Design and Evaluation of QoS-Aware Radio Resource Allocation for 5G Ultra-Dense Networks

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ABSTRACT

Lately, the heterogeneous deployment of ultra-dense small cells such as femtocells in the coverage region of conventional macrocells, which is referred to as ultra-dense networks (UDNs) is an efficient solution to the problem of network capacity and indoor coverage in the fifth generation (5G) mobile networks. However, the main challenges associated with such solution are severe interference and inadequate quality-of-service (QoS) provisioning, due to the unplanned and the ultra-dense deployment of femtocells. Hence, efficient radio resource allocation (RRA) algorithms with self-organizing capabilities are crucial for interference mitigation and QoS provisioning in each femtocell. The majority of the RRA algorithms in the literature are not efficient for UDNs because they have not effectively addressed the afore-mentioned challenges. Therefore, in this paper, we design a QoS-aware RRA (QRRR) algorithm with consideration for imperfect spectrum sensing as well as users with heterogeneous services. The QRRR problem is formulated as a mixed integer non-linear programming problem and solved using the Lagrangian dual decomposition approach. Then, the performance of the designed QRRR algorithm is evaluated using MATLAB. Finally, the simulation results reveal that the proposed algorithm minimizes interference and satisfies the QoS of different users in terms of throughput with fast convergence when compared with other existing RRA algorithms.

Keywords: 5G, ultra-dense small cells, femtocells, macrocells, interference, QoS.

1. INTRODUCTION

The demands for bandwidth intensive applications by users continue to grow in an unprecedented way as a result of rapid deployment of smart terminals and wearable devices [1], [2]. In fact, it is predicted by Cisco that the compound annual growth rate (CAGR) of mobile data traffic will get to 47% between 2016 and 2021 [3], extending to 49 exabytes per month by 2021. In addition, statistical analysis on wireless usage shows that a significant percentage of data traffic and total voice calls originates from indoors [4]. Moreover, the emerging applications such as machine to device to device (D2D) communications, internet-of-things (IoT), machine (M2M) communications, wearable devices and financial technology [5] are being deployed indoors, where path loss, multipath fading, and shadowing make it very difficult to receive high signal quality and achieve reliable data rate. Recently, it has been revealed that the existing heterogeneous networks (HetNets) consisting of indoor small cells such as femtocells overlaying the conventional macrocells may not be able to satisfy the upcoming traffic demands in the next few years [6],[7]. Therefore, it is imperative for network operators to urgently deliver economical as well as effective solutions in indoor environments. Currently, research activities on the 5G mobile networks are ongoing in both academia and telecommunication companies. The goals of 5G include achieving a thousand-fold capacity increase, very low end-to-end (E2E) latency, ultra-high reliability, massive connectivity and ultra-low energy consumption [5-9]. Ultra-dense network (UDNs) consisting of macrocells and femtocells, which is one of the key techniques to achieve these goals in 5G, is a cost-effective solution for providing network capacity and indoor coverage in the next-generation wireless networks [6],[9-13].

FAPs work in three different access modes namely: close-, open- and hybrid-access modes [14-18]. In the close-access mode, only registered users also called femto users are authorized to access the FAP. These registered users are referred to as closed subscriber group (CSG). All nearby macro users can have access to a device in the open access mode. The hybrid-access mode is considered in this paper, which is the trade-off between the close- and the open- access modes. Higher priority is given to the femto users in CSG but limited resources are available to nearby macro users. It offers differentiable services to the registered femto users and nearby unregistered macro users that are in the coverage area of the FAP.

There are two types of radio resource assignment that can be adopted in the co-existence of macrocells and femtocells, which are dedicated assignment and co-channel assignment. The macrocells and femtocells use different frequency bands in the dedicated assignment. This type of assignment totally avoids interference but not feasible for the ultra-dense deployment of femtocells. In the co-channel assignment, both the macrocells and femtocells share the same frequency bands, this enhances spectral efficiency but severe interference occurs. Since the licensed spectrum (radio resource) is limited and costly, the co-channel assignment is more preferred by wireless network operators, but interference must be coordinated to fully enjoy its benefits. There are two types of co-channel interference, these are cross-tier interference (interference between macrocells and femtocells) and co-tier interference (interference between neighbouring femtocells) [17-19]. Moreover, the unplanned and ultra-dense deployment of femtocells that adopt co-channel resource assignment will lead to interference and throughput degradation considering different users with heterogeneous services, if radio resources are not efficiently allocated. Hence, an efficient radio resource allocation (RRA) algorithm with self-organizing capabilities is crucial for cross-tier and co-tier interference mitigation, as well as quality-of-service (QoS) provisioning.

