

Multi-Agent Actor Critic for Channel Allocation in Heterogeneous Networks

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ABSTRACT

Heterogeneous networks (HetNets) can equalize traffic loads and cut down the cost of deploying cells. Thus, it is regarded to be the significant technique of the next-generation communication networks. Due to the non-convexity nature of the channel allocation problem in HetNets, it is difficult to design an optimal approach for allocating channels. To ensure the user quality of service as well as the long-term total network utility, this article proposes a new method through utilizing multi-agent reinforcement learning. Moreover, for the purpose of solving computational complexity problem caused by the large action space, deep reinforcement learning is put forward to learn optimal policy. A nearly-optimal solution with high efficiency and rapid convergence speed could be obtained by this learning method. Simulation results reveal that this new method has the best performance than other methods.

KEYWORDS

Channel Allocation, Deep Reinforcement Learning, Heterogeneous Cellular Networks

INTRODUCTION

With the number of wireless devices increasing fast, mobile communication networks (Kaushik et al., 2019; Yue et al., 2019) are confronting the enormous challenge of increasing network capacity (Huang et al., 2017; Zhao et al., 2017; Zhao et al., 2019a). Densifying existing cells using the pico base station (PBS) with different transmit power and coverage is an effective solution. Heterogeneous networks (HetNets) (Xia et al., 2018; Helmy et al., 2018; Alhabo et al., 2019) make the service provider possible to unload the user equipment (UE) from the macro base station (MBS) to the PBS, which can not only balance traffic load but also cut down the cost of deploying cells (Wu et al., 2018; Papazafeiropoulos et al., 2018). Furthermore, since the same channel can be shared by PBSs, the overall spectrum efficiency of cellular networks can be improved accordingly (Zhang et al., 2018; Panahi et al., 2018;). Therefore, HetNets have been considered as an effective approach to increase the network capacity and energy efficiency of cellular networks.

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Many performance optimization issues can be seen in HetNets (Zhao et al., 2019b), in which channel allocation is a common problem (Dao et al., 2018; Xu et al., 2018). Channel allocation was considered as an important measure to solve the issue of load balancing in HetNets. In (Zhao et al., 2018a; Wang et al., 2018; Wang et al., 2018), authors investigated the problem of channel allocation. However, the optimization problem has the non-convex features, obtaining a globally optimal strategy is very difficult. Many new methods have been developed to solve these problems, such as Markov approximation (Chen et al., 2013), game-theoretic approach (Zhang et al., 2018) and linear programming method (Elsherif et al., 2015). Almost accurate and complete network information are required to effectively obtain the optimal strategies for these methods. However, it is hard to achieve complete information, which makes the calculation of the optimal maneuver intractable to handle. In this paper, reinforcement learning (RL) is deployed in HetNets.

RL methods (Katayama, 2016; Dulac-Arnold et al., 2016; Levine et al., 2017) can achieve approximate optimal strategy through interacting with the environment. RL agents do not simply optimize the current rewards, but also take long-term goals into account (Degris et al., 2006; Dung et al., 2006; Ereemeev et al., 2018), which is very significant for time-varying dynamic systems. Policy Gradient (PG) and Q-learning are widely utilized RL approaches. In (Chai et al., 2019), the authors utilized the PG based algorithm to obtain the optimal policy for joint rate and power optimization. The authors in (Asheralieva et al., 2016) proposed a substantive Q-learning algorithm to comply the scheme of power and channel selection. In the RL framework, the substantive agents can select the corresponding action without cooperation, which may cause volatility behavior in learning strategies (Talor et al., 2009; D'Eramo et al., 2017). In addition, considering that the behaviors of other UEs may inevitably affect a UE's cumulative reward, multi-agent reinforcement learning (MARL) (ElTantawy et al., 2013) should be considered. However, many issues of MARL need to be considered to achieve the optimal strategy, such as multiple equilibrium.

Moreover, channel allocation has a large state space (Nguyen et al., 2019; Challita et al., 2019; Wang et al., 2019), it is difficult to acquire an optimal strategy with Q-learning. Through combining deep neural network (DNN) (Mnih et al., 2015) with Q-learning, Deep Q-Network (DQN) (Al-Jumeily et al., 2015) can effectively improve learning speed and learning performance. Another RL method is PG, by combining with the DNN, the PG approach performs well in regard to convergence and system performance. Recently, DRL-based approaches have been used in many fields, such as power allocation (Chao et al., 2019), cloud computing (Qing et al., 2019), channel access (Asuhaimi et al., 2019). In our previous work, we adopted the DQN to solve the mobile video offloading problem in HetNets (Zhao et al., 2018). However, little work is done to utilize the DRL way to tackle the channel allocation issue.

In this paper, we propose a channel allocation problem in HetNets. In order to achieve the better capacity of the whole system through satisfying the UEs' QoS requirement, we formulate the channel allocation issue as a Markov Decision Process (MDP) (Slimeni et al., 2015). We investigate the optimal policy to allocate the channel to UEs. Considering the characteristics of combined features and non-convex, a new MADRL strategy is proposed. We adopt MAAC (Multi-Agent Actor Critic) approach to achieve the optimal strategy. A near-optimal solution can be provided by MAAC with faster converge speed. Simulation illustrates that better capability have been achieved compared with Q-learning and DQN.

ENVIRONMENT MODEL AND PROBLEM FORMULATION

A two-tier heterogeneous network is introduced as shown in Figure 1, which comprised of K BSs as well as N UEs randomly distributed in the network. The BSs set is characterized as $BS = \{MBS_1, PBS_1, \dots, PBS_K\}$, with indices of BSs set denoted as $I = \{0, 1, \dots, K-1\}$. Assume that each BS and each UE equips one antenna and the BSs work on M shared orthogonal channels.

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