and d_1 are set to 10 m, and 50m, respectively, similar to [10]. The edge server at the CPU has computation capacity of $f^{CPU} = 100$ GHz, while all users are equipped with the same computation capacity of $f_k^{\max} = 1$ GHz. Furthermore, each bit requires 500 clock cycles to be processed, i.e., $N_{cpb} = 500$. A time step Δt is set to 1ms, and each user generates a task with a random size that is uniformly distributed in the range of 2.5 to 7.5 kbits, corresponding to a rate of 2.5 Mbps to 7.5 Mbps, at the beginning of every time step t . Without loss of generality, each user demands the task to be processed within the same interval, i.e., $t_k^d \leq \Delta t = 1\text{ms}$, for every time step. Meanwhile, we assume that a channel does not change over each time step, i.e., $\tau_c = 1\text{ms}$. The simulation parameters are summarized in Table II.

For the proposed MADDPG-based JCCRA, both actor and critic networks of each agent are implemented with fully

Table II: Simulation parameters

Notation	Parameter	Value
f^{CPU}	Computation capacity of the server in the CPU	100 GHz
f_k^{\max}	Maximum local computation capacity	1 GHz
N_{cpb}	Number of cycles to process one bit task	500 cycles/bit
ς	Effective switched capacitance of the devices	10^{-27}
t_k^d	Application deadline for user k	1 msec
W	System bandwidth	5 MHz
p_k^{\max}	Maximum uplink transmit power	0.1 W
f	Carrier frequency	1.9 GHz
h_{AP}	AP antenna height	15 m
h_u	User antenna height	1.65 m
σ_{sh}	Standard deviation of the shadow fading	10 dB
T_o	Noise temperature	290 K
η_f	Noise figure	9 dB
K_B	Boltzmann constant	1.381×10^{-23} J/K

Table III: Simulation hyperparameters for MADDPG training

Hyperparameter	Value
Discount factor ε	0.99
Soft update rate τ	0.005
Critic learning rate	0.001
Actor learning rate	0.0001
Mini batch size	128
Replay buffer size	10000

connected neural networks, which consist of three hidden layers, each with 128, 64, and 64 nodes, respectively. All the hidden layers are activated by ReLu function, while the outputs of the actors are activated by sigmoid function. The target networks at each agent are copies of the respective actor and critic networks. The parameters of critic and actor networks are updated with adaptive moment (Adam) optimizer with learning rate 0.001 and 0.0001. Further, the discount factor and target networks update parameter are set to $\gamma_k = 0.99$ and $\tau = 0.005$, respectively, while the size of a mini batch is set to 128. The agents are trained with MADDPG algorithm for several episodes, each consisting of 100 steps. Table III summarizes the hyperparameter values used in our simulations.

B. Performance Evaluation

In this section, we present the performance of the proposed distributed MADDPG-based JCCRA. For performance comparison, we consider the following three benchmarks:

- **Centralized DDPG-based JCCRA scheme:** This approach refers to DDPG-based centralized resource allocation scheme at the CPU. We adopt the same neural network structure and other hyperparameters as the MADDPG scheme to train the actor and critic in the single DDPG agent. However, the agent has full observation of the environment state, given in dimension of

$K \times 3$, during training and execution. The action has dimension of $K \times 2$, with each row corresponding to joint resource allocation for a particular user. Since global information of the entire network is processed centrally at the CPU to make JCCRA decisions for all users, we can potentially obtain the most efficient resource allocation. Therefore, it can potentially serve as a target performance benchmark. However, as discussed in the previous sections, due to the significant signaling and communication overhead, this scheme is infeasible to support time-sensitive applications.

- **Offloading-first with an uplink fractional power control (FPC) scheme:** This approach preferably offloads the computation to the edge server with the aim of aggressively exploiting the reliable access link provided by cell-free massive MIMO while saving the local processing energy consumption. The uplink transmit power for the k -th user is given by the standard fractional power control (FPC) [38,39] as follows:

$$p_k = \min(p_k^{\max}, p_0 \lambda_k^{-\nu}), \quad (25)$$

where $p_0 = -35$ dBm, $\lambda_k = \sum_{m=1}^{N_k} \beta_{mk}$, and $\nu = 0.5$.

