Enhanced Intercell Interference Coordination in HetNets: Single vs. Multiflow Approach

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Abstract—In this article, we focus on enhanced Inter-Cell Interference Coordination (e-ICIC) techniques in heterogeneous network (HetNet) deployments, whereby macro- and picocells autonomously optimize their downlink transmissions in time and frequency domain and with minimum coordination. This problem is cast as a multi-agent system, in which the macro- and picocells (i.e., agents) learn their optimal transmission strategies (power levels, cell range expansion (CRE) bias and frequency), with minimum information exchange. Specifically, we examine the frequency domain ICIC scenario, and propose a two-level learning procedure in which picocells learn their optimal CRE bias and transmit power allocation, as well as suitable frequency bands for multi-flow transmission. In turn, the macrocell optimizes its downlink transmission by serving its users, while adhering to the picocell interference constraint. To substantiate our theoretical findings, Long Term Evolution Advanced (LTE-A) based system level simulations are carried out. Interestingly, it is shown taht the proposed dynamic multi-flow solution outperforms the single-flow approach. Improvements of 60% in total throughput and 240% in cell-edge UE throughput are obtained in the case of dynamic multi-flow approach with 8 picocells per macrocell.

I. INTRODUCTION

The 3rd Generation Partnership Project (3GPP) is currently discussing small cell enhancements for Long Term Evolution (LTE)-Advanced Release 12 and beyond [1]. Among the highest priorities is carrier aggregation (CA) based enhanced intercell interference coordination (e-ICIC) to support high data rates, improve cell-edge throughput and increase system capacity [2]–[4].

CA is instrumental in heterogeneous network (HetNet) deployments and is currently discussed in 3GPP Release 12 [10], in which multiple carriers enable interference management between different classes of low power nodes. Therein, long-term resource partitioning is carried out by exclusively dedicating carriers to a certain cell (i.e. macro- and picocell). Further interference management approaches include sharing those carriers among cells by assigning distinct component carriers to interfering cells or using power control [6]–[9].

In a HetNet deployment, a multi-carrier network may be configured so that cells of different tiers are allocated only a subset of the DL carriers, and are not allowed to transmit on the remaining downlink (DL) carriers. As a result, low power nodes (e.g., picocells) in the vicinity of a high power node (e.g., macrocell) may use carriers not used by the high-power node to serve their own UEs, without being interfered by the DL transmission from the high power node.

Instead of a strict carrier partitioning among different tiers, it is possible to use all carriers by all cells. For this purpose, two different types of CA are discussed in LTE-Advanced. In the first case, a UE can be served only by one tier at a time. This is known as single-flow CA [1], [11]. In the second case, named multi-flow CA, a UE can be simultaneously served by two (or more) tiers, but on different component carriers (CC). Besides the multi-flow CA technique, another approach to provide an efficient and flexible network performance improvement is to split the control and user plane (C-and U-plane). This concept was introduced and discussed in [12], [13] whereby, the C-plane is provided by the macrocell at low frequency band to maintain good connectivity and mobility. On the other hand, the U-plane is provided by the small cells at higher frequency bands for data transfer. Since small cells are not configured with cell-specific signals and channels, they are named *Phantom Cells* [12].

To further expand the picocell coverage, achieve better load sharing between macro- and picocells and perform time-domain ICIC, 3GPP discussed cell range expansion (CRE) allowing UEs to be served by a cell with weaker received power [7]. In this way, picocells share more network load, in which their coverage is extended by *virtually* increasing the DL received power. This procedure enables better resource reuse and improves system capacity. While there is a sizeable body of literature on time-domain ICIC, beyond [14], little can be found on frequency-domain ICIC and notably multi-flow CA.