1.1 Related Work

Self-organizing network is proposed to achieve the potential high-performance gain in UDN [20]. Recently, cognitive radio (CR) technology is integrated into femtocells to enhance the efficiency of spectrum access and mitigate interference in 5G networks. CR-enabled femtocells have capabilities to execute self-organization roles, for example, sensing the radio environment, making decisions based on the sensed information and then intelligently allocating the radio resources [21-24]. There are some previous works in the literature solving the problems of RRA, which are based on cognitive radio technology such as [25], [26]. In [25], the authors propose a dynamic RRA for a cognitive femtocell that adopts hybrid access mode. The algorithm focused on a centralized OFDMA-based UDNs architecture to maximize the throughput of femtocell users. The RRA problem is formulated as a sum-utility maximization problem and solved using the dual decomposition method. The authors in [26] study the subchannel allocation problem for hybrid/underlay cognitive femtocell networks in order to enhance the performance of the networks. The subchannel allocation problem is formulated as a coalition game among users. In these works, perfect spectrum sensing is assumed, which is difficult to achieve as a result of rapid changes in radio environments. In addition, some works have studied joint subchannel and power allocation for cognitive femtocell networks using power control based approach [27],[28], adaptive management based method [29], reinforcement learning based technique [30], and game theory approach [31] but the aspect of user satisfaction needs further investigation. Moreover, some algorithms have considered RRA for user's satisfaction in UDNs [32-34]. In [32], the authors study the downlink RRA to improve user experience in ultra-dense small cell networks based on multi-dimensional heterogeneities with regards to cells, spectrum, and user requirements and propose a concurrent best response iterative algorithm that can ensure the convergence to Nash equilibrium while maximizing the satisfaction of users across the entire network. The aspect of a user-centric QoS-aware interference coordination is investigated in [33] for ultra-dense cellular networks to guarantee desired signal quality for each user by avoiding the main inter-cell interference (ICI) and allocate resource with priorities to each user according to its QoS requirements. In [34], the authors propose a novel scheme for dynamic RRA for a cluster of heavily overlapped small cells to avoid interference. In all these algorithms the aspect of incorporating self-capability based on CR technology has not been considered. Some authors such as in [35], [36] considered imperfect spectrum sensing in cognitive femtocell networks to mitigate interference and enhance throughput of femtocell users. The methods proposed cannot be directly applied to networks with massive femto-cells because the authors assume co-tier interference to be negligible, while the aspect of users with different QoS requirements has not been considered.

1.2 Contributions and Organization

Different from the previous works on RRA, in this paper, we propose a QoS-aware RRA(QRRA)algorithmforultra-densefemtocellnetworksbasedonCRtechnologywithconsideration for users with heterogeneous services during the

downlink transmission. The effects of imperfect spectrum sensing (spectrum sensing error) on the proposed algorithm is also considered.

Our objective is to maximize the overall throughput of all femtocell users in the network by considering the service requirement and location of each user and. A preliminary investigation of this work has been published in [37]. This extended work has considered different users with heterogeneous services in addition to imperfect spectrum sensing in the formulation of QRRA problem. The contributions of this paper are summarized as follows:

- (i) The throughput maximization problem for the joint RRA (subchannel and power) in the downlink transmission of an UDN is formulated as an optimization problem subject to the constraints of maximum transmit power, QoS requirements, fairness, cross-tier and co-tier interference.
- (ii) The formulated optimization problem belongs to the category of mixed integer non-linear programming (MINLP), which is non-deterministic polynomial-time (NP)-hard. However, to find the optimal solution, the Lagrangian dual decomposition (LDD) approach is used to get an optimal solution.
- (iii) Based on the obtained solution, we propose an RRA algorithm termed QoS-based radio resource allocation (QRRA). The algorithm has the capability of mitigating cross-tier and co-tier interference and providing adequate QoS to femtocell users in terms of throughput and fairness in sharing radio resource in 5G wireless networks.
- (iv) Finally, we demonstrate through extensive simulations that the proposed QRRA algorithm converges to a near optimal value, compared with an existing algorithm.

The organizations of this paper are as follows: In Section II, the system model under consideration is discussed. In section III, the QoS-aware RRA problem is formulated for throughput maximization and interference mitigation. Then, section IV presents the proposed algorithm and its computational complexity. Next, the simulation results are discussed in section V. Finally, section VI gives the concluding remarks.

2. METHODOLOGY

In our study, we consider the orthogonal frequency division multiple access (OFDMA) based downlink communication of an UDN comprising a total of N number of cognitive FAPs, which are deployed in the coverage area of a macro base station (MBS) termed M in a random manner as illustrated in Fig. 1. The MBS serves a total number of J macro user equipment (MUEs). The total number of femto user equipment (FUEs) in the network is denoted by U . Each cognitive femtocell adopts a co-channel resource assignment. It is assumed that both the MBS and the cognitive FAPs belong to the same wireless system such as long-term evolution-advanced (LTE-A), where the frame structures of both are the same. The OFDMA system has a total bandwidth of B , which is divided into K subchannels as depicted in Fig. 1. The

Fig. 1. System model showing the deployment of ultra-dense FAPs within the coverage region of an MBS and the division of bandwidth into subchannels.

The channel model for each subchannel consists of frequency flat Rayleigh fading and pathloss. Each FAP performs cooperative spectrum sensing with its affiliated FUEs to determine if a subchannel is occupied or vacant using the energy detection scheme of CR technology. There are U_1 real-time (RT) FUEs with minimum rate requirements as well

as U_2 non-real time (NRT) and best effort (BE) FUEs with a proportional rate constraint φ_U . Let U_A represents the set of RT FUEs, while U_B denotes the set of NRT and BE FUEs. Therefore, $U = U_A \cup U_B$ denotes the set of all FUEs in the network. The signal-to-interference-plus-noise ratio (SINR) $\gamma_{n,u,k}$ of the received signal of a considered FUE $u \in U$ from its serving FAP n on subchannel k according to the Shannon's theorem of capacity can be expressed as:

$$\gamma_{n,u,k} = \frac{p_{n,u,k} h_{n,u,k}^{FF}}{\beta(I_M + I_F + \sigma^2)} \quad (1)$$

