Online Antenna Tuning in Heterogeneous Cellular Networks with Deep Reinforcement Learning

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Abstract

We aim to jointly optimize the antenna tilt angle, and the vertical and horizontal half-power beamwidths of the macrocells in a heterogeneous cellular network (HetNet) via a synergistic combination of deep learning (DL) and reinforcement learning (RL). The interactions between the cells, most notably due to their coupled interference and the large number of users, renders this optimization problem prohibitively complex. This makes the proposed deep RL technique attractive as a practical online solution for real deployments, which should automatically adapt to new base stations being added and other environmental changes in the network. In the proposed algorithm, DL is used to extract the features by learning the locations of the users, and mean field RL is used to learn the average interference values for different antenna settings. Our results illustrate that the proposed deep RL algorithm can approach the optimum weighted sum rate with hundreds of online trials, as opposed to millions of trials for standard Q-learning, assuming relatively low environmental dynamics. Furthermore, the proposed algorithm is compact and implementable, and empirically appears to provide a performance guarantee regardless of the amount of environmental dynamics.

Index Terms

Deep reinforcement learning, online antenna tuning, Q-learning, HetNets, 5G.

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I. Introduction

Cellular networks will rapidly densify for 5G and beyond, largely through the opportunistic addition of small cells over time [1]. A significant performance advantage of cellular networks (as opposed to e.g. WiFi) is the use of directional antennas at the base station, which concentrates transmit (and receive) power both horizontally and vertically, as well as having an appropriate downtilt. Properly setting these three antenna parameters has important ramifications not only the desired received power by users (UEs) but also on the interference due to neighboring cells. Traditionally these settings have been implemented manually and/or by trial and error, but clearly this is far from optimal as well as not scalable for dense networks, particularly when new BSs can be added at any time or other aspects of the environment can change. Unfortunately, a centralized optimum solution of these parameters is unscalable and NP hard, as well as impractical since the UE locations are unknown.

The goal of this paper is to develop a scalable and distributed near-optimal method for setting these antenna parameters in an online manner. In particular, we wish to dynamically maximize the (arbitrarily weighted) sum rate of the users in the network by having each base station autonomously set their beamwidths and tilt based on ongoing feedback from the users in their own cell. Since the optimum antenna settings change relatively slowly – the cellular topology and propagation conditions change slowly – deep reinforcement learning is a promising tool which has had significant recent success in challenging problems with analogous characteristics [2]-[4].

A. Related Work and Motivation

Tuning the antenna parameters of macrocells has been extensively studied in the literature under the mantle of self organizing networks (SONs) [5]. Many works in this line of research have focused on the antenna tilt angle utilizing methods from conventional optimization theory [6] in an attempt to optimize the capacity and coverage [7]-[13]. These optimizations tend to be restricted to some special handcrafted rules.
and heuristics, and do not learn the dynamics of the environment. This leads to the loss of adaptability especially for a time-varying environment.

Reinforcement learning (RL) on the other hand can learn and adapt to the dynamics of the environment. One of the first attempts to make use of RL for the antenna tilt optimization was for single-tier cellular networks [14]. The major limitation of this study is that it requires a single macrocell at a time to optimize its parameters in a static environment. This assumption was relaxed in [15] by allowing macrocells to simultaneously optimize their parameters. Both [14] and [15] addressed the curse-of-dimensionality problem in RL via a combination of fuzzy logic and RL [16]. This fuzzy RL framework was also used for the optimization of the antenna tilt and transmission power [17]. However, fuzzy RL activates more than one membership function while discretizing the continuous state and action variables, which complicates parsing the reward signal. Sparse sampling is another technique that can handle the curse-of-dimensionality problem [18]. This method was utilized for the self-optimization of the coverage through the antenna tilt optimization [19]. The recent advances in deep RL reveal that neither fuzzy RL nor sparse sampling is as efficient as deep learning (DL) based models.

One paper [20] that considers a HetNet, as opposed to a single-tier of base stations, attempts to increase the user fairness via a dynamic antenna tilt optimization. However, their model does not address the scalability problem, and hence is limited to a simple environment with very few cells. Motivated by the recent success of deep RL algorithms [2]-[4], our paper aims to develop an online Deep RL-based antenna tuning algorithm for a more complex and realistic network topology, e.g. for highly dynamic HetNets and with all three key antenna parameters considered simultaneously.

B. Contributions

The main contribution of this paper is a novel and practical deep RL algorithm for optimizing the antenna parameters of macrocells in HetNets in an attempt to maximize the weighted sum-rate of the users. For this purpose, we first design a RL-based framework to transform the weighted sum-rate optimization problem into a Markov Decision Process (MDP) by defining states, actions and rewards according to
the available control signals in macrocells. This framework leverages the merits of the recently proposed mean field RL, which treats all neighboring agents as a single virtual agent, to make the RL problem scalable and tractable [21]. Specifically, mean field RL enables us to consider the inter-cell interference – which is the main impediment in weighted sum-rate optimization problems – as the cumulative policy of neighboring cells. The proposed framework is fairly general in that it can be used for any weighted sum-rate optimization problem. Tuning the antenna parameters of macrocells, the focus in this paper, is just one example.

Using the designed RL-framework, we propose a novel practical deep RL algorithm for optimizing the antenna parameters of macrocells in HetNets. In particular, antenna tilt angle, and vertical and horizontal half-power beamwidths of macrocells are jointly optimized with the proposed algorithm, which relies on feature based Q-learning with linear function approximation. These features are extracted with the help of DL and mean field RL. Specifically, the locations of UEs are learned with a deep neural network (DNN) by exploiting the correlations among SINRs [22]. This enables us to estimate the immediate impact of any possible antenna setting without actually taking the time to test it, which would require setting it and then processing feedback from the users. In what follows, the mean interference values are learned as features in response to an antenna setting of a macrocell via the sequential decisions made by a mean field RL structure. This selection of features decreases the required online trials from millions to hundreds. The other key insights for the proposed deep RL algorithm are as follows:

- Despite having just hundreds online trials, the proposed algorithm can approach the performance of the optimum solution, which can be estimated by solving a standard Q-learning algorithm that requires millions of trials for relatively low environmental dynamics.
- Even if the relative variance of the environment dynamics is high, the proposed algorithm appears to guarantee a certain performance gain. Specifically in our simulations, regardless of how high the relative variance is, we empirically observe about 0.6\(\Delta\) dB SINR gain when the optimum solution provides \(\Delta\) dB SINR gain.
The proposed algorithm is quite compact in that 80\% of the states in the state space are mapped to a small subset of the action space. Because many states map to the same actions (antenna settings), the antenna arrays will not have to be changed very often.

