ÉNERGIE ET RADIOSCIENCES

Inter-cell Interference Coordination for Backhaul-aware Small Cell DTX

Antonio De Domenico and Dimitri Kténas
CEA LETI, Minatec Campus, antonio.de-domenico@cea.fr; dimitri.ktenas@cea.fr

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Introduction

Europe targets to develop low-carbon and energy efficient technologies through the 2020 roadmap. On the other hand, forecast on ICT industry states an exponential increase in data traffic going through wireless cellular networks. A dense deployment of small cells (SCs) is necessary to satisfy the future traffic requirements, which results in a fast increase of energy consumption with more challenging operational costs for the mobile industry. Hence, the wireless community has a tremendous interest for improving the energy efficiency (EE) at system level and there is a large effort for finding innovative solutions in order to improve the network sustainability. Current activities in the domain of the green wireless networks are mainly focusing on four research axes [1]: the definition of models and tools to evaluate the EE of current Radio Access Network (RAN) and backhaul (BH), the investigation of new adaptive hardware solutions, the design of innovative multi-layer architectures based on dense SCs deployment, and the proposal of flexible management schemes that adapt the network parameters with respect to service load variations.

Discontinuous transmission (cell DTX) is a well-known solution to improve the network EE by dynamically deactivating most of the eNB hardware components when data is absent in a given transmission time interval [2]. Cell DTX jointly combined with buffering and cooperative transmissions can achieve additional gains by exploiting spatial diversity and the energy-delay trade-off [3]. More recently, we have shown that by deploying a SDN-like controller, it is possible to orchestrate both the SCs and the corresponding BH facilities, which have a large impact on the overall network energy consumption [4]. However, in this context, spikes of interference have been observed when two neighboring SCs are activated simultaneously, and large packet error rate losses can be perceived in scenarios characterized by high data rate requirements.

Therefore, in this study, we present an architecture for an Inter-cell Interference Coordination (ICIC) controller to manage backhaul-aware SC DTX in dense heterogeneous wireless networks.

This paper is organized as follows: in the first section the need for joint RAN and backhaul optimization mechanisms is discussed. Afterwards, the proposed ICIC framework for Backhaul-aware cell DTX is presented in Section 2. In Section 3 we introduce the used reinforcement learning mechanisms. In Section 4, we provide more detail on the architecture of the proposed scheme. Finally, in Section 5, we show preliminary results that confirm the advantages of our solution.

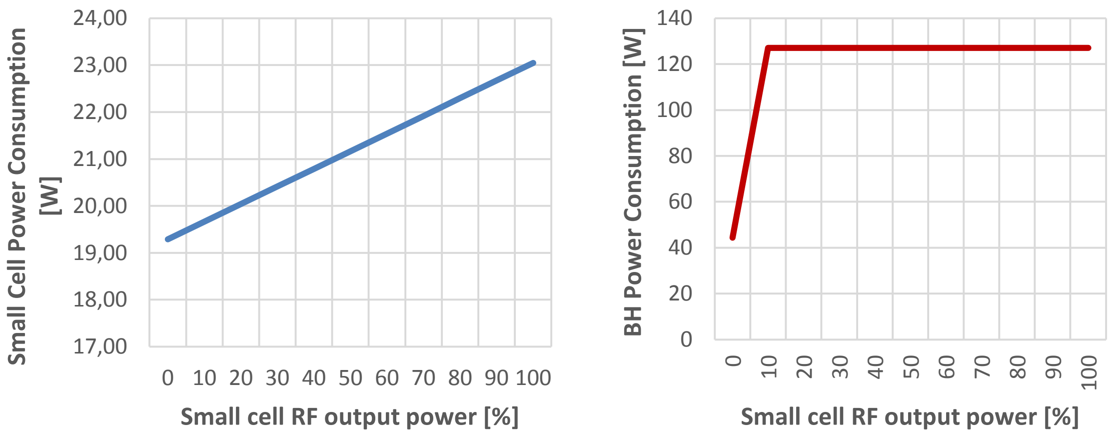

Figure 1. Small-cell and associated microwave BH power consumption [5].

1. Joint RAN/BH Network Optimization

To enable massive SC deployment in 5G networks, wireless BH gains more and more interest from operators.
In fact, SCs may need to be deployed where it is either difficult or too expensive to deploy fixed broadband or line-of-sight-based microwave solutions for BH. Wireless BH is flexible and cost-efficient but cannot provide ultra-broadband and low latency transmission as optical fibre could do. Therefore, the BH becomes a critical element of the infrastructure since the

performance of a conventional RAN architecture is affected by the BH capacity and latency, which highly depends on the selected technology and the topology used for connecting SCs.