where $p_{n,u,k}$ is the required transmit power of a particular FAP n to its attached FUE u on subchannel k . $h_{n,u,k}^{FF}$ is the channel gain between a cognitive FAP n and its associated FUE u on subchannel k . $\beta = \frac{-\ln(5BER)}{1.5}$ is the signal-to-noise ratio(SNR) gap of an uncoded quadrature amplitude modulation (QAM) [36] and BER is a given bit error rate for FUE u attached to an FAP n on subchannel k . $I_M = p_{j,k}^M h_{M,j,u,k}^{MF}$ and $I_F = \sum_{z=1, z \neq n}^N \sum_{w=1}^U p_{z,w,k} h_{n,u,w,k}^{FF}$ are the interference caused by the MBS and the FAPs respectively. $p_{j,k}^M$ is the transmit power of the MBS M to its affiliated MUE j on subchannel k . $h_{M,j,u,k}^{MF}$ is the channel gain between the MBS M and its MUE j to a nearby FUE u on subchannel k . $p_{z,w,k}$ is the undesirable transmit power of another FAP $z \neq n$ to a nearby FUE $w \neq u$ on subchannel k . $h_{n,u,w,k}^{FF}$ represents the channel gain between FAP n serving FUE u to a nearby FUE w on subchannel k . σ^2 represents the additive white Gaussian noise (AWGN) power. The achievable transmission rate (throughput) $R_{n,u,k}$ of an FUE u attached to an FAP n on subchannel k is given as:

$$R_{n,u,k} = W \log_2(1 + \gamma_{n,u,k}), \quad (2)$$

where $W = \frac{B}{K}$ is the bandwidth of each subchannel.

The ultra-dense and unplanned deployment of femtocells in the coverage area of macrocell networks lead to cross-tier and co-tier interference, which occurs as a result of out-of-band (OOB) emissions and spectrum sensing error (imperfect spectrum sensing) [22].

2.1 Out-of-band (OOB) Emissions

The OOB emissions originate from the power leakage in the sidelobes of the orthogonal frequency division multiplexing (OFDM) signals. The sum of OOB interference power introduced into a given subchannel q , which is occupied by MUE j , as a result of FUE u attached to an n th femtocell transmitting on subchannel k with unit transmit power is given as:

$$I_{n,u,k}^{MF} = h_{n,u,j,k}^{MF} \int_{\Delta_k^c - \frac{B}{2}}^{\Delta_k^c + \frac{B}{2}} \varphi_{n,u,k}(f) df, \quad (3)$$

where $I_{n,u,k}^{MF}$ is the cross-tier interference due to OOB emissions, experienced by an FUE u in a cognitive FAP n on subchannel k . $h_{n,u,j,k}^{MF}$ represents the channel gain from a cognitive FAP n serving an FUE u to the MUE j on subchannel k . Δ_k^c denotes the distance between subchannels. $\varphi_{n,u,k}(f) = \frac{1}{T} \left(\frac{\sin \pi(f - f_k^c)T}{\pi(f - f_k^c)T} \right)^2$ represents the power spectrum density (PSD) of the OFDM signal on subchannel k , where T , f and f_k^c are duration of an OFDM symbol, the starting frequency, and the centre frequency of subchannel k respectively. Similarly, an FUE u belonging to an n th femtocell transmitting on subchannel k may cause interference to a nearby FUE w . The co-tier interference caused by this signal is given as:

$$I_{n,u,k}^{FF} = h_{n,u,w,k}^{FF} \int_{\Delta_k^c - \frac{B}{2}}^{\Delta_k^c + \frac{B}{2}} \varphi_{n,u,k}(f) df, \quad (4)$$

where $I_{n,u,k}^{FF}$ is the co-tier interference caused by OOB emissions, experienced by an FUE u in an FAP n on subchannel k . $h_{n,u,w,k}^{FF}$ is the channel gain between an n th FAP and an FUE u to a nearby FUE w .

2.2 Spectrum Sensing Error

The spectrum sensing error arises once a cognitive FAP cannot detect the weak signals, which fall below the spectrum sensing pre-determined values. This makes a cognitive FAP to sense a subchannel as vacant or idle, when it is truly occupied in its actual state. This type of spectrum sensing error is referred to as mis-detection error, which results in co-channel interference. Additionally, a subchannel may be vacant in its actual state while a cognitive FAP senses that it is occupied. This type of error is called false-alarm error, which leads to lost opportunities for transmission of a cognitive FAP. This decreases the overall femto cell network throughput.

Let Q_k represent the hypothesis that a subchannel k is occupied in its actual state, while V_k denotes the hypothesis that the subchannel k is vacant in its actual state. Let $\tilde{Q}_k$ and $\tilde{V}_k$ represent the sensing result of an FAP as being occupied and vacant respectively. Denote K_o and K_v as the sets of occupied and vacant subchannels respectively. Let Pr_k^{md} , Pr_k^{fa} , and Pr_k^j denote the probabilities of mis-detection error, false alarm error and MUE j 's occupation in a subchannel k respectively. There are four possible events for spectrum sensing as summarized in Table I, which are:

- 1) subchannel k is occupied in its actual state, and the decision by an FAP for subchannel k is occupied.
- 2) subchannel k is occupied in its actual state and the decision by an FAP for subchannel k is vacant.
- 3) subchannel k is vacant in its actual state, and the decision by an FAP for subchannel k is occupied.
- 4) subchannel k is vacant in its actual state and the decision by an FAP for subchannel k is vacant.

