Distributed Deep Reinforcement Learning for Latency Optimized Computation Offloading in Aerial-Assisted MEC Networks

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Abstract

The ultra-low latency requirements of mission-critical applications necessitate high computation power. To accomplish this objective, multi-access edge computing (MEC) is a crucial technology that brings computation resources closer to user equipments (UE) and provides an offloading option. In situations where terrestrial MEC cannot meet the requirements, aerial-assisted MEC with unmanned aerial vehicles (UAVs) can be utilized due to their flexible deployment and enhanced coverage. However, for a latency-optimized optimal offloading strategy, it is essential to consider the challenges posed by the environment's dynamics, the availability of resources at UAVs, and the computation requirements of UEs. To address these challenges, we present four distributed deep reinforcement learning (DRL) frameworks for efficient computation offloading in aerial-assisted MEC networks.

1. Introduction

A multitude of mission-critical applications are emerging and gaining popularity, leading to a surge in computation demand and support for ultra-low latency requirements. However, the user equipments (UE) have substantially limited processing capacity. It is challenging for the UEs to process both latency-sensitive applications, such as intelligent transportation and telemedicine, which are highly interactive and real-time, and susceptible to even the smallest time delays, and computationally expensive applications, such as image and video processing for surveillance, which require a significant amount of computation capability. In such scenarios, we consider multi-access edge computing (MEC) as a potential solution by taking into account the specifications, reports, and white papers published by the European telecommunications standards institute (ETSI) MEC [1]. It brings computation resources closer to UEs at the edge of the network allowing UEs to offload their tasks to MEC servers, mostly positioned over terrestrial base stations.

As a result, it can support ultra-low latency applications while significantly reducing the delay experienced and energy consumption of the UEs. However, in some instances (e.g., malfunction, overload, or out-of-coverage region), terrestrial MEC may fail to deliver reliable computation offloading and resource allocation services. Aerial-assisted MEC has been suggested as a promising paradigm where UAVs equipped with computation resources serve as an aerial base station (ABS) to alleviate the strain from UEs and enhance the user experience owning to the benefits of flexible deployment and wide coverage, as illustrated in Fig. 1, this understanding is in line with the standardization put forth by the third generation partnership project (3GPP) in Releases 17 and 18 [2].

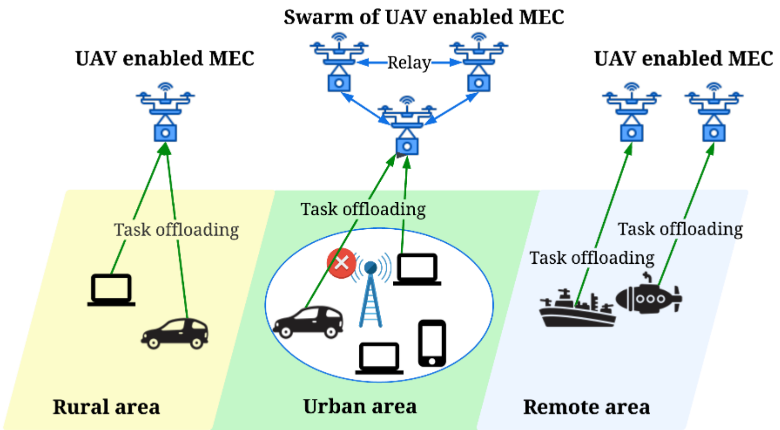

Fig. 1. Aerial-Assisted MEC Network.

The aerial-assisted MEC can significantly enhance the computational performance of UEs. The UEs can decide to either process the task locally or offload the task partially or entirely to the edge server onboard the UAV. To realize the benefits of edge computing, it is essential to develop an optimal computation offloading strategy. A poorly designed strategy might result in a substantial communication burden and a significant delay in transmitting the task for remote execution. In addition, it may cause an overload on the MEC server and drastically increase the entire task processing time.