In this paper, we propose decentralized strategies for joint cross-tier interference management and cell association procedures in a HetNet scenario in frequency domain. Here, picocell base stations (PBSs) *optimally* learn their CRE bias, CC and power allocation, while satisfying the QoS requirements of their own picocell UEs (PUEs). In turn, the macrocell self-organizes so as to serve its own macrocell UEs (MUEs), while adhering to the picocell interference constraint. Using tools from reinforcement learning (RL) [15], we propose e-ICIC algorithms for both, single- and multi-flow techniques.

This paper is organized as follows. In Section II, the system model is presented. Section III describes the dynamic RL based e-ICIC procedure for single- and multi-flow CA. Section IV, introduces the simulation scenarios and presents the system level simulation results. Finally, conclusions are summarized in Section V.

II. System Model

A network deployment with multiple picocells overlaying a macrocellular network consisting of 3 sectors per macrocell is considered. A HetNet is assumed that consists of a set of $\mathcal{M} = \{1, \ldots, M\}$ macrocells and a set of $\mathcal{P} = \{1, \ldots, P\}$ uniformly positioned picocells per macro sector. We consider that the total bandwidth (BW) is divided into subchannels with bandwidth $\Delta f = 15$ kHz. Orthogonal frequency division multiplexing (OFDM) symbols are grouped into resource blocks (RBs). Both macro- and picocells operate in the same frequency band and have the same amount R of available RBs. All transmitters and receivers are assumed to have a single-antenna. A set of UEs $\mathcal{U} = \{1, \ldots, U\}$ is dropped according to scenario #4b in [16] within the macrocellular network. We denote by $u(m)$ a MUE, while $u(p)$ refers to a PUE. We denote by p_r^m and p_r^p the DL transmit power of MBS m and PBS p in RB r, respectively. The SINR at MUE $u(m)$ allocated in RB r of macrocell m is:

$$\gamma_r^{u(m)} = \frac{p_r^{m(u),\mathrm{M}} g_{m,u,r}^{\mathrm{MM}}}{\underbrace{\sum_{j=1, j \neq m}^{M} p_r^{j(u),\mathrm{M}} g_{j,u,r}^{\mathrm{MM}}}_{I^{\mathrm{M}}} + \underbrace{\sum_{p=1}^{P} p_r^{m(u),\mathrm{P}} g_{p,u,r}^{\mathrm{PM}}}_{I^{\mathrm{P}}} + \sigma^2}. \quad (1)$$

Here, $g_{m,u,r}^{\mathrm{MM}}$ indicates the channel gain between the transmitting MBS m and its MUE u; $g_{j,u,r}^{\mathrm{MM}}$ indicates the link gain between the transmitting MBS j and MUE u in the macrocell at BS m; $g_{l,u,r}^{\mathrm{PM}}$ indicates the link gain between the transmitting PBS l and MUE u of macrocell m; σ^2 is the noise power. I^{M} and I^{P} are the interference terms caused by the MBSs and the PBSs, respectively.

The SINR at PUE $u(p)$ allocated in RB r of picocell p is:

$$\gamma_r^{u(p)} = \frac{p_r^{p(u),\mathrm{P}} g_{p,u,r}^{\mathrm{PP}}}{\underbrace{\sum_{j=1, j \neq p}^{P} p_r^{j(u),\mathrm{P}} g_{j,u,r}^{\mathrm{PP}}}_{I^{\mathrm{P}}} + \underbrace{\sum_{k=1}^{K} p_r^{p(u),\mathrm{M}} g_{m,u,r}^{\mathrm{MP}}}_{I^{\mathrm{M}}} + \sigma^2}. \quad (2)$$

Here $g_{p,u,r}^{\mathrm{PP}}$ indicates the link gain between the transmitting PBS p and its PUE u; $g_{j,u,r}^{\mathrm{PP}}$ indicates the link gain between the transmitting PBS j and PUE u in the picocell at PBS p; $g_{m,u,r}^{\mathrm{MP}}$ indicates the link gain between the transmitting MBS m and PUE u of PBS p.