TABLE I: CONDITIONAL PROBABILITY DETAILS FROM SPECTRUM SENSING

Event	Actual state	Sensing result	Probability Detail
1	Occupied Q_k	Occupied $\tilde{Q}_k$	$Pr_{k,1} = Pr\{(Q_k) (\tilde{Q}_k)\}$
2	Occupied Q_k	Vacant $\tilde{V}_k$	$Pr_{k,2} = Pr\{(Q_k) (\tilde{V}_k)\}$
3	Vacant V_k	Occupied $\tilde{Q}_k$	$Pr_{k,3} = Pr\{(V_k) (\tilde{Q}_k)\}$
4	Vacant V_k	Vacant $\tilde{V}_k$	$Pr_{k,4} = Pr\{(V_k) (\tilde{V}_k)\}$

The first and the fourth events are accurately sensed. The second and the third events are mis-detection and false alarm respectively. The conditional probabilities of all events using Bayes' theorem [22] are detailed as follows:

Event 1: $Pr_{k,1}$ is the probability that subchannel $k \in K_o$ is occupied in its actual state by an MUE j (Q_k) given that the sensing result of an FAP is occupied ($\tilde{Q}_k$), which can be expressed as:

$$Pr_{k,1} = Pr\{(Q_k)|(\tilde{Q}_k)\}, \quad (5)$$

$$Pr_{k,1} = \frac{Pr\{(\tilde{Q}_k)|(Q_k)\}Pr\{(Q_k)\}}{Pr\{(\tilde{Q}_k)|(Q_k)\}Pr\{(Q_k)\} + Pr\{(\tilde{Q}_k)|(V_k)\}Pr\{(V_k)\}}, \quad (6)$$

$$Pr_{k,1} = \frac{(1 - Pr_k^{md})Pr_k^j}{(1 - Pr_k^{md})Pr_k^j + Pr_k^{fa}(1 - Pr_k^j)}, \quad (7)$$

Event 2: $Pr_{k,2}$ is the probability that subchannel $k \in K_v$ is truly occupied by an MUE j (Q_k) given that the sensing result of an FAP is vacant ($\tilde{V}_k$), which can be expressed as:

$$Pr_{k,2} = Pr\{Q_k|(\tilde{V}_k)\}, \quad (8)$$

$$Pr_{k,2} =$$

$$\frac{Pr\{(\tilde{V}_k)|(Q_k)\}Pr\{(Q_k)\}}{Pr\{(\tilde{V}_k)|(Q_k)\}Pr\{(Q_k)\}+Pr\{(\tilde{V}_k)|(V_k)\}Pr\{(V_k)\}}, \quad (9)$$

$$Pr_{k,2} = \frac{Pr_k^{md} Pr_k^j}{Pr_k^{md} Pr_k^j + (1 - Pr_k^{fa})(1 - Pr_k^j)} \quad (10)$$

Event 3: $Pr_{k,3}$ is the probability that subchannel $k \in K_o$ is truly vacant in its actual state, (V_k) given that the sensing result of an FAP is occupied $(\tilde{Q}_k)$, which can be expressed as:

$$Pr_{k,3} = Pr\{(V_k)|(\tilde{Q}_k)\}, \quad (11)$$

$$Pr_{k,3} = \frac{Pr\{(\tilde{Q}_k)|(V_k)\}Pr\{(V_k)\}}{Pr\{(\tilde{Q}_k)|(V_k)\}Pr\{(V_k)\}+Pr\{(\tilde{Q}_k)|(Q_k)\}Pr\{(Q_k)\}}, \quad (12)$$

$$Pr_{k,3} = \frac{Pr_k^{fa}(1 - Pr_k^j)}{Pr_k^{fa}(1 - Pr_k^j) + (1 - Pr_k^{md})Pr_k^j}, \quad (13)$$

Event 4: $Pr_{k,4}$ is the probability that subchannel $k \in K_v$ is truly vacant in its actual state, (V_k) given that the sensing result of an FAP is vacant $(\tilde{V}_k)$, which can be expressed as:

$$Pr_{k,4} = Pr\{(V_k)|(\tilde{V}_k)\}, \quad (14)$$

$$Pr_{k,4} = \frac{Pr\{(\tilde{V}_k)|(V_k)\}Pr\{(V_k)\}}{Pr\{(\tilde{V}_k)|(V_k)\}Pr\{(V_k)\}+Pr\{(\tilde{V}_k)|(Q_k)\}Pr\{(Q_k)\}}, \quad (15)$$

$$Pr_{k,4} = \frac{(1 - Pr_k^{fa})(1 - Pr_k^j)}{(1 - Pr_k^{fa})(1 - Pr_k^j) + Pr_k^{md} Pr_k^j} \quad (16)$$

where $Pr_{k,1}$ and $Pr_{k,2}$ denote interference as a result of OOB emissions and mis-detection error respectively. $Pr_{k,3}$ represents the false-alarm error. $Pr_{k,4}$ represents the accurate sensing level of a cognitive FAP. Therefore, the downlink cross-tier interference $\tilde{I}_{n,u,k}^{MF}$ as a result of OOB emissions and imperfect spectrum sensing on subchannel k can be written as:

$$\tilde{I}_{n,u,k}^{MF} = p_{n,u,k} \left(\underbrace{\sum_{k \in K_o} Pr_{k,1} I_{n,u,k}^{MF} + \sum_{k \in K_v} Pr_{k,2} I_{n,u,k}^{MF}}_{\tilde{I}_{n,u,k}^{MF}} \right). \quad (17)$$