- **Local execution-first with an uplink fractional power control (FPC) scheme:** The entire local processing capability is fully utilized, i.e., $f_k^{\text{local}} = f_k^{\max}$, and the remaining task bits are offloaded to the edge server with uplink transmit power given according to (25).

In Fig. 5, we investigate the learning convergence of the proposed scheme by evaluating the total reward achieved while comparing it against other benchmark schemes. In contrast to the two heuristic approaches, it can clearly be observed that the learning-based schemes, i.e., centralized DDPG and the proposed MADDPG-based JCCRA, entertain higher reward values, which reflects lower total energy consumption while meeting the respective application deadlines of the users. The rewards per episode have smoothly increased in both learning schemes until they finally converge. A closer look at the convergence rate, however, reveals that the centralized scheme has converged faster than the distributed variant. This is attributed to the advantage of globally processing system wide information at the CPU to derive JCCRA policy for all users. Nevertheless, as the training episodes increase, the proposed algorithm has closed the gap and converged to the target benchmark, i.e., the centralized counterpart. This implies that by relying on local observation and additional information provided during the offline centralized training phase, the agents manage to learn efficient joint resource allocation, which is also adaptive with respect to the dynamics in the mobile edge network. It is also evident from Fig. 5 that conservative use of local computation resources leads to high energy consumption, while aggressively offloading results in ineffective utilization of the limited communication and computing resources.

In Fig. 6, we compare the average success rate of the users in meeting the delay constraint of the time-sensitive applications. For the proposed MADDPG-based and centralized single-agent DDPG-based JCCRA schemes, the success