The capacity of the transport network largely affects the amount of signalling information that can be exchanged to enable coordination in PHY/MAC functionalities (such as ICIC). Moreover, BH technologies such as DSL or microwave can also introduce bottlenecks to the end-user throughput. Additionally, the latency of the BH affects the CSI/CQI reliability. Therefore, interference management schemes implemented through centralised transmission and reception schemes or coordinated scheduling may not lead to notable gains when the transport network induces high latencies. In the same way, high BH latency increases handover preparation time, which may lead to an increasing handover failure rate.

Finally, Figure 1 compares the power consumption at a SC and at the associated microwave BH with respect to the SC output RF power [5]. It confirms that the SC power consumption cannot be the only aspect considered when assessing or optimizing the network EE. This analysis motivates the definition of future management solutions that consider jointly the impact of the SC and BH on the overall system performance.

2. ICIC framework for Backhaul-aware cell DTX

Figure 2 describes the proposed architecture to achieve reliable communications when implementing backhaul-aware small cell DTX. A network controller is in charge of managing jointly the activity of the BH and SC networks and to dynamically (at frame level) adapt their duty cycle to the momentary cell load and latency requirements of the ongoing services. Additionally, the network controller exploits information on the inter-cell interference to coordinate the activation of neighbouring small cells to improve the Quality of Service (QoS). Such a smart orchestration also reduces the packet retransmissions, which further enhances the system EE.

Finally, in the proposed architecture we deploy a backhaul aggregation node, which receives the data from the core network and stores it in a dedicated buffer. When required, it transfers the data to the SC through a microwave BH link. Thereafter, the activated SC will autonomously manage available radio resources to transmit the received data towards the associated users. It is worth to underline that the BH latency has to be taken into account in order to avoid additional packet loss.

The design of the network controller has multiple challenges: first, due to the stochastic environment (fast fading, interference, and packet arrival), it is not possible to describe the controller as a deterministic optimization problem. Second, due the problem complexity, the controller cannot provide simultaneously the coordination of a large set of small cells. Finally, it is necessary to define how to reliably capture the inter-cell interference impact without requiring continuous activation of the small cells.

To deal with these challenges, we propose a controller based on Fuzzy Q-learning (FQL), which exploits 1) the Q-learning capabilities of finding an optimal controller in a stochastic environment without requiring a priori models on the behaviour of the stochastic variables and 2) the fuzzy logic, which enables to simplify the description of the system state and actions. With FQL the network controller targets to learn, by interacting with the radio environment, the policy that maximizes a multi-objective reward function, which takes into account the SC and BH power consumption and the packet losses due to the service requirements and the inter-cell interference, leading to notable improvements in terms of EE and QoS.

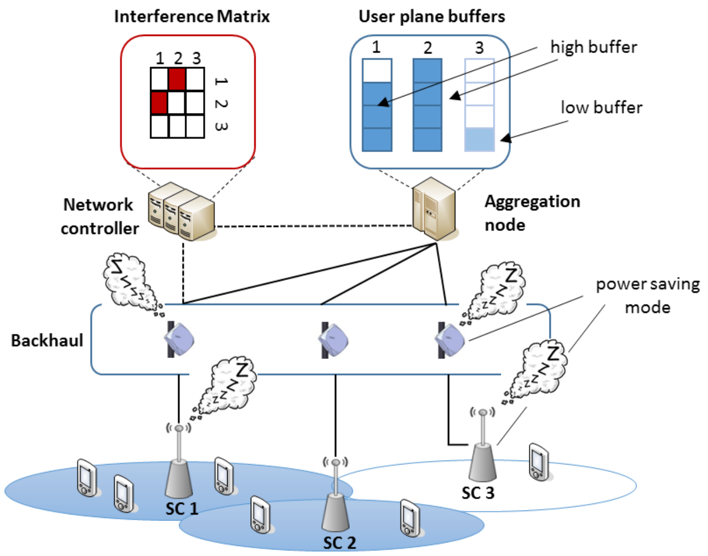

Figure 2. Framework of the proposed ICIC for Backhaul-aware Small Cell DTX.