The paper is organized as follows. The system model and problem statement are given in Section II. The proposed RL framework for weighted sum-rate maximization is introduced in Section III, which is employed in developing the deep RL algorithm for dynamically tuning the antenna parameters of macrocells in HetNets in Section IV. The simulation results are given in Section V and the paper ends with concluding remarks and suggested future work in Section VI.

II. SYSTEM MODEL AND PROBLEM STATEMENT

We consider an urban HetNet deployment, which is composed of many macrocells and small cells. Macrocells are one of the three sectors of an eNodeB (eNB, i.e. a base station). Small cells refer to pico or femtocells [23]. All the parameters of cells are initially set to their default values, e.g., see [24] for the 3GPP Release-13. According to these settings, the uniformly distributed UEs are connected to one of the cells. Specifically, each UE is assigned to the cell from which it receives the strongest signal. Under this scenario, i.e., after cell selection each macrocell dynamically tunes its antenna-related parameters uniquely according to their UEs and environment. In particular, the antenna tilt angle $\theta_t$, and vertical and horizontal half-power beamwidths, denoted by $\theta_{3dB}$ and $\phi_{3dB}$, of macrocells are jointly tuned, e.g., $\psi_k = (\theta_{t,k}, \theta_{3dB,k}, \phi_{3dB,k})$ for the $k^{th}$ macrocell. Optimizing these parameters considering the environment (or interference) can greatly enhance SINRs. To illustrate, the antenna gain for a particular horizontal and vertical angle is [25]

$$A(\phi, \theta) = -\min \left[-(A^{(h)}(\phi) + A^{(v)}(\theta)), 25 \right] \text{dB}$$  \hspace{1cm} (1)

where

$$A^{(h)}(\phi) = -\min \left[12 \left(\frac{\phi}{\phi_{3dB}}\right)^2, 25 \right] \text{dB}$$  \hspace{1cm} (2)
and

\[ A^{(v)}(\theta) = -\min \left[ 12 \left( \frac{\theta - \theta_t}{\theta_{3dB}} \right)^2, 20 \right] \text{dB}. \]  

In words, an inappropriate antenna setting can lead to a 20 or 25 dB power loss for a UE.

There can be a large gain by dynamically configuring the antenna parameters of each macrocell uniquely according to its UEs and environment. However, it is not easy to find the optimum antenna configuration for a macrocell because of the conflicts among UEs and coupling amongst cell nearby BS settings. For example, one antenna configuration at one BS can increase the data rate of one UE while simultaneously decreasing the data rate of another UE in its own or neighboring cell. Hence, the problem is formulated so as to maximize the weighted sum-rate of users while guaranteeing \(1 - \epsilon_{cov}\) coverage. In this manner, each macrocell optimizes the antenna parameters according to the typical low mobility UEs that use that macrocell most of the time. This is because it is not reasonable to tune the antenna parameters based on the highly mobile UEs, which anyway will only be present in the cell for a short time.

A key point when it comes to optimizing antenna parameters is that the acquired solution has to be utilized for a fairly long period of time, because it is not practical to change the antenna settings very frequently. Thus, the optimization problem is expressed for \(K\) macrocells, each of which has \(U\) number of typical UEs with \(V\) spatial streams as

\[
\arg\max_{\psi=(\psi_1, \ldots, \psi_K)} \mathbb{E} \left[ \sum_{n=1}^{N} \sum_{k=1}^{K} \sum_{u=1}^{U} \sum_{v=1}^{V} \lambda_{k,u,v}[n] \log_2(1 + \rho_{k,u,v}[n]) \right]
\]

subject to

\[
\mathbb{P}[\rho_{k,u,v}[n] < \rho_{min}] < \epsilon_{cov}, \forall n, k, u, v
\]

\[
\theta_{t,k}^{\min} \leq \theta_{t,k} \leq \theta_{t,k}^{\max}, \forall k
\]

\[
\theta_{3dB,k}^{\min} \leq \theta_{3dB,k} \leq \theta_{3dB,k}^{\max}, \forall k
\]

\[
\phi_{3dB,k}^{\min} \leq \phi_{3dB,k} \leq \phi_{3dB,k}^{\max}, \forall k
\]

The first constraint is to ensure \(1 - \epsilon_{cov}\) coverage in which \(\rho_{min}\) is the minimum necessary SINR for a successful transmission, and all the other constraints satisfy the minimum and maximum allowed values.
of the optimization variables. The $\lambda_{k,u,v}[n]$’s are the nonnegative input parameters and can be determined by network operators to prioritize users or control data rate increase in cell-interior or cell-edge. Note that

$$\rho_{k,u,v}[n] = \frac{P_{k,u,v}[n]A_{k,u,v}[n]G_{k,u,v}[n]}{\sum_{j \neq k} P_{j,u,v}[n]A_{j,u,v}[n]G_{j,u,v}[n] + \sigma^2_n}$$

(5)

where $P_{k,u,v}[n]$, $A_{k,u,v}[n]$ and $G_{k,u,v}[n]$ are the transmit power, antenna gain and channel gain respectively. The noise power is denoted as $\sigma^2_n$. Throughout the paper, it is assumed that macrocells transmit at full power.