III. RL Based e-ICIC in Frequency Domain

In this section, we present our self-organizing learning procedures for frequency domain ICIC. Without loss of generality, we consider a system with two CCs. Our approach is based on a dynamic reinforcement learning procedure with an emphasis on single and multi-flow CA, as illustrated in Fig. 1. In single-flow CA, the picocell is the victim cell on both CCs. Therefore, the picocell selects its primary CC to perform CRE and serves ER PUEs on this CC. In turn the macrocell reduces its transmit power on picocell's primary CC. In multi-flow CA, the role of aggressor and victim is dynamically alternated per carrier.
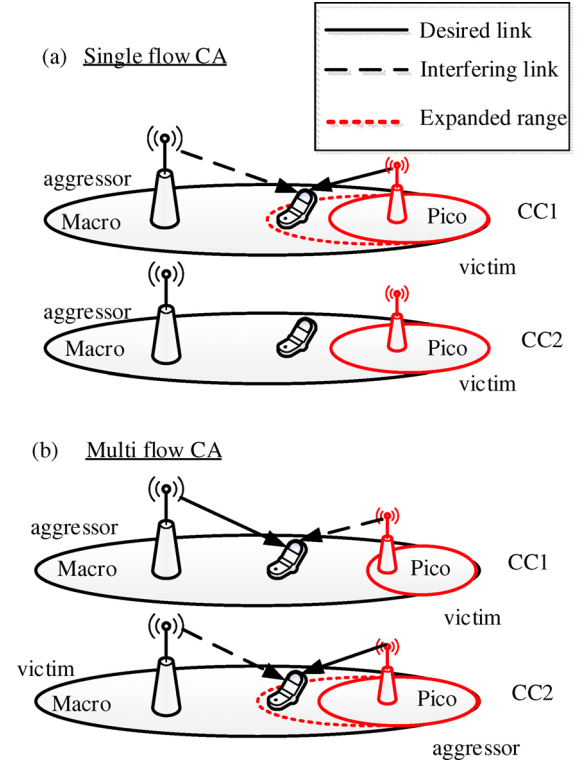

Figure 1: Illustration of a) single-flow CA, where PBS's primary CC is CC2 and b) multi-flow CA with pico CRE on CC1 and macro CRE on CC2.

Multi-flow CA necessitates a smart mechanism in which a UE selects on each CC its serving BS based on the maximum biased received power, while a tier performs range expansion on the CC, on which it is the victim tier.

To model the CA e-ICIC algorithm, we consider the Q-learning formulation, which consists of a set $\mathcal{P} = \{1, \ldots, P\}$ of PBSs and a set $\mathcal{M} = \{1, \ldots, M\}$ of MBSs, denoted as the players/agents. We define a set of states $\mathcal{S}$ and actions $\mathcal{A}$ aiming at finding a policy that minimizes the observed costs over the interaction time of the players. In detail, every player explores its environment, observes its current state s and takes a subsequent action a according to its decision policy $\pi : s \rightarrow a$. For all players, individual Q-tables maintain their knowledge of the environment based on which autonomous decisions are made using local and limited information. The Q-learning has been shown to converge to optimal values in Markov decision process (MDP) environments [15], where the goal of a player is to find an *optimal* policy $\pi^*(s)$ for each state s, that minimizes the cumulative costs over time.

A. Dynamic Frequency-Domain e-ICIC for Single-Flow CA

In contrast to existing frequency domain ICIC solutions where PBSs select one CC and apply a fixed CRE bias, we consider a heterogeneous case where different CRE bias values are used across different CCs in a self-organizing manner. In the proposed dynamic frequency domain e-ICIC algorithm for

Algorithm 1 Dynamic Q-learning based e-ICIC algorithm for single flow CA.