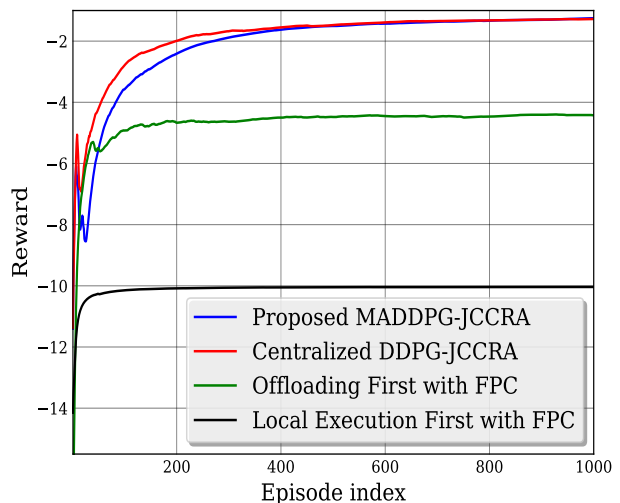


Fig. 5. Total reward with training process

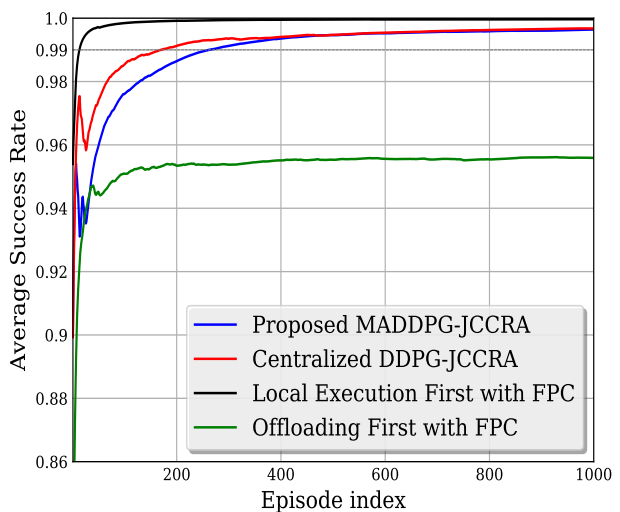


Fig. 6. Average success rate with training process

rate under the simulation setup has gradually increased with episode indices to eventually reach more than 99%, showing only a marginal gap from *local execution-first* approach. The 100% success rate in the latter scheme is, however, at the cost of unreasonably high energy consumption, which is 5 times more compared to the learning-based schemes, as observed in Fig 5. Moreover, the fact that the learning-based schemes outperform the conventional *offloading-first* approach implies that even if cell-free massive MIMO can provide reliable access links to the users, aggressive computation offloading can result in performance degradation due to the ineffective use of the finite communication and computing resources, thereby subjecting users to service outage due to the failure to attain the tight delay constraints. It is, therefore, evident that an adaptive joint resource optimization is very critical to fully unleash the potential of the available communication and computing resources in the mobile edge network.

To further investigate a gain obtained by the joint resource allocation, we then compare the proposed JCCRA scheme with

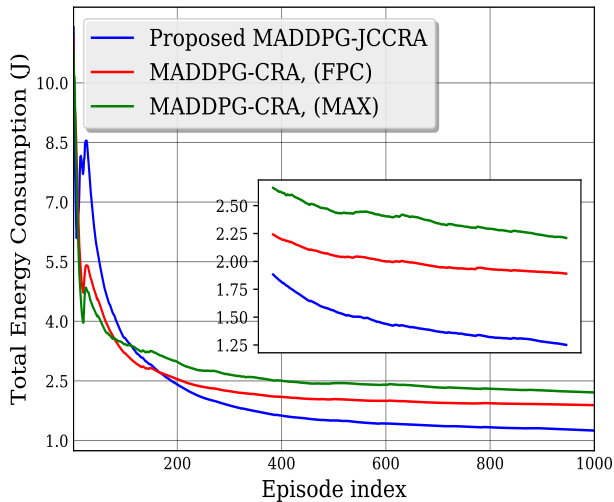


Fig. 7. Comparison of the proposed JCCRA approach against variants with computing resource allocation optimization only

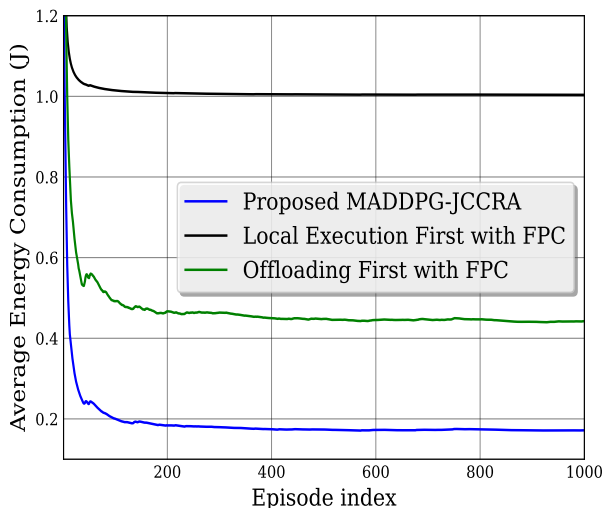


Fig. 8. Per user average energy consumption at the testing stage

two variants that adopt MADDPG algorithm for optimizing computing resource allocation (CRA) only, i.e. without taking power control into account. Additionally, we consider the heuristic fractional power control mechanism given in (25) for the first variant, referred to as MADDPG-CRA (FPC), while in the other variant, users offload computation with the maximum transmit power of $p_k = p_k^{\max}, \forall k \in \mathcal{K}$, referred to as MADDPG-CRA (MAX). From Fig. 7, the performance degradation is readily observed in the variant schemes, which is reflected by 33% and 42% rise in total energy consumption of the user devices in MADDPG-CRA (FPC), and MADDPG-CRA (MAX), respectively. This can be attributed to two factors. The first one is due to the critical role of power control in handling co-channel interference among different clusters during computation offloading. Thus, the adaptive MADDPG-based power control gives the proposed approach an edge over