The primary challenges regarding the optimization problem (4) in addition to it being non-causal due to requiring a decision at current time for the next $N$ time intervals are as follows. This is a non-convex optimization problem and the network-wide global optimum solution can be found by a centralized station with many control signaling only through an exhaustive search or the branch-and-bound algorithm [26]. Clearly, this is not a scalable or feasible approach. More importantly, this optimization is NP-hard due to inter-cell interference [27]. Given these challenges, this paper proposes to approach the solution of (4) in a distributed way by having each macrocell individually using an RL-based algorithm. This also addresses the causality problem. Specifically, a novel practical deep RL algorithm is developed where each macrocell makes autonomous decisions. Although the performance gap between this distributed solution and the network-wide globally optimum solution is very difficult to quantify exactly, it is valuable to find distributed solutions for this complex weighted sum-rate optimization problem as stated in [26] and references therein.

III. A REINFORCEMENT LEARNING FRAMEWORK FOR WEIGHTED SUM-RATE MAXIMIZATION

In a distributed optimization that maximizes the weighted sum-rate of users, the decision given by a macrocell, which optimizes the antenna parameters from its local observations, triggers the future interference values of its UEs because of the interactions among neighboring cells. To capture these interactions, multi-agent RL modeling is necessary. However, multi-agent RL leads to exponentially

$^1$The $\phi, \theta$ terms in antenna gain are omitted for brevity.
increasing dimensions, and infeasible or intractable learning due to the increased number of agents as well as instability [29]. This limits the relevance of multi-agent RL for HetNets, which would have a very large number of agents. Mean field RL was proposed as a remedy to cope with these challenges, which approximates the average effect of all neighboring agents as a single virtual agent [21]. This reduces the RL problem to two agents: the target agent and the virtual agent. Interestingly, this mean field RL approach is inherently applicable to the weighted sum-rate maximization problems, because it is sufficient to adapt to the cumulative effect (i.e. the cumulative interference) of neighboring cells to make the optimum decision for the target cell.

A. Mean Field Reinforcement Learning

Leveraging mean field RL requires associating the interference term in the SINR expression with the cumulative interference of neighboring cells. This means that the interference term in the objective function of (4) can be treated as a random variable

$$\beta_{j,u,v}[n] = \sum_{j \neq k} P_{j,u,v}[n] A_{j,u,v}[n] G_{j,u,v}[n],$$

whose distribution depends on the set of target macrocell events that determine $A_{k,u,v}[n]$. This interpretation can enable us to learn the interference from past experiences with the environment in the context of RL. Then, the centralized optimization in (4) can be relaxed into a distributed optimization, which can be solved by each macrocell individually as

$$\arg \max_{\psi=(\theta_t, \theta_{3dB}, \phi_{3dB})} \mathbb{E} \left[ \sum_{n=1}^{N} \sum_{u=1}^{U} \sum_{v=1}^{V} \lambda_{u,v}[n] \log_2(1 + \rho_{u,v}[n]) \right]$$

subject to

$$\mathbb{P}[\rho_{u,v}[n] < \rho_{\text{min}}] < \epsilon_{\text{cov}}, \forall n, u, v$$

$$\theta_{\text{min}} \leq \theta_t \leq \theta_{\text{max}}$$

$$\theta_{\text{min}} \leq \theta_{3dB} \leq \theta_{\text{max}}$$

$$\phi_{\text{min}} \leq \phi_{3dB} \leq \phi_{\text{max}}$$

where

$$\rho_{u,v}[n] = \frac{P_{u,v}[n] A_{u,v}[n] G_{u,v}[n]}{\beta_{u,v}[n] + \sigma_n^2}.$$
In conventional RL problems, agents learn the environment through observations before choosing an action, and rewards are received in response to actions [28]. To adapt this RL framework to our distributed optimization problem, macrocells are treated as agents, and the HetNet (from a single macrocell point of view) is the environment as depicted in Fig. 1(a). In our problem formulation, we utilize standard UE feedback such as rank indicator (RI), channel quality indicator (CQI), and acknowledgments (ACKs), where RI indicates the number of transmission layers that UE can distinguish, CQI discloses the quality of the channel, and ACKs/NACKs notify which transmission succeeded (if SINR is greater than $\rho_{\text{min}}$, UE sends the ACK signal to the macrocell) or failed.

The aforementioned RL framework is employed to solve (7) by converting it an MDP. However, this is nontrivial and its efficiency depends on the selection of states, actions and rewards. For this purpose, we uniquely define states, actions and craft a reward mechanism. An action is taken for each state that leads to receiving a reward, whose cycle is depicted in Fig. 1(b). This cycle is repeated throughout the training period. Once the optimum action is found according to the expected long term rewards, it remains fixed for a long period of time and would only change if significant sustained changes in the environment were
observed, e.g., if a new BS was added nearby.

B. State Space

The environment can be represented as a state space such that the current state gives the latest status of the environment. Since interference is seen as part of the environment, states are defined as the SINRs of UEs. More specifically, states are defined in terms of quantized SINRs (in dB scale) to reduce the dimensionality of the problem. Macrocells can obtain quantized SINRs from CQIs. Specifically, the $v^{th}$ spatial stream of the $u^{th}$ UE has a quantized SINR $\gamma_{u,v}^{(q)}[n]$ at time period $n$ such that $\gamma_{u,v}[n] = 10 \log_{10}(\rho_{u,v}[n])$ and one period is defined as the necessary time frame to collect the CQIs of all typical UEs\(^2\). The concatenation of all quantized SINR defines the state of the environment in macrocells. In accordance with this definition, the state at the $n^{th}$ period becomes

$$s = [\gamma_{1,1}^{(q)}[n] \cdots \gamma_{U,V}^{(q)}[n]]$$

(9)

where $s \in \mathbb{S}$, and $\mathbb{S}$ is the set of all possible combinations. For a quantized SINR with $M$ bins there are

$$|\mathbb{S}| = M^{N_{str}}$$

(10)

possible environment states, in which $N_{str}$ is the total number of streams.