1: **loop**
2:    **for** player p **do**
3:       Select primary CC $C^p \in \{1,2\}$
4:       Select bias value b^p for primary CC C^p
5:       Select power level a_r^p according to $\arg\min_{a\in A^p} Q^p(s,a)$ on both CCs
6:    **end for**
7:    Inform player m about primary CC C^p
8:    **for** player m **do**
9:       Select player p's secondary CC as primary CC C^m
10:      Select power level $a_r^m \in A^m$ according to

$$\arg\min_{a\in A^m} Q^m(s,a)$$

11:    **end for**
12:    Receive an immediate cost c
13:    Observe the next state s'
14:    Update the table entry according to equation (3)
15:    $s = s'$
16: **end loop**

Algorithm 2 Dynamic Q-learning based e-ICIC algorithm for multi flow CA.

1: **loop**
2:    **for** player p **do**
3:       Select primary CC $C^p \in \{1,2\}$
4:       Select bias value b^p for primary CC C^p
5:       Select power level a_r^p according to $\arg\min_{a\in A^p} Q^p(s,a)$ on both CCs
6:    **end for**
7:    Inform player m about primary CC C^p
8:    **for** player m **do**
9:       Select player p's secondary CC as primary CC C^m
10:      Select bias value b^p for primary CC C^p
11:      Select power level $a_r^m \in A^m$ according to $\arg\min_{a\in A^m} Q^m(s,a)$
12:    **end for**
13:    Receive an immediate cost c
14:    Observe the next state s'
15:    Update the table entry according to equation (3)
16:    $s = s'$
17: **end loop**

single-flow CA, we divide the problem into primary CC selection, bias value selection and power allocation sub-problems. Each picocell, as a player, first selects its optimal CC to perform CRE, then the bias value for CRE in the selected CC, after which the transmit power is allocated accordingly. Hence, we consider a three-stage decision making process with a heterogeneous deployment of picocells. Additionally, we consider the MBS as a second type of player. The MBS is informed about the PBS's primary CC via the X2 interface. MBS selects PBS's secondary CC as its primary CC and learns its optimal power allocation strategy[1]. While MBS selects low power levels on its secondary/PBS's primary CC, it selects higher power levels on its primary CC. The rationale behind considering two different power levels the for MBS's primary and secondary CC is to reduce interference on the ER PUEs, which are served on the PBS's primary CC. Formally speaking, the player, state, action and perceived cost associated to the Q-learning procedure are defined as:

- **Player:** PBS p, $\forall 1 \le p \le P$ and MBS m, $\forall 1 \le m \le M$.
- **State:** The state representation of player n at time t in RB r is given by the vector state $\vec{s}_r^n = \{I_r^{u(p)}, I_r^{u(m)}\}$.

$$I_r^{u(n)} = \begin{cases} 0, & \text{if } \Gamma_r^{u(n)} < \Gamma_{\text{target}} - 2 \text{ dB} \\ 1, & \text{if } \Gamma_{\text{target}} - 2 \text{ dB} \le \Gamma_r^{u(n)} \le \Gamma_{\text{target}} + 2 \text{ dB} \\ 2, & \text{otherwise} \end{cases}$$

with $n = \{p,m\}$, $\Gamma_r^{u(n)} = 10\log\left(\gamma_r^{u(n)}\right)$ is the instantaneous SINR of UE u in dB in RB r and $\Gamma_{\text{target}} = 20$ dB is the selected target value.

- **Action:** For player PBS p the action set is defined as, $A^p = \{C_i^p, \beta^p, a_r^p\}_{r\in\{1,...,R\}}$, where $C_{i_{i\in\{1,2\}}}^p$ is the com-

ponent carrier index that can be selected in order to perform CRE on the selected CC, w.o.l.o.g. $\beta^p \in \{0, 6, 12\}$ dB is the bias value for CRE on selected C_i^p of PBS p and a_r^p is the transmit power level of PBS p over a set of RBs $\{1,...,R\}$. Hence, the PBSs will independently learn which CC it performs range expansion, with which bias value and how to optimally perform the power allocation. For player MBS m the action set is defined as, $A^m = \{a_{r,C_i}^m\}_{r\in\{1,...,R\}}$, where a_{r,C_i}^m is the transmit power level of MBS m over a set of RBs $\{1,...,R\}$ on CC C_i. Different power levels are defined for MBS's primary and secondary CC.