3. Preliminary on Reinforcement Learning

Machine learning, and more precisely reinforcement learning, represents a powerful tool to operate a whole small cell network in the most efficient way. In fact, the latter acquires the capability to dynamically optimize itself to meet the requirements in terms of Quality of Service (QoS) as well as optimizing the energy consumption. The learning process is achieved through continuous interaction with the environment to enable dynamic reconfiguration when needed. Moreover, when preliminary knowledge of the environment behavior is available or cooperation among small cell is feasible, the learning phase is accelerated.

To solve the problem of learning from interaction, reinforcement learning relies on the agent-environment framework illustrated in Figure 3. The latter is composed of an agent that corresponds to the decision-maker and an environment that represents all the factors that likely influence the decision making.

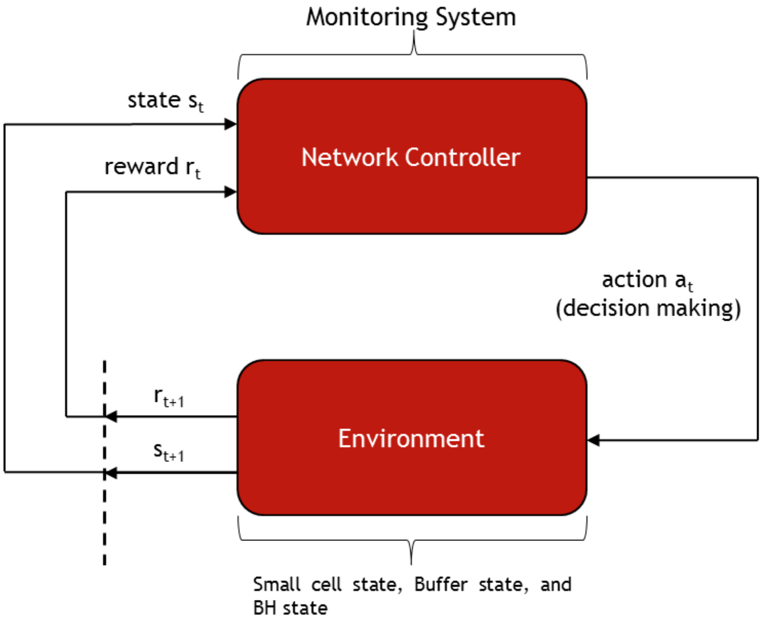

Figure 3. The agent-environment interaction in reinforcement learning [6].

At each time step t, the agent receives a representation of the environment's state $\vec{\mathbf{s}}_t \in S$, where S is the set of possible states, and selects an action $\mathrm{a}_t \in A$ accordingly, where A is the set of possible actions. As a consequence of its action, the agent receives in the next time step a numerical cost $c \in C$, and perceives a new state $\vec{\mathbf{s}}_{t+1}$.
Each pair state-action can be defined by its Q-value $\mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a})$, which represents the expected total discounted cost counting from the state-action pair $(\vec{\mathbf{s}}, \mathrm{a})$, over an infinite time

$$\mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a}) = \mathrm{E}\{\textstyle\sum_{t=0}^{\infty} \gamma^t c(\vec{\mathbf{s}}_t, \mathrm{a}_t) \mid \vec{\mathbf{s}}_0 = \vec{\mathbf{s}}\,, \mathrm{a}_0 = \mathrm{a}\,\} \tag{1}$$

where $\gamma \in [0,1]$ is the discount rate that determines the current value of future costs. In other words, the Q-value estimates in the long-term how good it is for the agent to choose a particular action in a given state.

During the learning process, the agent visits a finite number of states and collects the cost each time an action is taken. The objective is to find an optimal policy, i.e., a state-action mapping that minimizes the expected cumulative cost of the agent when visiting the state space. More specifically, in the Q-learning algorithm, the Q-values are first arbitrarily initialized, and then the optimal Q-values are computed in a recursive method. In each iteration, after the execution of an action a in a state $\vec{\mathbf{s}}$, the agent receives an immediate cost, perceives a new state $\overrightarrow{\mathbf{s}'}$, and updates the value of $\mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a})$ as:

$$\mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a}) \leftarrow \mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a}) + \alpha \cdot \Delta\mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a})$$

$$\Delta\mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a}) = \mathrm{c}(\vec{\mathbf{s}}, \mathrm{a}) + \gamma \min_{a' \in A} \mathrm{Q}\left(\overrightarrow{\mathbf{s}'}, \mathrm{a}'\right) - \mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a})$$