C. Action Space

Each action corresponds to one possible antenna configuration of a macrocell in terms of the antenna tilt angle $\theta_t$, and vertical and horizontal half-power beamwidths denoted as $\theta_{3dB}$ and $\phi_{3dB}$. Hence, one action $a$ is described as

$$a = (\theta_t, \theta_{3dB}, \phi_{3dB})$$

(11)

where $a \in \mathbb{A}$, and $a$ refers to $\psi$ in (7). The cardinality of $\mathbb{A}$ or the possible number of actions can be expressed as

$$|\mathbb{A}| = |\theta_t||\theta_{3dB}||\phi_{3dB}|.$$ 

(12)

\(^2\)Note that quantized and unquantized SINRs are denoted as $\gamma_{u,v}^{(q)}[n], \gamma_{u,v}[n]$, respectively in dB scale.
All set of actions constitute the action space $A$, which can be treated as having a probability distribution function over actions, i.e., associating each action to a probability, which is also called a policy. Initially, all actions have some probabilities over a state and these probabilities are updated with rewards in the training period.

**D. Rewards**

A reward mechanism has to be crafted in addition to defining problem-specific states and actions. For this purpose, the immediate reward taken one step ahead of the selected action is designed. An immediate reward is received when ACKs come from all the typical UEs; otherwise a large penalty is applied. This is directly related with the objective function and the first constraint of (7). More precisely, suppose that the quantized SINR of the $v^{th}$ stream of the $u^{th}$ UE is $\gamma_{u,v}^{(q)}[n]$. Then, the immediate reward becomes

$$r[n] = \sum_{u=1}^{U} \sum_{v=1}^{V} c_{u,v}[n] f_r(\gamma_{u,v}^{(q)}[n])$$  \hspace{1cm} (13)

where

$$f_r(\gamma_{u,v}^{(q)}[n]) = \begin{cases} 10(\log_{10} 2) \log_2(1 + 10^{\frac{\gamma_{u,v}^{(q)}[n]}{10}}) & \text{if ACK received} \\ \xi & \text{o.w.} \end{cases}$$  \hspace{1cm} (14)

If $\gamma_{u,v}[n]$, which is determined by the chosen action and environment, is greater than $\gamma_{min}$, which is equal to $10\log_{10}(\rho_{min})$, UE sends the ACK signal to the macrocell; otherwise a large penalty is received, which is represented by $\xi$. Then, the expected long-term rewards can be trivially stated in terms of the immediate rewards in (13) for a given state and action as

$$R = \mathbb{E}[r[n] + \alpha r[n + 1] + \alpha^2 r[n + 2] + \cdots | S = s, A = a]$$  \hspace{1cm} (15)

where $\alpha$ is the discount factor that determines the importance of future rewards.


E. Problem Formulation

The defined states and actions in (9), (11) as well as the crafted reward mechanism in (13) leads to the canonical RL problem of

\[
\arg \max_a R \\
\text{subject to } a \in A.
\]

Solving an RL problem refers to finding the optimum action for a given state through rewards, which can be seen as finding the optimum policy. If the state transitions and rewards were given as a priori information, the optimum policy would be readily found with dynamic programming by the agents. However, it is not possible to know these dynamics in our problem. Thus, we use online temporal-difference (TD) learning in which neither state transitions nor rewards are known as a priori information, and the agent acts in the environment and uses its experience to find the optimum policy. Specifically, Q-learning, which is one of the most appropriate methods for TD learning, is employed to solve the problem in (16).

The optimization problem of (7) and (16) give the same solution for quantized SINRs when \( c_{u,v}[n] = \lambda_{u,v}[n]/(\alpha^n 10 \log_{10} 2) \), which can be readily shown as follows. The objective function and the first constraint of (7) are ensured by (13) in (16). Since \( a \) corresponds to \( \psi \), the other constraints of (7) is held by the first constraint of (16). The optimization problem in (7) can be solved through a brute-force search by a genie-aided method, which knows the future interference values for all \( N \) time intervals in response to each antenna setting. Although this is not a realistic solution, the same optimum solution can be obtained by solving (16) via canonical Q-learning if the \( |S||A| \) number of state-action pairs visited many times implying millions of trials [28]. This is obviously also not plausible and practical for wireless networks. Hence, we trade the optimum performance with less online sample complexity by developing a practical Q-learning based algorithm to solve (16) that requires only hundreds of trials using the merits of DL and mean field RL.
A feature-based Q-learning algorithm is now developed, in which the features are obtained with the help of DL and mean field RL. Before going into the details of the proposed algorithm, we first overview the Q-learning to make the notation clear and propose a scheduling for exploration, then design the feature sets for our problem, and finally propose a novel practical algorithm by trading the performance with online sample complexity, which corresponds to the number of trials in online environment that consumes bandwidth and power.

A. Q-learning

The basic idea in Q-learning is to update the quality or q-values of state-action pairs iteratively according to the rewards by following a policy $\pi_n$. More precisely,

$$q_{\pi_n}(s, a) \leftarrow q_{\pi_n}(s, a) + \mu(r[n] + \alpha q_{\pi_n}(s', a') - q_{\pi_n}(s, a))$$  \hspace{1cm} (17)

where $\mu$ is the learning rate, $\alpha$ is the discount factor for future rewards, $s'$ and $a'$ are the next state and action, and $s$ and $a$ are the current state and action. The optimum policy $\pi^*$ for (17) can be found after some iterations as

$$\lim_{n \to T} \pi_n = \pi^*$$  \hspace{1cm} (18)

through $\epsilon$-greedy algorithm where $\epsilon$ provides a balance between exploration and exploitation [28]. In $\epsilon$-greedy algorithm, the maximum q-valued action is chosen for a given state with probability $1 - \epsilon$, or a random action is taken with probability $\epsilon/|A|$ at each step so that

$$\pi_n(s, a) = \begin{cases} \epsilon/|A| + 1 - \epsilon, & \text{if } a^* = \arg \max_a q_{\pi_n}(s, a) \\ \epsilon/|A|, & \text{otherwise} \end{cases}$$  \hspace{1cm} (19)

where $\pi_n(s, a)$ shows the probability of selecting the action $a$ for the state $s$ under the policy $\pi_n$. 
RL problems in wireless networks are much more sensitive to the value of $\epsilon$ than in other fields due to wasting scarce resources such as power and bandwidth, which are consumed in proportion to the number of trials. Due to that, we set

$$\epsilon = 1/k$$

(20)

where $k$ is initially taken as 1 and increases with period $T_\epsilon$, that is $k \to k + 1$, if $n \mod T_\epsilon = 0$.