- **Cost:** The considered cost in RB r of player n is

$$c_r^n = \begin{cases} 500, & \text{if } P_{\text{tot}}^n > P_{\text{max}} \\ (\Gamma_r^{u(n)} - \Gamma_{\text{target}})^2, & \text{if otherwise} \end{cases}$$

The rationale behind this cost function is that the Q-learning aims to minimize its cost, so that the SINR at UE $u(n)$ is close to a selected target value Γ_{target}. Furthermore, the Q-learning equation is updated as follows:

$$Q_r^n(s,a) \leftarrow (1-\alpha)Q_r^n(s,a) + \alpha[c_r^n + \lambda\min_a Q_r^n(s',a)], \tag{3}$$

where $\alpha = 0.5$ is the player's willingness to learn from its environment and $\lambda = 0.9$ is the discount factor.

In Algorithm 1 we summarize the steps of the dynamic e-ICIC for single-flow CA.

B. Dynamic Frequency-Domain e-ICIC for Multi-Flow CA

In contrast to single-flow CA, in which the MBS is always the aggressor cell, in multi-flow CA either MBS or PBS can be the aggressor cell. This is because both, MBS and PBS, perform CRE on their primary CCs, so that a UE can be served on different CCs by different BSs based on its biased received power. The proposed dynamic e-ICIC algorithm for multi-flow CA is a two-level approach with loose coordination
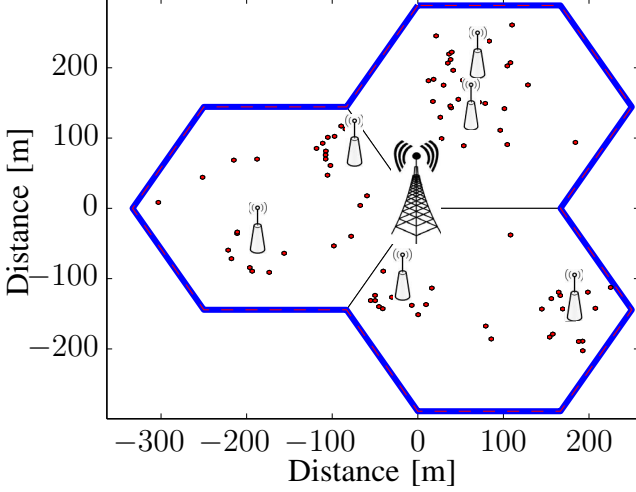
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[1]If a PBS has more than one secondary CC, MBS can either select only one out of PBS's secondary CCs or all of them as its primary CC. In a system with more than one PBS, in which each PBS selects different primary CCs, the MBS selects the PBS's secondary CC with minimum interference.

Figure 2: Simulated HetNet scenario.

Figure 3: CDF of the UE throughput for single and multi flow e-ICIC learning algorithms for 2 picocells per macrocell.

among macro- and picocell tiers, in which the main idea is to automate the network whereby macro- and picocells dynamically learn their optimal bias values and transmit power levels to maximize the overall system performance.

Similar to the single-flow CA learning algorithm, the multi-flow CA based e-ICIC learning algorithm considers PBSs and MBS as players. The main difference to the single-flow CA based e-ICIC learning algorithm, is the action definition, which is redefined as follows:

- **Action:** For player PBS p the action set is defined as, $A^p = \{C_i^p, \beta^p, a_r^p\}_{r \in \{1,...,R\}}$, and for player MBS m the action set is defined as, $A^m = \{C_i^m, \beta^m, a_r^m\}_{r \in \{1,...,R\}}$, where $C_{i_{i \in \{1,2\}}}$ is the component carrier index that can be selected in order to perform CRE on the selected CC, $\beta \in \{0, 6, 12\}$ dB is the bias value for CRE on selected CC C_i and a_r is the transmit power level over a set of RBs $\{1, ..., R\}$. Hence, the PBSs and the MBS will independently learn which CC they perform range expansion, with which bias value and how to optimally perform the power allocation. Since, both the PBSs and the MBS can be aggressor cells, different power levels are considered for CCs on which the BSs perform CRE and regular CCs without CRE.