where $\alpha \in [0,1]$ is the learning rate, a' is the next state optimal action, and $\mathrm{Q}\left(\overrightarrow{\mathbf{s}'}, \mathrm{a}'\right)$ is the next state Q-value.
Watkins et al. [7] have proven that if each admissible state-action pair is visited infinitely often and the learning rate is decreased in a suitable way, then the Q-value will converge to an intermediate minimal $\mathrm{Q}^*(\vec{\mathbf{s}}, \mathrm{a})$ with probability 1. Therefore, we can determine the optimal action a^* with respect to the current state such that $\mathrm{Q}^*(\vec{\mathbf{s}}, \mathrm{a})$ is minimal

$$\mathrm{a}^* = \operatorname*{argmin}_{a \in A} \mathrm{Q}^*(\vec{\mathbf{s}}, \mathrm{a}) \tag{2}$$

Finally, the optimal state-action pairs are stored into a look-up-table, which is used for the optimal control of the system.
In general, it is difficult to define appropriate state and action spaces for RL problems. The discretization of the state space has to be rather fine to cover all possibly relevant situations and there can also be a wide variety of actions to choose from. As a consequence, there exists a combinatorial explosion problem when trying to explore all possible actions from all possible states.
To solve dimensionality problems, the fuzzy inference system (FIS) is a suitable candidate. The FIS relies on fuzzy logic in which, unlike standard conditional logic, the truth of any statement is a matter of degree. In other words, the statement "*x* is a member of *X*" is not necessary true of false and the degree to which any fuzzy statement is true is denoted by a value between 0 and 1. Additionally, each object is defined as a linguistic variable, that is, a variable whose values are words or

sentences such as "high" and "low" [8]. Each linguistic variable x_i is associated with a term sets $T(x_i)$ that includes all the fuzzy sets corresponding to the names of the linguistic values of x_i.

Let's consider an input state vector **x**, represented by L fuzzy linguistic variables; then, by denoting the set of state vectors of L linguistic variables as $\bar{S} = \{\bar{\boldsymbol{s}}_1, \dots, \bar{\boldsymbol{s}}_N\}$, and for each state $\bar{\boldsymbol{s}}_j$, the set of actions $A = \{a_1, \dots, a_K\}$, the fuzzy inference rule R_j that associates state vectors with actions have the following form:

$$R_j : \textbf{IF x } \textit{is in } \bar{\boldsymbol{s}}_j \textbf{ THEN } \textit{the action is } a_s.$$

Generally, the FIS relies on a priori or expert knowledge to set the correct control action a_s for a given rule R_j. However, this is not efficient in case of many complex problems.
For this reason, we consider the Fuzzy Q-Learning (FQL) algorithm, which consists on tuning the FIS through Q-Learning. The rules in FQL are defined as follow:

$$\begin{aligned} R_j : \textbf{IF x } \textit{is in } \bar{\boldsymbol{s}}_j \textbf{ THEN } & \textit{action } a_1 \text{ with } q(\bar{\boldsymbol{s}}_j, a_1), \\ \textbf{OR } & \textit{action } a_2 \text{ with } q(\bar{\boldsymbol{s}}_j, a_2), \\ & \dots\dots\dots \\ \textbf{OR } & \textit{action } a_N \text{ with } q(\bar{\boldsymbol{s}}_j, a_N), \end{aligned}$$

where $q(\bar{\boldsymbol{s}}_j, a_i)$ is the fuzzy Q-value of the state-action pair $(\bar{\boldsymbol{s}}_j, a_i), 1 \leq j \leq N, 1 \leq i \leq K$. For more information on FQL, please refer to our previous work [4].

4. Small Cell Controller based on Reinforcement Learning

Let S be a finite set referred to as the small cell *state space* and defined as
$S = Q \times C \times UE \times L \times I$, where Q, C, UE, L, and I are the state sets that describe the buffer state, the cell capacity, the number of active UEs per SC, the backhaul latency, and the Interference level, respectively.
In particular, at each time step, a small cell queue is described through the couple $\boldsymbol{q} = (\boldsymbol{t}, \boldsymbol{n}) \in Q$, where the vectors $\boldsymbol{n}$ and $\boldsymbol{t}$ indicate the size (in bits) and the Time To Live (TTL) of the packets in the queue, respectively. Moreover, $c \in C, u \in UE, d \in D$, and $i \in I$ describe the expected number of successfully tranmitted bits in one transmission time-slot, the number of served UEs, the BH link latency, and the interference level estimate.
Therefore, each small cell state can be represented through the state vector $\boldsymbol{s} = (\boldsymbol{q}, c, u, d, i)$. Note the variable u may vary in a long time scale (seconds or minutes), d is rather static since it depends mainly on the BH technology, and the other variables change in a short time scale (milliseconds).