Equation (17) can be re-written as follows:

$$\tilde{I}_{n,u,k}^{MF} = p_{n,u,k} \tilde{I}_{n,u,k}^{MF}, \quad (18)$$

where $\tilde{I}_{n,u,k}^{MF}$ can be referred to as channel gain on subchannel k from n th femtocell to an MUE j . Similarly, when two neighbouring femtocells use the same subchannel, there will be co-tier interference. Therefore, the downlink co-tier interference $\tilde{I}_{n,u,k}^{FF}$ can be expressed as:

$$\tilde{I}_{n,u,k}^{FF} = P_{n,u,k} \left(\underbrace{\sum_{k \in K_o} Pr_{k,1} I_{n,u,k}^{FF} + \sum_{k \in K_v} Pr_{k,2} I_{n,u,k}^{FF}}_{\tilde{I}_{n,u,k}^{FF}} \right). \quad (19)$$

Equation (19) can also be re-written as follows:

$$\tilde{I}_{n,u,k}^{FF} = P_{n,u,k} \tilde{I}_{n,u,k}^{FF}, \quad (20)$$

where $\tilde{I}_{n,u,k}^{FF}$ is the channel gain on subchannel k from n th femtocell to an FUE u to nearby FUE w .

2.3 Problem Formulation

The objective of our work is to maximize the throughput of femtocell networks, while mitigating cross-tier and co-tier interference as well as satisfying the QoS requirements of different users with heterogeneous services. Hence, the QoS-aware RRA problem is formulated in (21) subject to the constraints in C1 - C8 as:

$$\begin{aligned}
 & \max_{\alpha_{n,u,k}, p_{n,u,k}} \sum_{n=1}^N \sum_{u=1}^U \sum_{k=1}^K \alpha_{n,u,k} R_{n,u,k} \quad (21) \\
 & s.t. \text{ C1 : } \sum_{k=1}^K \alpha_{n,u,k} p_{n,u,k} \leq P_{max} \quad \forall n, u \\
 & \text{ C2 : } p_{n,u,k} \geq 0 \quad \forall n, u, k \\
 & \text{ C3 : } \sum_{n=1}^N \sum_{k=1}^K \alpha_{n,u,k} R_{n,u,k} \geq R_u^{min} \quad \forall u \in \mathcal{U}_A \\
 & \text{ C4 : } \frac{\sum_{n=1}^N \sum_{k=1}^K \alpha_{n,u,k} R_{n,u,k}}{\sum_{u \in \mathcal{U}_B} R_{n,u,k}} = \phi_u \quad \forall u \in \mathcal{U}_B \\
 & \text{ C5 : } \sum_{u=1}^U \alpha_{n,u,k} \leq 1 \quad \forall n, k \\
 & \text{ C6 : } \alpha_{n,u,k} \in \{0, 1\} \quad \forall n, u, k \\
 & \text{ C7 : } \sum_{n=1}^N \sum_{u=1}^U \alpha_{n,u,k} p_{n,u,k} \tilde{I}_{n,u,k}^{MF} \leq \tilde{I}_{th,k}^{MF} \quad \forall k \\
 & \text{ C8 : } \sum_{n=1}^N \sum_{u=1}^U \alpha_{n,u,k} p_{n,u,k} \tilde{I}_{n,u,k}^{FF} \leq \tilde{I}_{th,k}^{FF} \quad \forall k.
 \end{aligned}$$

The constraint C1 represents the upper bound on the maximum transmit power P_{max} . The constraint C2 guarantees efficient utilization of power. Also, the constraint C3 is the minimum QoS requirement R_u^{min} for every RT FUE. The constraint in C4 shows the QoS requirements for NRT and BE FUEs. The QoS requirements of RT FUEs are satisfied first. The remaining radio resources are shared based on a proportional rate ϕ_u among NRT and BE FUEs. The constraint C5 makes sure that subchannel k is allocated to at most one FUE at a time. Moreover, the constraint C6 is a subchannel binary decision indicator, $\alpha_{n,u,k} = 1$, if subchannel k is allocated or $\alpha_{n,u,k} = 0$, otherwise. $\alpha_{n,u,k}$ is relaxed in the range $[0,1]$ to indicate the amount of time required by an FAP n to allocate subchannel k to an FUE u according to [22]. The constraints C7 and C8 indicate the maximum cross-tier $\tilde{I}_{th,k}^{MF}$ and co-tier interference $\tilde{I}_{th,k}^{FF}$ allowed on subchannel k respectively. Solving the problem in (21) has a very high computational complexity due to the variables involved. Therefore, we solve the problem using the Lagrangian dual decomposition (LDD) method to get an optimal solution. The method involves three steps: formulation of dual decomposition, solution of dual decomposition and updating the dual variables [38], [39].