In addition, we consider the case of one player formulation, in which the PBS is the only player. In this case, PBS carries out the multi flow CA based Q-learning procedure and informs MBS about its primary CC and MBS uses reduced power levels on this CC. However, even if no CRE is performed by the MBS, a UE can be served by both PBS and MBS on different CCs at the same time. This learning algorithm is coined as multi flow (*MF*) *static QL* whereas the two player algorithm is named *MF dynamic QL*. In Algorithm 2 we summarize the steps of the dynamic e-ICIC for multi-flow CA.
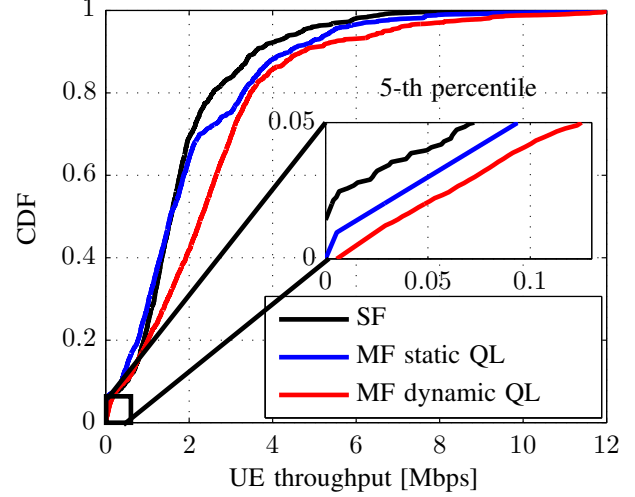
IV. SIMULATION RESULTS

In this section, the proposed solutions are validated in an LTE-A system-level simulator. The scenario used in our system-level simulations is based on configuration #4b in 3GPP as illustrated in Fig. 2 [16]. We consider a macrocell consisting of three sectors and $P = \{2, 4, 8\}$ PBSs per macro sector, which are uniformly distributed within each sector. $U = \{10, 30, 50, 70\}$ UEs are generated within each macro sector from which $U_{\text{hotspot}} = \lceil \frac{2}{3} U/P \rceil$ [2] are randomly and uniformly dropped within a 40 m radius of each PBS. The remaining UEs are uniformly distributed within the macrocellular area. All UEs have an average speed of 3 km/h. A full buffer traffic model is assumed. We consider a proportional fair scheduler. The carrier frequency is 2 GHz and the system bandwidth is 10 MHz, with 5 MHz per CC on both layers.

For the proposed frequency domain e-ICIC algorithms an analysis of the tradeoffs for single flow CA, *SF QL*, and multi flow CA, *MF static QL* and *MF dynamic QL* is provided. Fig. 3 plots the UE throughput for two picocells per macrocell. While the *SF QL* and *MF static QL* algorithms are (on average) very close to each other, the *MF dynamic QL* algorithm shows a performance improvement of 47% on average. A close-up on the cell-edge UE throughput further shows that the multi-flow CA algorithms outperform the single-flow case. This is because in multi-flow CA, cell-edge UEs are served by macro- and picocell at the same time.