The key challenge to find the optimum policy for (16) with Q-learning is the large number of state-action pairs. This not only increases the convergence time but also wastes resources due to trial and error mechanism based on feedback. To cope with the large number of state-action pairs, approximating the q-values with a function seems appropriate. The main advantage of this method is that there is no need to see all state-action pairs, which provides faster convergence. The q-values can be approximated in terms of a vector $w$ such that

$$q_{\pi_n}(s, a) \approx \hat{q}(s, a, w)$$

(21)

and once $w$ is trained, q-values can be directly determined for every state and action. Additionally, any function approximator for Q-learning generalizes the learning from seen state-action pairs to unseen pairs, which is based on the intuition that nearby states should behave similarly.

The proposed deep RL algorithm relies on the method of linear function approximation with feature extraction. In this method, the q-values in (17) are approximated as the linear combination of features given by

$$\hat{q}(s, a, w) = x^T w$$

(22)

where $x$ is the feature vector. In linear function approximation, $w$ can be found by defining a cost function that minimizes the mean square error between the actual and approximated q-values as

$$J(w) = \mathbb{E}[(q_{\pi_n}(s, a) - \hat{q}(s, a, w))^2]$$

(23)

where

$$q_{\pi_n}(s, a) = r[n] + \alpha \hat{q}(s', a', w)$$

(24)
due to TD learning. Since (23) is a quadratic function with respect to \( w \), and stochastic gradient descent can remove the expected value, \( w \) can be iteratively updated as

\[
\mathbf{w} \leftarrow \mathbf{w} + \mu(r[n] + \alpha \hat{q}(s', a', \mathbf{w}) - \mathbf{x}^T \mathbf{w}) \mathbf{x}.
\]  

(25)

B. Feature Extraction

The key point in feature-based Q-learning is to craft features, i.e., design \( \mathbf{x} = [x_1, \ldots, x_{U,V}] \). Although it is well-known that each feature should give some information about the impact of the selected action, the overall feature selection process is a nontrivial task. Our approach for feature selection is associated with the immediate rewards in (13) that are used to find the q-values. More precisely, the q-values in (17) are composed of the scaled and summed immediate rewards, and thus approximating them via immediate rewards seems reasonable. Therefore, we define the features in terms of the SINRs in a dB scale as

\[
x_{u,v} = \gamma_{u,v}[0] + \Delta A_{u,v} - \bar{\beta}(s, a),
\]  

(26)

where the first term on the right hand side of (26) denotes the initial quantized SINR, the second term is the difference between the antenna gain due to the selected antenna setting at the current time \( n \) and the initial setting as

\[
\Delta A_{u,v} = A_{u,v}(\phi_n, \theta_n) - A_{u,v}(\phi_{init}, \theta_{init}),
\]  

(27)

and the last term is the mean value of the change in the interference due to taking the current action for the current state, given by

\[
\bar{\beta}(s, a) = \mathbb{E}[\beta(s_n, a_n)]
\]  

(28)

where the expectation is taken over \( n \).

It is apparent that this feature selection requires us to know the immediate impact of the selected antenna gain as well as its effect to the mean interference level before receiving feedback. To overcome this, we propose learning the locations of the UEs by exploiting the correlations among their SINRs with a DL model so as to easily calculate the antenna gain. In what follows, we learn the mean interference value
for the relevant state-action pair from the past behaviors within the framework of mean field RL. These
points are further elaborated next.

1) Learning UE Locations via Deep Learning: The features defined in (26) depend on the locations of
UEs due to $\phi_{u,v}$ and $\theta_{u,v}$, which are not known by macrocells. To leverage these features and propose an
algorithm accordingly, a supervised DNN is designed so as to learn the locations of UEs at macrocells by
exploiting the correlations among their SINRs. For this problem we do not have to learn the UE locations
very accurately, because rewards come as quantized SINRs in the problem formulation implying that the
q-values are expressed in terms of quantized SINRs, and thus we do not need to know the exact SINRs to
approximate them. Hence, the locations are learned in cluster-basis. This means that the coverage area of
a macrocell is divided into clusters, and then which UEs are in which clusters is learned. Our approach is
different than the prior works that find the UEs locations via measuring the multipath characteristics of the
received signal [30], [31] or the received signal strength [32], [33] as the location fingerprint. Specifically,
we exploit a pattern among clusters in terms of SINR to find the UE locations as opposed to using a
database.

Clusters are formed in polar coordinates directly related to the aim of optimizing the antenna parameters.
These clusters for a macrocell are illustrated in Fig. 2(a) when there are $N$ clusters, e.g., it is 20 for this
illustration. Every cluster has a value $i_k$ for $k = 1, 2, \cdots, N$, which shows the average SINRs of UEs in
that cluster assuming that there can be more than one UEs in one cluster. It is highly unlikely that any two
clusters have the same average value because of the HetNet (asymmetrical) topology. The cluster values
vary according to a pattern associated with the environment. The goal is to learn these cluster values by
exploiting this pattern using a supervised DNN. Once cluster values are learned, UEs can be mapped to
the clusters, in particular to the one which has the closest SINR with. This enables to learn the locations
of UEs in cluster-basis.