At each iteration, the network controller selects, according to the small cell state, an action $\mathrm{a}^* \in A = \{0,1\}$, where $\mathrm{a}^* = 0$ corresponds to set the small cell and the associated BH link in *sleep* mode, while $\mathrm{a}^* = 1$ indicates that the small cell is activated and $b = \min\left(c, \sum_{j=1}^{|n|} n_j\right)$ bits are transferred from the aggregation node to the small cell through the wireless BH (see Figure 2).

Since we aim at optimizing the system in terms of the energy efficiency and QoS, we define the cost associated with each state-action pair (see eq. (1)) as

$$\mathrm{c}(\boldsymbol{s}, \mathrm{a}) = P(\boldsymbol{s}, \mathrm{a}) - \beta \cdot \left(b(\boldsymbol{s}, \mathrm{a}) - l(\boldsymbol{s}, \mathrm{a})\right) \quad (3)$$

where $P(\boldsymbol{s}, \mathrm{a})$ describes the sum of the BH and small cell power consumption, β is a weighting factor that prioritizes between the power consumption and the QoS, and $l(\boldsymbol{s}, \mathrm{a})$ indicates the packet lost due to latency constraints and to the perceived interference. For more detail on the power consumption models, please refer to our previous work [4].

We now describe the implementation of the proposed algorithm in a SDN-empowered architecture for 5G wireless networks. Figure 4 shows the Message Sequence Chart (MSC) supporting the proposed Fuzzy Q-Learning Network Controller. Four entities are included in this figure: the network controller is responsible to control the operational states of small cells and BH nodes. Functions such as radio resource management and signal processing are still locally implemented at the SC. This functional split supports the proposed control functions also in environments characterized by high-latency low-capacity BH.
The aggregation node is responsible for aggregation, storing, and forwarding of data towards the associated SCs through the wireless BH according to a first in, first out policy. The FQL Network Controller relies on information concerning both the RAN and the BH network. Here we assume that the SCs periodically signal to the network controller the number of associated UEs, the momentary cell capacity and interference level (step 1 in Figure 4), which is used to decide the correct amount of data that can be backhauled. The BH latency also affects the packet TTL: the higher the latency, the lower the time a packet can remain in the queue before being transmitted. This information is captured at the controller through measurements done by BH nodes (step 2). Based on this feedback and the buffer information received by the aggregation node (step 3), each ms, the controller determine the activity at small cells and associated BH links (step 4). When an activation is required, a control information is sent to BH nodes (step 5) to enable successful data delivery to the activated SCs. Finally, a control signal is sent by the network controller to the aggregation node and the underlying small cells (step

6) According to this message, data related to deactivated SCs is stored at the aggregation node (step 7) while the activated SCs receive the data traffic (step 8) to be forwarded to their active UEs.