2.4 Formulation of Dual Decomposition

The optimization problem in (21) is complex due to the constraint in C4. We can rewrite the C4 according to [40] as follows:

$$R_1 : R_2 : \dots : R_{U_2} = \phi_1 : \phi_2 : \dots : \phi_{U_2} \quad \forall u \in \mathcal{U}_B. \quad (22)$$

Equation (22) can be substituted into C4 in (21). Therefore, the Lagrangian function of (21) can be reformulated as:

$$\begin{aligned}
 L(\eta, \rho, \xi, \lambda, \theta, \mu) = & \left(\sum_{n=1}^N \sum_{u=1}^U \sum_{k=1}^K \alpha_{n,u,k} R_{n,u,k} \right) \\
 & + \sum_{n=1}^N \sum_{u=1}^U \eta_{n,u} \left(P_{max} - \sum_{k=1}^K p_{n,u,k} \right) \\
 & + \sum_{n=1}^N \sum_{u=1}^{U_1} \rho_{n,u} \left(\sum_{k=1}^K \alpha_{n,u,k} R_{n,u,k} - R_u^{min} \right) \\
 & + \sum_{n=1}^N \sum_{u=2}^{U_2} \xi_{n,u} \left(\phi_u \sum_{k=1}^K \alpha_{n,u,k} R_{n,u,k} - \sum_{k=1}^K R_{n,u,k} \right) \\
 & + \sum_{n=1}^N \sum_{k=1}^K \lambda_{n,k} \left(1 - \sum_{u=1}^U \alpha_{n,u,k} \right) \\
 & + \sum_{k=1}^K \theta_k \left(\tilde{I}_{th,k}^{MF} - \sum_{n=1}^N \sum_{u=1}^U \alpha_{n,u,k} p_{n,u,k} \tilde{\Gamma}_{n,u,k}^{MF} \right) \\
 & + \sum_{n=1}^N \sum_{k=1}^K \mu_k \left(\tilde{I}_{th,k}^{FF} - \sum_{n=1}^N \sum_{u=1}^U \alpha_{n,u,k} p_{n,u,k} \tilde{\Gamma}_{n,u,k}^{FF} \right),
 \end{aligned} \tag{23}$$

where $\eta, \rho, \xi, \lambda, \theta$, and μ are the Lagrange multipliers associated with C1, C3, C4, C5, C7 and C8 in (21) respectively. The Karush-Kuhn-Tucker (KKT) conditions according to [41] are applied to the constraints C2 and C6 in problem (21) respectively to yield:

$$\left. \frac{\partial L(\eta, \rho, \xi, \lambda, \theta, \mu)}{\partial p_{n,u,k}} \right|_{p_{n,u,k}=p_{n,u,k}^*} = 0 \tag{24}$$

$$\left. \frac{\partial L(\eta, \rho, \xi, \lambda, \theta, \mu)}{\partial \alpha_{n,u,k}} \right|_{\alpha_{n,u,k}=\alpha_{n,u,k}^*} = 0 \tag{25}$$

where $\alpha_{n,u,k}^*$ is the optimal subchannel allocated to an FUE u in a cognitive FAP non subchannel k , while $p_{n,u,k}^*$ is the corresponding optimal power allocated to the FUE u on subchannel k .

2.5 Solution of Dual Decomposition

The Lagrangian dual problem formulation analogous to the primal problem in (23) is expressed as:

$$\min_{\eta, \rho, \xi, \lambda, \theta, \mu \geq 0} \max_{\alpha_{n,u,k}, p_{n,u,k}} L(\alpha_{n,u,k}, p_{n,u,k}, \eta, \rho, \xi, \lambda, \theta, \mu), \tag{26}$$

where:

$$\max_{\alpha_{n,u,k}, p_{n,u,k}} L(\alpha_{n,u,k}, p_{n,u,k}, \eta, \rho, \xi, \lambda, \theta, \mu) = \vartheta(\eta, \rho, \xi, \lambda, \theta, \mu). \tag{27}$$

The Lagrangian dual problem in (26) is decomposed into two problems: a master and a slave problem. The master problem is the outer minimization in (26). It is re-written as:

$$\min_{\eta, \rho, \xi, \lambda, \theta, \mu} \vartheta(\eta, \rho, \xi, \lambda, \theta, \mu), \quad (28)$$

$$s. t. \eta \geq 0, \rho \geq 0, \xi \geq 0, \lambda \geq 0, \theta \geq 0, \mu \geq 0.$$

The inner maximization in (26) represents the slave problem consisting of $N \times U$ subproblems, which is solved to compute the subchannel and power assignment for the given values of $\eta, \rho, \xi, \lambda, \theta$, and μ . The slave problem defined in (27) can be re-written as:

$$\begin{aligned} \vartheta(\eta, \rho, \xi, \lambda, \theta, \mu) = \\ \max_{\alpha_{n,u,k}, p_{n,u,k}} L(\alpha_{n,u,k}, p_{n,u,k}, \eta, \rho, \xi, \lambda, \theta, \mu) = \\ \max_{\alpha_{n,u,k}, p_{n,u,k}} \left[\sum_{n=1}^N \sum_{k=1}^K L_{n,k}(\alpha_{n,u,k}, p_{n,u,k}, \eta, \rho, \xi, \lambda, \theta, \mu) \right. \\ \left. + \sum_{n=1}^N \sum_{u=1}^U \eta_{n,u} P_{max} - \sum_{n=1}^N \sum_{u=1}^{U_1} \rho_{n,u} R_{n,u,k}^{min} \right. \\ \left. - \sum_{n=1}^N \sum_{u=2}^{U_2} \xi_{n,u} R_{n,u,n} + \sum_{n=1}^N \sum_{k=1}^K \lambda_{n,k} \right. \\ \left. + \sum_{k=1}^K \theta_k \bar{I}_{th,k}^{MF} + \sum_{n=1}^N \sum_{k=1}^K \mu_k \bar{I}_{th,k}^{FF} \right]. \end{aligned} \quad (29)$$