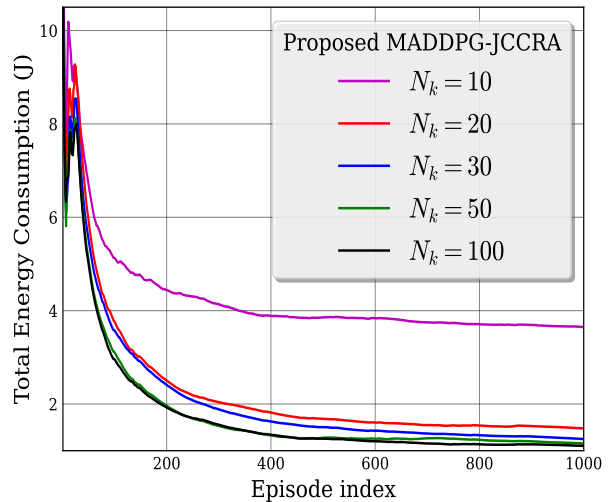
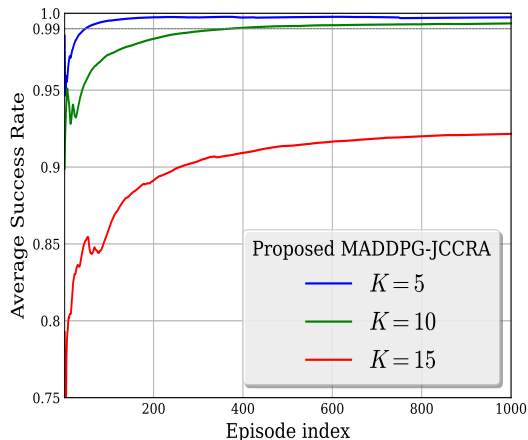


Fig. 9. Effect of cluster size

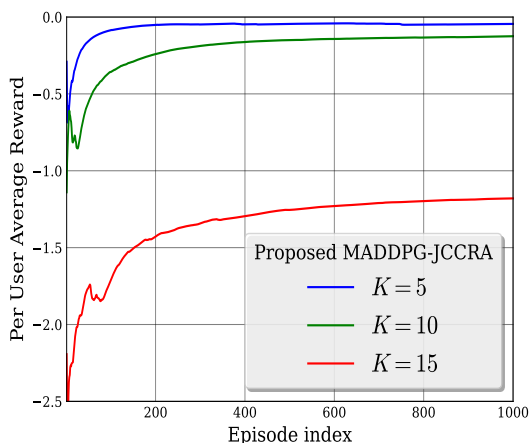
the variant schemes. The second factor is that computing and communication resource management in multi-user mobile edge network are inherently inter-dependent. Consequently, the proposed joint communication and computing resource allocation (JCCRA) optimization approach in the proposed scheme yields additional gain as compared with the separate optimization of computing resources in the other two variants.

After demonstrating the learning convergence and performance matching to the target centralized DDPG-based JCCRA scheme during the offline training stage, we then test the performance of the proposed JCCRA scheme in the dynamic mobile edge environment. Note that the execution phase is fully decentralized in the sense that the agents perform inference based on their local observations only, alleviating the burden associated with signaling in the centralized scheme. Specifically, in accordance with the learned policy, each MADDPG agent relies on its own actor network to map their local observation of the environment into efficient joint resource allocation in real time. Fig. 8 presents the per-user average energy consumption of the schemes during the execution stage. As it can be seen, the proposed approach achieves the lowest energy consumption, which is roughly 2.5 and 5 times lower than the *offloading-first with FPC* and *local execution-first with FPC* baseline schemes, respectively. We can deduce that the offline centralized training has successfully addressed the learning challenges of the multi-agent setting. In other words, the training has enabled the agents to effectively capture the complicated dynamics of the mobile edge network and perform well during the fully decentralized testing phase, as shown in Fig. 8. Such a distributed approach can be a useful means to handle time-sensitive applications while reducing energy consumption in individual mobile device.