A supervised fully connected DNN model is designed that is composed of an input layer, two hidden
layers and an output layer as shown in Fig. 2(b). The input layer takes a single cluster value and produces
Fig. 2. Learning the UE locations in cluster-basis, which are formed in polar coordinates, via training a DNN that can exploit the correlations among SINRs determined by the environment: (a) The clusters in polar coordinates for one sector of a macrocell. (b) Fully connected DNN architecture to learn all cluster values at the output from a single (input) cluster value. Note $N = 20$ in both (a) and (b).

all cluster values via the hidden layers. To train this DNN model, all cluster values are measured many times offline, which yields many cluster vectors. In what follows, one specific entry –which can be determined arbitrarily– of all cluster vectors is picked, and used as the input data. More precisely, each input data sample and the corresponding cluster vector constitute one training sample, in which the latter is the labeled data. The proposed DNN model is trained according to this training data set using gradient descent and the backpropagation algorithm. In the online phase, any small cell, whose location is known by a macrocell, measures the SINR of their UEs and reports the average value to the macrocell, which corresponds to that cluster value. Then, all the cluster values are learned via the DNN. Our model hinders the frequent updates of the offline cluster values, since the pattern among clusters changes rarely, due to significant environmental changes. The further details of the model that shows the type and size of each layer as well as the activation functions are depicted in Table I. Here, the rectified linear unit (ReLU) is employed in the hidden layers to capture the non-linear relations.

2) **Learning mean interference values:** Assume that all the states are ordered on a real line according to their indices and taking one action at time $n$ moves the current state to the $s_{n'}$. Then, the next state
| Layer   | Type             | Size  | Activation |
|---------|------------------|-------|------------|
| In      | Inputs           | 1     | -          |
| Hidden-1| Fully Connected  | N/4   | ReLU       |
| Hidden-2| Fully Connected  | N/2   | ReLU       |
| Out     | Outputs          | N     | Linear     |

$s_{n+1}$ is

$$s_{n+1} = s_{n}' + z(s_n, a_n)$$  \hspace{1cm} (29)

where $z(s_n, a_n)$ is a discrete real number determined by the cumulative effects of neighboring cells for the current state and action, and $\beta(s_n, a_n)$ is the quantized SINR counterpart of $z(s_n, a_n)$ number of state change. Since in RL there is a sequence of $(s_n, a_n, r_n, s_{n+1}, a_{n+1}, r_{n+1}, \cdots)$ and we can determine the effect of $a_n$ for state $s_n$ thanks to learning the UEs locations, $z(s_n, a_n)$ and hence $\beta(s_n, a_n)$ can be trivially obtained. With this approach, the expected values of $\beta(s_n, a_n)$ can be learned for each state-action pair.

A key point that directly affects the efficiency is that this process can be done offline with a realistic simulation environment. This hinges on the fact that obtaining some statistical measures of a random process in offline setting yield much more accurate results than instantaneous realizations. To illustrate, if we aimed to obtain the outcome of a single experiment in a real environment with a simulation, this would be much more difficult than obtaining the mean value of this experiment. Additionally, the offline sample complexity (offline number of trials) can be further reduced by fitting a universal function to $\tilde{\beta}(s, a)$ by parameterizing it as $\tilde{\beta}_\theta(s, a)$. Since this machinery is similar to the above DNN structure, it is not repeated here.
C. A Novel Deep Reinforcement Learning Algorithm

The key challenge in utilizing RL-based algorithms for HetNets lies in consuming too much resources in learning the environment. Specifically, the total number of trials, which refers to the overall state-action-reward tuples, must be on the order of $|S||A|$ to learn the environment also known as sample complexity. This much overhead cannot be tolerated in HetNets if all trials are done online. Hence, we propose a novel feature based Q-learning algorithm that allows us to move most trials offline, i.e., in a simulation environment.

The proposed algorithm is composed of two steps, namely offline and online phases. In the first or offline step, a realistic simulation environment is constituted for the macrocells whose own locations as well as the locations of their typical UEs are known. In this step, the expected values of the interference are learned for each state-action pair as explained above. Since the locations of small cells and their behaviors in response to the actions of macrocells are unknown, the first step itself is not sufficient to learn the stochastic environment. Furthermore, there can be some mismatch between the simulation and real environment. These factors explain why we need the online step. In the second or online step, the parameters $w$ are trained as (25) using the learned expected values of the interference in the first step as well as the learned UE locations. With this information, the proposed Q-learning based algorithm starts training as if it can approximately know the expected value of immediate rewards. This significantly reduces the online sample complexity, e.g., from millions to hundreds at the expense of some performance loss, which is quantified in the next section.

The pseudo-code for the proposed algorithm is given in Algorithm 1. After the offline learning phase, in the online phase, the parameters of the DNN model responsible for learning the UE locations are first trained. In what follows, the $w$ is set to zero, and then iteratively updated based on observing state, taking actions and taking rewards as illustrated in Fig. 1(b). At each training iteration actions are selected using the $\epsilon$-greedy policy using the proposed scheduling in (20) according to the features in (26). Once $w$ is trained, the optimum action can be found for all states irrespective of how large the state-action pairs are.
thanks to the function approximation. This apparently alleviates the curse-of-dimensionality problem. In the operational phase, the quantized SINRs of the typical UEs are taken. This gives the input state, and the optimum action is selected for this state.

V. SIMULATIONS AND TRAINING

The proposed deep RL algorithm based on Q-learning is evaluated with extensive simulations. In particular, its performance is compared with the optimum solution, which can be acquired either by solving (7) with a genie-aided method or solving (16) with standard Q-learning that relies on optimum Bellman equation. We prefer the former method to find the optimum solution for a particular environment, because the latter requires millions of samples with careful selection of learning rate for each state-action pair, which can be too time consuming. To have a fair comparison with the proposed algorithm, the genie-aided method is allowed to choose one antenna configuration for a large period of \( N \) time intervals instead of taking the best action for each time interval. The genie-aided method takes this decision at current time knowing the antenna gains for each antenna setting and the responses of neighboring cells for each setting for the future \( N \) time intervals. It is obvious that such kind of solution can only be possible in a simulation environment. To show how the proposed practical deep RL algorithm approach this solution, we have developed an LTE simulator using Python libraries and generated a multi-cell HetNet simulation environment. For this simulation environment the performance of the algorithm is assessed through SciKit and TensorFlow libraries. In this section, the simulation environment is first clarified, then the states and actions for this specific simulation environment are explained, and the performance results are provided at last.