where

$$\begin{aligned} L_{n,k}(\alpha_{n,u,k}, p_{n,u,k}, \eta, \rho, \xi, \lambda, \theta, \mu) = \\ \left[\sum_{u=1}^U \alpha_{n,u,k} R_{n,u,k} - \sum_{u=1}^U \eta_{n,u} p_{n,u,k} \right. \\ \left. + \sum_{n=1}^N \rho_{n,u} \alpha_{n,u,k} R_{n,u,k} \right. \\ \left. + \xi_{n,k} \phi_u \sum_{k=1}^K \alpha_{n,u,k} R_{n,u,k} - \sum_{u=1}^U \alpha_{n,u,k} \right. \\ \left. - \theta_k \sum_{n=1}^N \sum_{u=1}^U \alpha_{n,u,k} p_{n,u,k} \bar{\Gamma}_{n,u,k}^{MF} \right. \\ \left. - \mu_{n,k} \sum_{n=1}^N \sum_{u=1}^U \alpha_{n,u,k} p_{n,u,k} \bar{\Gamma}_{n,u,k}^{FF} \right]. \end{aligned} \quad (30)$$

To obtain $p_{n,u,k}^*$ and $\alpha_{n,u,k}^*$ assigned to an FUE u is a cognitive FAP n on subchannel k for $\forall u \in U_A$ and $\forall u \in U_B$, we take the first-order derivatives of (29) with respect to $p_{n,u,k}$ and apply the KKT condition in (24) to obtain:

$$\frac{\partial L(\eta, \rho, \xi, \lambda, \theta, \mu)}{\partial p_{n,u,k}} = \left(\frac{(1 + \rho_{n,u})\alpha_{n,u,k}h_{n,u,k}^{FF} + (1 + \xi_{n,u})\alpha_{n,u,k}h_{n,u,k}^{FF}}{\ln 2(I_M + I_F + W\sigma^2 + p_{n,u,k}h_{n,u,k}^{FF})} \right) - \left(\sum_{z=1, z \neq n}^N \mu_{z,k}h_{z,u,w,k}^{FF} - \theta_k \bar{\Gamma}_{n,u,k}^{MF} \right) - \eta_{n,u} = 0. \quad (31)$$

Hence, the optimal power $p_{n,u,k}^*$ allocated to an FUE u in an FAP n is given as:

$$p_{n,u,k}^* = \begin{cases} \left[\frac{(1 + \rho_{n,u}) + (1 + \xi_{n,u})}{\ln 2 \left(\eta_{u,n} + \sum_{z=1, z \neq n}^N \mu_{z,k}h_{z,u,w,k}^{FF} + \theta_k \bar{\Gamma}_{n,u,k}^{MF} \right)} - \frac{I_M + I_F + W\sigma^2}{h_{n,u,k}^{FF}} \right]^+, & \text{if } \alpha_{n,u,k}^* = 1 \\ 0, & \text{otherwise} \end{cases} \quad (32)$$

where $[x]^+ = \max [0, x]$

Also, to obtain the optimal subchannel $\alpha_{n,u,k}^*$ allocated to an FUE u in a cognitive FAP n , we take the first-order derivatives of (29) with respect to $p_{n,u,k}$ and apply the KKT condition in (25), this yields

$$\frac{\partial L(\eta, \rho, \xi, \lambda, \theta, \mu)}{\partial \alpha_{n,u,k}} = \left((1 + \rho_{n,u}) + (1 + \xi_{n,u}) \right) \cdot \log 2 \left(1 + \frac{p_{n,u,k}^* h_{n,u,k}^{FF}}{\ln 2(I_M + I_F + W\sigma^2)} \right) - \frac{1}{\ln 2} \left(\frac{p_{n,u,k}^* h_{n,u,k}^{FF}}{p_{n,u,k}^* h_{n,u,k}^{FF} + I_M + I_F + W\sigma^2} \right) - \lambda_{n,k} = 0. \quad (33)$$

Denote

$$\psi = \left((1 + \rho_{n,u}) + (1 + \xi_{n,u}) \right) \cdot \log 2 \left(1 + \frac{p_{n,u,k}^* h_{n,u,k}^{FF}}{\ln 2(I_M + I_F + W\sigma^2)} \right) - \frac{1}{\ln 2} \left(\frac{p_{n,u,k}^* h_{n,u,k}^{FF}}{p_{n,u,k}^* h_{n,u,k}^{FF} + I_M + I_F + W\sigma^2} \right) \quad (34)$$

Hence, the optimal subchannel $\alpha_{n,u,k}^*$ allocated to an FUE u^* in a cognitive FAP n is given as:

$$\alpha_{n,u^*,k^*}^* = \begin{cases} 1, & \text{if } (n, u^*, k^*) = \arg \max \psi \\ 0, & \text{otherwise} \end{cases} \quad (35)$$