In Fig. 4 the sum-rate of the proposed frequency domain e-ICIC algorithms for different number of UEs in case of two picocells per macrocell is depicted. While the *MF dynamic QL* algorithm outperforms the other two algorithms, a trade-off between the *SF QL* and *MF static QL* algorithm can be seen. For more than 40 UEs per macrocell the *MF static QL*

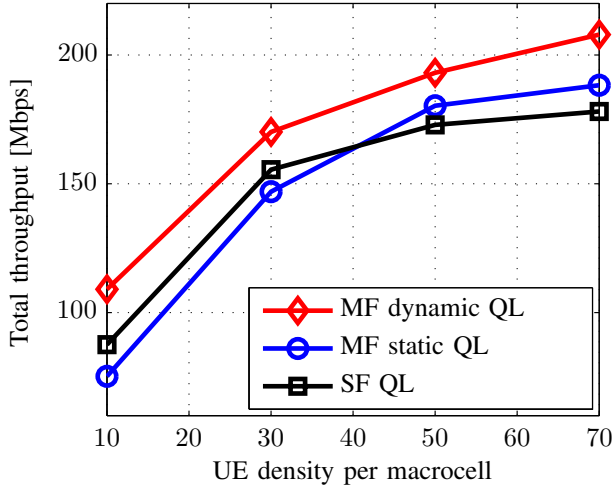[2]The baseline scenario is composed of $P = 2$ PBSs and $U = 30$ UEs per macro sector as proposed in [16].

Figure 4: Total throughput versus the number of UEs for 2 picocells in the frequency domain e-ICIC.

Figure 5: Total throughput and cell edge throughput versus the number of picocells in frequency domain e-ICIC.

algorithm outperforms the single flow case. Hence, the multi flow CA technique does not only protect cell-edge UEs, but also improves the total sum-rate at high loads.

Fig. 5 plots the total network throughput versus the density of small cells, for various single- and multi-flow approaches. Here, the solid curves on the left ordinate showing the total throughput and the dashed curves refer to the right ordinate reflecting the cell-edge UE throughput. It can be observed that the *MF dynamic QL* algorithm outperforms the other algorithms in terms of total throughput, while the *SF QL* algorithm is slightly better than the *MF static QL* algorithm with lesser number of picocells (and vice-versa for large number of picocells). The *SF QL* algorithm exhibits the lowest performance for cell-edge UE throughput. It can be concluded that cell-edge UEs benefit more from multi flow CA than from single flow CA. Interestingly, it can be observed that the *MF static QL* algorithm outperforms the *MF dynamic QL* for larger number of picocells. This is because in the two-player case, the MBS cannot fully adapt to the ICIC strategies of all PBSs in the network, when the density of PBS large.

V. CONCLUSION

In this paper, the problem of cross-tier interference mitigation within a HetNet scenario was studied from a reinforcement learning perspective in the DL. Dynamic Q-learning based algorithms are proposed for frequency domain e-ICIC, in which the macro- and picocells *dynamically* learn their optimal ICIC strategies with loose coordination. We discuss both, single- and mutli-flow techniques. The single and multi-flow CA demonstrate that the dynamic Q-learning based multi-flow approach outperforms the single-flow case. Improvements of 60% for the sum-rate and 240% for the cell-edge UE throughput are obtained in case of multi-flow dynamic Q-learning with 8 picocells per macrocell.
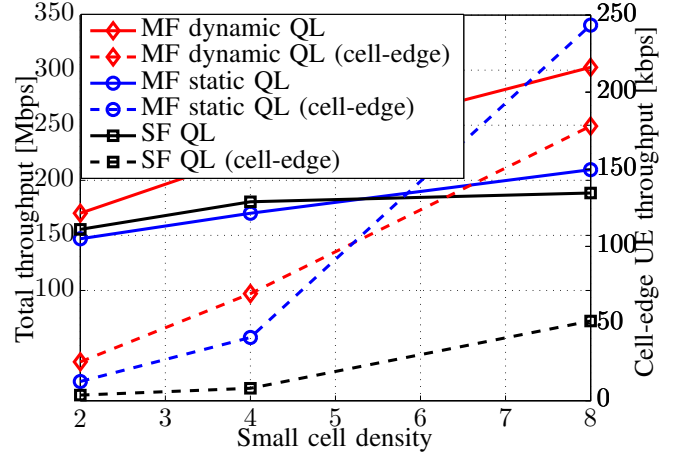
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