A. Simulation Environment

A two-tier HetNet is considered such that there are macrocells and picocells. All the nodes including the macrocells, picocells and UEs are randomly distributed over a square planar area, which is taken as \( 5 \times 5 \) km\(^2\). Specifically, macrocells and picocells are distributed according to the Poisson Point Process.
Algorithm 1 The training algorithm for the proposed feature based Q-learning

Input: \( s \in S \)

Output: \( a^* \in A \)

**Offline Phase:**

1. Learn \( \bar{\beta}(s,a) \)

**Online Phase:**

2. Train the DNN model in Table I

3. Set \( \mu, \alpha, \gamma_{\text{min}}, \lambda_{u,v}, k, T_{\epsilon} \)

4. Initialize the optimization parameters as \( \theta_1 = 15^\circ, \theta_{3dB} = 10^\circ, \phi_{3dB} = 70^\circ \)

5. Initialize \( w \)

6. Initialize the state \( s \)

7. Choose the action \( a \) for \( s \) using the step 1 with \( \epsilon \)-greedy policy in (26)

8. for \( n = 0 : \) training period do

9. Take the selected action \( a \)

10. Determine \( x_i, \forall i \) in (26)

11. Observe the next state \( s' \)

12. Observe the immediate reward \( r[n] \) using (13)

13. Update \( \epsilon \) according to (20)

14. Choose the next action \( a' \) using the step 1 with \( \epsilon \)-greedy policy in (26)

15. Update \( w \) according to (25)

16. Normalize \( w \) as \( w_i \leftarrow w_i / \sum_i w_i \)

17. Set \( s \leftarrow s' \)

18. Set \( a \leftarrow a' \)

19. end for
with a density of $\lambda_m = 0.25/\text{km}^2$ and $\lambda_p = 2/\text{km}^2$, respectively. There are 400 UEs that are distributed uniformly within the area of interest. The overall simulation environment is illustrated in Fig. 3.

Fig. 3. A two-tier HetNet environment with macrocells and picocells, in which the uniformly distributed UEs are connected to the strongest cell.

UEs are assumed to be equipped with a single antenna, and connected to one of the cells according to the maximum received signal strength, which is mainly determined by the transmission power, antenna gain, path loss and shadow fading. All these parameters for macrocells and picocells are set according to [24]. Specifically, the transmission powers of macrocells are 46 dBm with a maximum antenna gain of 15 dBi. On the other hand, the picocells transmit at a maximum power of 24 dBm using a omni-directional antenna gain with 0 dBi. The path loss model for macrocells is assumed to be $128.1 + 37.6 \log(d_m)$ where $d_m$ is in km scale, whereas it is $38 + 30 \log(d_p)$ for picocells and $d_p$ is in meters. There is log-normal shadow fading in the environment, whose standard deviation is 10 dB for macrocells and 6 dB for picocells.

Without loss of generality, the macrocell of the bottom left base station in Fig. 3 that covers the area between $0^\circ$ and $120^\circ$ is picked up for the performance measurements of the proposed deep RL algorithm. The UEs that are connected to this macrocell according to the maximum received signal strength is zoomed
in Fig. 4 in which distances are on the order of km. There may be other UEs located at the other sectors of this base station, but they are not shown on this plot for the sake of simplicity. There are 5 UEs connected to this macrocell, which are spread almost the entire coverage region. That is, the UEs are not clustered in a specific small sub-area under the coverage region. This is a quite complicated scenario to dynamically tune the antenna parameters according to the UEs and the time-varying environment including the effects of other cells. Hence, it can be interesting to observe the performance of the proposed deep RL algorithm for this scenario.

Fig. 4. The UEs that are connected to the selected macrocell, which are spread over the coverage region between $0^\circ$ and $120^\circ$ with distances from 0.05 km to 0.40 km.

**B. Training**

To train the proposed deep RL algorithm for the macrocell given in Fig. 4, the states and actions of this macrocell have to be clarified. Specifically, the states are defined by uniformly quantizing the SINRs of UEs with $2$ dB resolution, in which the minimum SINR is $0$ dB and the maximum SINR is $12$ dB. This results in $7^5 = 16807$ states for a selected macrocell that has (for example) 5 UEs, wherein $s_0 = [0, 0, 0, 0, 0]$, $s_1 = [0, 0, 0, 0, 2]$, and $s_{16806} = [12, 12, 12, 12, 12]$. The action space, which is composed of the possible antenna configurations, is defined in terms of $\theta_t$, $\theta_{3dB}$, $\phi_{3dB}$ in Table I
Accordingly, $|\theta_t| = 6$, $|\theta_{3dB}| = 5$, $|\phi_{3dB}| = 6$ leading to 180 different actions. The actions are ordered as $a_0 = (0^\circ, 4.4^\circ, 45^\circ), a_1 = (0^\circ, 4.4^\circ, 55^\circ), \ldots, a_6 = (0^\circ, 6.8^\circ, 45^\circ), \ldots, a_{179} = (15^\circ, 13.5^\circ, 85^\circ)$. The algorithm is trained with these definitions of states and actions according to the aforementioned simulation environment for a certain period of time.

### TABLE II

| Parameter                  | Notation | Possible Values |
|----------------------------|----------|-----------------|
| Tilt angle                 | $\theta_t$ | $\theta_t = \{0^\circ, 3^\circ, 6^\circ, 9^\circ, 12^\circ, 15^\circ\}$ |
| Vertical 3dB beamwidth     | $\theta_{3dB}$ | $\theta_{3dB} = \{4.4^\circ, 6.8^\circ, 9.4^\circ, 10^\circ, 13.5^\circ\}$ |
| Horizontal 3dB beamwidth   | $\phi_{3dB}$ | $\phi_{3dB} = \{45^\circ, 55^\circ, 65^\circ, 70^\circ, 75^\circ, 85^\circ\}$ |

After training, the parameters of the algorithm are set, which enables the agent to take an optimum action. The optimum action for a given state lasts for a long period of time until there is a sustained environmental changes that can greatly degrade the performance. If this happens, the algorithm has to be retrained to set the parameters according to the new environment. Note that this retraining does not have to be done from scratch. To illustrate, transfer learning can be employed to obtain the new parameters with minimum number of training samples [34].