Significant research has been conducted on computation offloading in aerial-assisted MEC networks. Reference [3] investigates the various technologies utilized to obtain optimal computation offloading policies. It has been observed that reinforcement learning (RL) is a valid artificial intelligence technique for handling the computation offloading problem. Since it does not require a priori knowledge of the environment, it can satisfy the need for real-time decision-making with minimal complexity and can be efficiently executed on the processor of UEs or UAVs. Furthermore, to speed up the training process, the parallel computation can be exploited using distributed architectures that can parallelize gradient descent and other parallelizable computations in RL. However, when numerous decision-makers are involved in a MEC system, a single RL agent struggles to identify an optimal solution. In such a situation, coordination between numerous RL agents is crucial. Distributed deep reinforcement learning enables coordination among agents by offering diverse information structures in which homogeneous or heterogeneous agents cooperate or compete to maximize the shared reward. Therefore, in this study, we present distributed deep RL-based frameworks for computation offloading in aerial-assisted MEC networks.

2. Challenges of computation offloading in Aerial-Assisted MEC Networks

To enable efficient computation offloading in aerial-assisted MEC networks, certain challenges should be carefully addressed. In the considered scenario where multiple UEs are offloading their tasks among multiple UAVs, the decision-making process is very complex. It requires making decisions regarding the portion of a task that should be offloaded when partial offloading is considered and where to offload the task when both vertical offloading (UEs to UAV) and horizontal offloading (UAV to UAV) are considered. In addition, the mobility of UEs and UAVs has a significant impact on the selection of edge servers since it might lead to handover and coverage issues [4].

The computation offloading problem is often formulated as an optimization problem with the objective of minimizing latency or UE's energy consumption or finding a trade-off between the two. To solve the optimization problem, RL is utilized in several recent studies to find the optimal solution. Since the defined optimization problem is usually a large-scale markov decision process (MDP) with high state space and continuous action, RL is integrated with deep learning and an actor-critic architecture is utilized to find an efficient solution. However, literature typically assumes a static environment with a single decision-maker. But in the real world, multiple decision-makers are involved, which leads to new challenges [5]. For example, the environment is mostly non-stationary as several UEs offload tasks simultaneously and the availability of resources at UAVs is constantly changing, this having a complex decision-making process. In addition, partial observability should be taken in consideration while formulating the optimization problem since UEs may not be fully aware of the decisions made by the other UEs. Furthermore, the increase in the number of UEs providing MEC services may lead to scalability issues resulting in a complex environment and hence causes more challenging decision-making process.

3. Distributed Deep Reinforcement Learning Frameworks for Latency Optimization

In this section, we present distributed DRL frameworks to address the computation offloading challenges mentioned in Section 2.

Fig. 2 presents different distributed DRL frameworks. Considering a scenario where only a single agent makes decisions at a time, a parallel RL distributed learning framework can be exploited where multiple parallel machines can be used to accelerate the training process and find an efficient solution [6]. In the aerial-assisted MEC network depicted in the fig. 1, UAV is the agent that takes the information about the complete environment. In cases where a single UAV is deployed in the environment, the above-mentioned approach can be utilized to design an optimal computation offloading strategy. However, when multiple UAVs are deployed in the environment and are taking decisions at the same time, different distributed learning frameworks, such as centralized training and decentralized execution (CTDE), independent learners (IL), and networked agents (NA), can be utilized [7].

In CTDE, the training phase is centralized where the agents exchange information to learn the optimal policy. However, the execution phase is decentralized with agents learning policies based on their local information. This approach can overcome the issues related to partial observability and non-stationarity. When the above distributed learning framework is utilized in the aerial-assisted MEC network, the actor network requires only the local information of the UAV while training whereas the critic network requires information from all the UAVs. Therefore, during the training phase, information from all the UAVs is collected to find the optimal policies. Upon completion of training, during the execution phase, only the actor network is required to determine the best policy. Each UAV takes action based on its own information and designs the optimal computation offloading strategy.