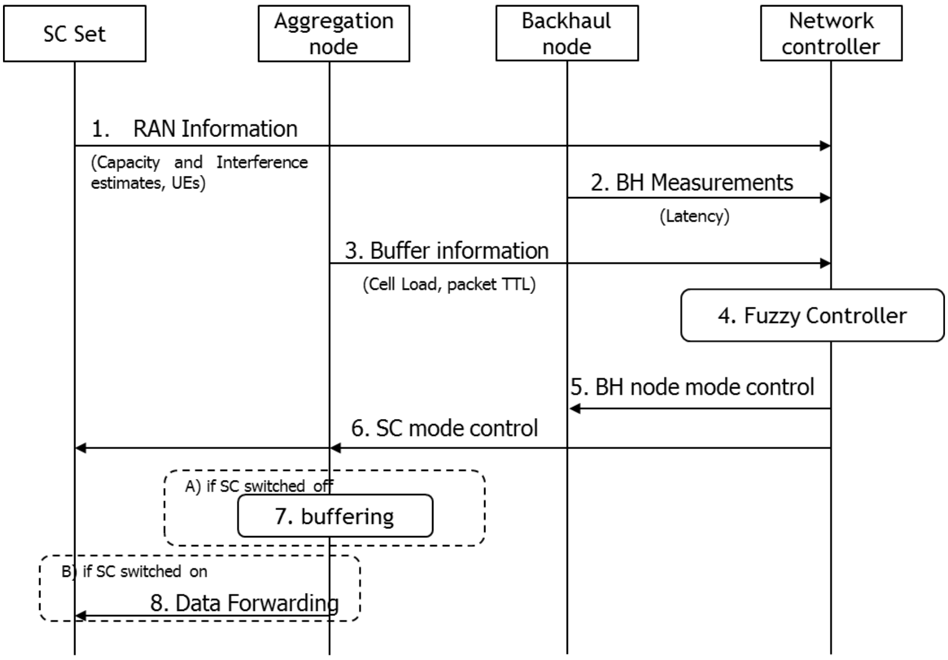

Figure 4. MSC for the proposed ICIC for Backhaul-aware Small Cell DTX

5. Preliminary Results

In this section, we evaluate the proposed FQL small cell controller through numerical results. A system-level simulator is used to mimic a wide area coverage scenario, where SCs are densely deployed (1 small cell per 50m^2). Near Real Time Video (NRTV) traffic (with latency constraints equal to 100 ms) is simulated for the small cell UEs. Results are averaged over 50 independent runs that simulate 10 seconds of network activity. Other key simulation parameters are detailed in TABLE I.

Figure 5 shows preliminary results, in terms of packet error rate, obtained by using the proposed interference-aware DTX controller based on fuzzy Q-learning for different rate requirements. This approach is compared with the solution [4] that does not consider the estimate of the interference in the state space and its impact in the cost function (see eq. (3)). These results confirm that the proposed solution may greatly enhance the energy efficiency of future wireless networks with a limited impact on the end user QoS. Avoiding small cell activation and transmissions in high interference regimes, the proposed solution limit retransmissions, which from one side have a negative effect on the system energy efficiency and on the other side increase the overall number of concurrent (re)transmissions that further increase the overall network interference.

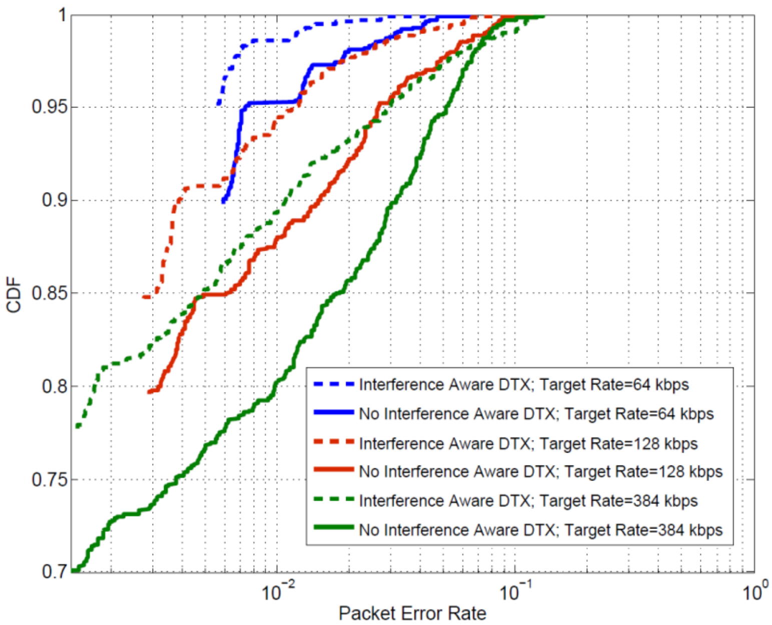

Figure 5. CDF of the Packet Error Rate for different QoS target rate with and without interference awareness mechanism.

TABLE I. Main Simulation Parameters

Parameter	Value	Parameter	Value
Cellular layout	Wide Area Coverage	Carrier frequency	3.5 GHz
SCeNBs density	1/50 m^2	SCeNB Tx power	30 dBmW
UE dropping	5 UEs uniformly distributed per small cell	Shadowing distribution	Log-normal
Min. dist. SC-UE	10 m	SCeNB antenna gain	0 dB
Small cell path loss	ITU Umi (Table B.1.2.1-1 [9])	Thermal noise density	$N0$=-174 dBm/Hz

6. Conclusion

In this paper, we have proposed an architecture based on a reinforcement learning framework to manage the activity of concurrent small cell to limit the network energy consumption without reducing the system QoS. Preliminary numerical results confirm that the proposed Fuzzy Q-Learning policy enables notable performance improvements with respect to the baseline approach. Future studies will focus on finalizing the performance evaluation, modelling the impact of the BH networks, and compare our solution to well-known ICIC schemes.

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