### C. Performance

The proposed algorithm performance is assessed for the aforementioned simulation environment with sparse network knowledge just by maximizing the long-term expected rewards according to the designed state and action spaces with moderate number of online training samples. Specifically, 200 online training samples are used to set the parameters of $w$ after the offline training. This is quite reasonably considering the fact that there has to be at least $\kappa \ast 16807 \ast 180$ online samples for conventional Q-learning, where $\kappa$ is some polynomial bound [35]. Without loss of generality, the hyper-parameters are selected as $\mu =$
$0.8, \alpha = 0.9, \gamma_{\text{min}} = 2, \lambda_{u,v} = 1, \forall u,v$. Furthermore, $T_e$ is taken 10 for the designed scheduling in (20), and $w$ is initialized to all zeros before online training.

The performance of the proposed algorithm is compared with the optimum solution, which is obtained via a highly idealistic genie-aided method using the simulation environment. In particular, our aim is to see what percentage of the optimum solution, which is quantified in terms of a SINR gain, can be obtained with the proposed algorithm. For this purpose, we normalize the performance so that 1 refers to perfectly having the optimum performance. The plot that shows the performance in terms of relative variance, which is the ratio of variance to mean of the environment dynamics, is depicted in Fig. 5. There are 2 important takeaways that can be inferred from this plot. First, for low relative variance the proposed algorithm provides near-optimum performance. This makes total sense. The dynamics of the environment in the offline phase becomes exactly the same as for the online environment when the variance is 0, which also makes the relative variance 0, and hence we can achieve the optimum performance. When the variance increases, the mismatch between the offline and online environments increases and the performance decreases due to using a small number of training samples. Second, there is apparently some performance guarantee for the proposed algorithm, because the performance is saturated around 0.6 of the optimum even at very high relative variance. That is, even if there is a performance degradation for increasing variance, the performance does not drop below 60% of the optimum solution. This can be simply quantified as having $0.6\Delta$ dB SINR gain with hundreds of trials instead of getting $\Delta$ dB SINR gain with millions of trials.

A key metric besides the performance in RL-based algorithms for general wireless networks is the compactness of the algorithm. That is, how different states map to actions is important, especially for the case of antenna tuning, in which changing the antenna parameters after training is too costly. Here, what is desired is to map all the states into a small subset of actions to reduce the need for the antenna configuration change when the state of the system alters. The compactness of our algorithm is illustrated in Fig. 6. As can be seen, nearly 80% of the states are mapped to actions whose indices are between 70
Fig. 5. The performance of the proposed algorithm with respect to the optimum solution depending on the relative variance of the environment dynamics. 

and 90. This compactness can be mainly associated with using a function approximation. This implies that most of the time even if the state changes, we do not have to change the antenna configuration. Notice that our algorithm needs the UE locations while using the features. Next, we evaluate how efficiently macrocells can learn the UE locations.

Fig. 6. Mapping the 16,807 states to 180 actions according to the proposed deep RL algorithm based on Q-learning.
D. Learning the UE Locations

The locations of UEs are learned by placing them to the correct clusters as presented in Fig. 2(a). In this direction, the coverage region of the macrocell is divided into 20 virtual clusters with 0.1 km resolution in radius and 30° resolution in angle. This cluster definition only leads to 0.68 dB loss in average antenna gain according to (1) when UEs are located at the edge of the clusters and we consider them at the center. This seems reasonable considering that rewards are received in 2 dB resolution.

To find the locations of UEs, we need to learn the online values of the clusters via the proposed supervised DNN model in Table I. In this experiment, a synthetic dataset is generated to train and test the the proposed DNN model using the simulation environment in Fig. 3, in which the data used for training and test is separated. Once DNN is trained, UEs are assigned to one of these clusters according to their averaged SINRs. The main reason for using the average SINR instead of the instantaneous SINR lies in the fact that average SINR can give a closer value with respect to the corresponding cluster value. Notice that this is only possible for low mobility, which is the case in our optimization problem. By this is meant that if there is a high mobility, the UEs have to be clustered using the instantaneous SINR.

The accuracy of the proposed model is found by comparing the average SINRs of UEs with the ground truth cluster values in the test data according to the minimum distance criterion. Specifically, if the average SINRs of UEs is the closest with the correct cluster in the ground truth, this means success; otherwise an error comes. To better understand the benefit of the proposed DNN model, its performance is compared with the conventional fingerprinting approach, in which the offline cluster values are averaged and then UEs are assigned to one of the clusters according to the minimum distance criterion directly, i.e., without exploiting a pattern. This comparison is provided in Fig. 7 indicating that the proposed model can give a very accurate result as long as a sufficient number of training samples are employed.

VI. Conclusions

In this paper, we aim to dynamically optimize the antenna parameters of macrocells in HetNets in order to maximize the weighted sum-rate of the users in the macrocell. This optimization problem is first turned
into an RL problem via defining states, actions and rewards according to the available control signals in macrocells. Then, a practical algorithm is developed to tackle the large sample complexity and curse-of-dimensionality problems. Specifically, we use DL and a mean field multi-agent RL approach to design a novel and practical deep RL algorithm that needs only hundreds of samples in an online environment. Despite such a small number of online samples, the proposed algorithm can give performance approaching the optimum distributed solution for low relative variance of the environmental dynamics. Even in the case of high relative variance, the proposed algorithm appears to ensure some performance gain regardless of how high the variance goes. As future work, a rigorous analysis to determine the performance gap between the distributed optimum solution and the centralized global optimum solution would be valuable. Additionally, it could be interesting to further enhance the performance of the proposed algorithm in the case of high relative variance. The proposed RL framework and algorithm can also be applied for other parameter optimizations such as transmit power.

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