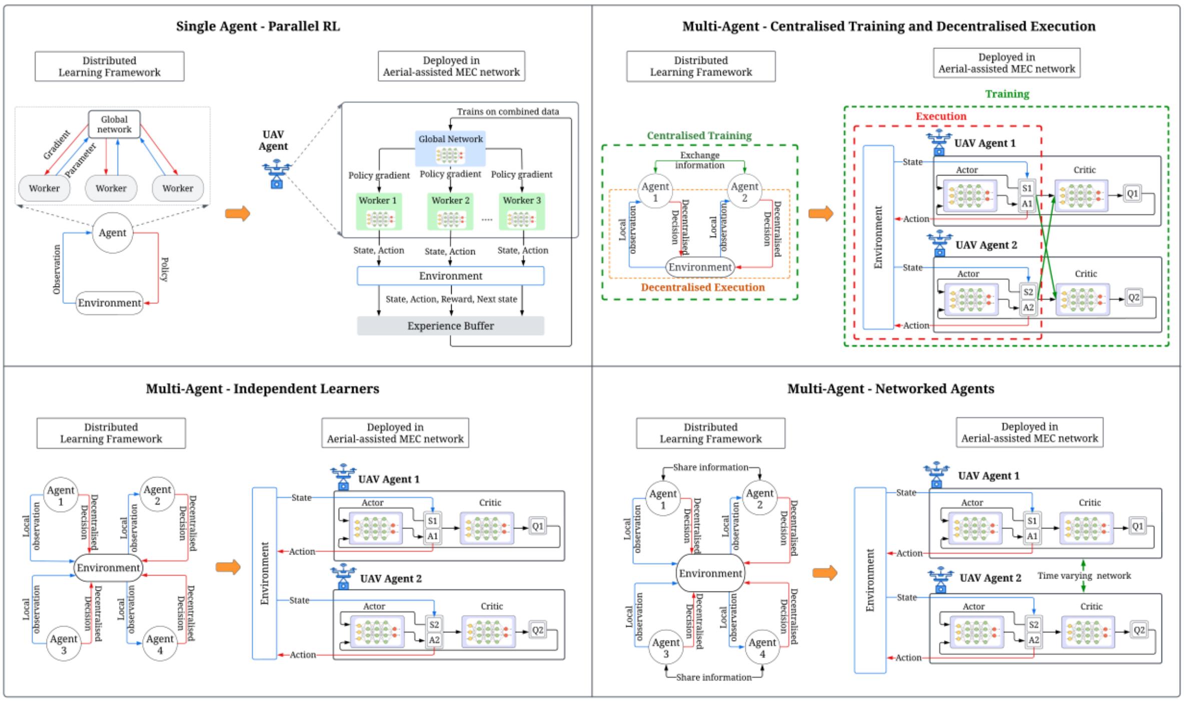

Fig. 2. Distributed DRL frameworks for Aerial-Assisted MEC Network.

IL is a fully decentralized approach where both the training phase and the execution phase are decentralized. The agents independently examine their local information and optimize their policies to maximize their reward. This approach overcomes the issue of scalability. When this approach is utilized in aerial-assisted MEC network, each UAV takes action based on its own state information, ignoring the existence of the other UAV agents and their impact on the environment.

With NA, the agents learn to cooperate through information exchange via a communication structure between the neighboring agents. Furthermore, heterogeneous agents with distinct reward functions can coordinate in order to maximize their reward. This approach overcomes non-stationarity, partial observability and scalability. When applied in aerial-assisted MEC networks, a time-varying network is utilized between the neighboring UAVs. These interconnected UAVs cooperatively make decisions and find the optimal computation offloading policy.

Finally, we present a comparative analysis in Table 1 highlighting the ability of each approach in relation to resolving the aforementioned challenges along with their limitations.

Table 1. Comparative study on different distributed DRL framework for Aerial-assisted MEC addressing following challenges: Non-Stationarity (NS), Partial Observability (PO) and Scalability (SC).

Distributed DRL	Resolved challenges			Limitations
	NS	PO	SC	

Framework				
Parallel RL	No	No	No	UAV collects information about the environment and take actions independently. Therefore, it suffers from non-stationarity, partial observability, and scalability issues.
CTDE	Yes	Yes	No	UAVs collect information from other UAVs. Consequently, it suffers from scalability issues as the number of UAVs increases.
IL	No	No	Yes	UAVs take action independently. Therefore, it suffers from non-stationarity and partial observability issues.
NA	Yes	Yes	Yes	A communication network is required between the neighboring UAVs, which is not always feasible and may even increase complexity.

4. Conclusion

In this article, we focus on investigating computation offloading in aerial-assisted MEC networks. The dynamics of the environment and the need for coordination among UAV agents necessitate the adoption of distributed DRL to find an optimal offloading strategy. We present four different distributed architectures, including parallel RL, CTDE, IL and NA, to accelerate the training process and overcome issues such as non-stationarity, partial observability, and scalability. The proposed architectures are intended to facilitate the real-world implementation of aerial-assisted MEC.

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