Next, we investigate the effect of cluster size on the performance of the proposed framework. As discussed in Section III.A, we form a user-centric cluster of APs \mathcal{C}_k to serve a given user by including N_k APs with the largest β_{mk} (large-scale channel fading). In Fig. 9, we evaluate the average energy consumption by the different sizes of cluster, i.e., setting $N_k = 0.1M, 0.2M, 0.3M, 0.5M, M$ for $M = 100$. It can



(a) Average success rate with different number of users



(b) Per user average reward with different number of users

Fig. 10. Effect of the number of users in the mobile edge network

be observed that the case of $N_k = 0.1M, \forall k \in \mathcal{K}$ has the highest energy consumption since the cell-free access rate is highly constrained to support computation offloading. The agents, therefore, have to either predominantly depend on local computation or increase the transmission power to meet the requirements of the multimedia applications, thus incurring high energy cost. On the other hand, as N_k increases to $0.2M$ and $0.3M$, the performance drop becomes more and more marginal compared to the canonical case where all APs serve every user, i.e., $N_k = 100$. In fact, the case of $N_k = 50$ has negligible performance drop in contrast to $N_k = 100$. This indicates that with a sufficient number of APs in a cluster, a user-centric cell-free massive MIMO can effectively establish a reliable link for computation offloading with negligible performance loss. It should be noted that the user-centric approach requires a limited computational complexity for pilot detection and data processing, in contrast to the canonical counterpart. In practice, therefore, a legitimate cluster size must be set to deal with complexity and deployment cost while solving the JCCRA problem.

The effect of the number of users on the performance of the proposed JCCRA scheme is investigated in Fig. 10, fixing

$M = 100$ and $N_k = 0.3M$. One can observe that the proposed algorithm has converged in all cases. Since there are abundant communication and computing resources for a small number of users in the system, e.g., $K = 5$, the agents entertain almost 100% success rate in accomplishing the intensive tasks within the deadline, while collecting the highest average reward, implying the lowest energy consumption compared to the other two cases. However, as the number of users increases, the competition among the users for limited communication and computing resources becomes more severe. In other words, the per-user resource reduces with an increasing number of users, e.g., the link rate decreases as K increases. In particular, the case $K = 15$ represents a very constrained scenario that suffers from a significant outage. Herein, the available resources are not sufficient enough or the performance requirements are too strict to support all the devices within the stringent delay constraints, subjecting some users to service outage. This implies for critically constrained scenarios, either relaxing the performance requirements, for instance with soft delay constraints, or injection of more resources are required to support more users without outage.

VI. CONCLUSION AND FUTURE WORKS

In this paper, motivated by its capability of realizing a reliable access link without cell edge, we presented a cell-free massive MIMO-enabled mobile edge network to address the stringent requirements of the next generation advanced services. We formulated a user-centric joint communication and computing resource allocation (JCCRA) problem to minimize energy consumption of the user devices while satisfying the corresponding delay constraints. We then proposed a fully distributed solution approach based on cooperative multi-agent reinforcement learning framework, wherein each user is implemented as a learning agent to make joint resource allocation relying on local information only. The simulation results demonstrate that our distributed approach matches the performance of the target centralized DDPG-based benchmark, significantly alleviating the signaling and communication overhead. Such a fully distributed and adaptive framework can be a promising tool to realize edge intelligence for supporting the envisaged applications in dynamic mobile edge network. In the future, it would be interesting to extend this mobile edge network to handle efficient and robust 6G-based sophisticated scenarios, e.g., user-centric QoS/mobility management with AP clustering and location-based optimization along with soft application delay consideration. In particular, the current user-centric joint formulation can be extended further to determine a set of APs that are adaptive to dynamic user mobility and channel condition.

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