2.6 Updating the Dual Variables

The subgradient method is used to solve the master problem in (28) to update the Lagrangian multipliers $\eta, \rho, \xi, \theta, \mu$. The subgradient method is used to design a step-size sequences $s_t^{(\ell)}$, as:

$$\eta_{n,u}^{(\ell+1)} = \left[\eta_{n,u}^{(\ell)} - s_1^{(\ell)} \left(P_{max} - \sum_{k=1}^K \alpha_{n,u,k} p_{n,u,k} \right) \right]^+, \quad \forall n, u \quad (36)$$

$$\rho_{n,u}^{(\ell+1)} = \left[\rho_{n,u}^{(\ell)} - s_2^{(\ell)} \left(\alpha_{n,u,k} R_{n,u,k} - R_{n,u,k}^{min} \right) \right]^+, \quad \forall n, u \quad (37)$$

$$\xi_{n,u}^{(\ell+1)} = \left[\xi_{n,u}^{(\ell)} - s_3^{(\ell)} \left(\phi_u \sum_{k=1}^K \alpha_{n,u,k} R_{n,u,k} - \sum_{k=1}^K R_{n,u,n} \right) \right]^+ \quad (38)$$

$$\theta_k^{(\ell+1)} = \left[\theta_k^{(\ell)} - s_4^{(\ell)} \left(I_{th}^{MF} - \sum_{n=1}^N \sum_{u=1}^U \alpha_{n,u,k} p_{n,u,k} h_{n,u,k}^{MF} \right) \right]^+ \quad (39)$$

$$\mu_{n,k}^{(\ell+1)} = \left[\mu_{n,k}^{(\ell)} - s_5^{(\ell)} \left(I_{th}^{FF} - \sum_{n=1}^N \sum_{u=1}^U \alpha_{n,u,k} p_{n,u,k} h_{n,u,k}^{FF} \right) \right]^+ \quad (40)$$

where: $s_1^{(\ell)}, s_2^{(\ell)}, s_3^{(\ell)}, s_4^{(\ell)}$ and $s_5^{(\ell)}$ are the iteration step sizes. ℓ is the iteration number. The Lagrangian multipliers $\eta, \rho, \xi, \theta, \mu$, are updated until convergence. The termination condition is $\ell = \ell^{max}$ as long as $s_t^{(\ell)}$ is chosen to be sufficiently small [41]. The step sizes are required to satisfy the following conditions [22]

$$\sum_{\ell=1}^{\infty} s_t^{(\ell)} = \infty, \quad \lim_{\ell \rightarrow \infty} s_t^{(\ell)} = 0, \quad \forall t \in \{1, 2, \dots, 5\} \quad (41)$$

2.7 Computational Complexity Analysis

QRRA requires the complexity of $O(NK \log_2 U)$ to determine the Lagrange multiplier vectors for different users. Its complexity is $O(A^{max})$ in each iteration to find the optimal subchannel $\alpha_{n,u,k}^*$ and the corresponding optimal power $p_{n,u,k}^*$ in each FAP, where A^{max} is the maximum number of iterations for QRRA to converge. The worst-case complexity of finding a suitable subchannel is $O(NU \log_2 K)$. Therefore, the overall complexity of QRRA algorithm is $O(NK \log_2 U) + O(A^{max}) + O(NU \log_2 K) = O(NUK A^{max} (\log_2 U + \log_2 K))$, compared with the exhaustive search, which has the exponential complexity of $O(NU)K$ as shown in Table II

TABLE II: COMPUTATIONAL COMPLEXITY COMPARISON

Algorithm	Computational Complexity
Exhaustive Search	$O(NU)K$
QRRA	$O(NUK A^{max} (\log_2 U + \log_2 K))$

The procedure for the QRRA is summarized in Algorithm 1:

Algorithm 1: QRRA

1: Initialization:

set $\alpha_{n,u,k}$, η , ρ , ξ , λ , θ , μ , and $p_{n,u,k} = 0$

2: Each FAP measures $h_{n,u,k}^{FF}$ and calculates $\gamma_{n,u,k}$ according to (1)

3: Each FAP allocates equal power to each subchannel $\forall n, u, k$

4: Every FAP performs spectrum sensing on each

subchannel to determine $\mathcal{K}_o$ and $\mathcal{K}_v$

5: **while** $\bar{I}_{n,u,k}^{MF} \leq \bar{I}_{th}^{MF}$ and $\bar{I}_{n,u,k}^{FF} \leq \bar{I}_{th}^{FF}$ **do**

6: (a) find $u^* \in \mathcal{U}_A$ if $R_{u^*} \leq R_{u^*}^{min}$ **then**

7: (b) compute $\alpha_{n,u^*,k}^* = 1, \mathcal{K}_v = \mathcal{K}_v - k^*$ using (35)

8: (c) compute corresponding $p_{n,u^*,k}^* \forall u \in \mathcal{U}_A$ using (32)

9: **end if**

10: **end while**

11: **while** $\mathcal{K}_v \neq \emptyset$ **do**

12: (a) find $u^* \in \mathcal{U}_B$ if $\frac{R_{u^*}}{\sigma_{u^*}} \leq R_{u^*}$ **then**

13: (b) compute $\alpha_{n,u^*,k}^* = 1, \mathcal{K}_v = \mathcal{K}_v - k^*$

14: (c) compute corresponding $p_{n,u^*,k}^*$ for $u^* \in \mathcal{U}_B$

15: **end if**

16: **end while**

17: **for** $k = 1$ to K ,

18: Each FAP updates

(a) $\alpha_{n,u^*,k}^*$, and $p_{n,u,k}^*$ according to (35), and (32) respectively

19: (b) η, ρ, ξ , and μ according to (36)-(38), (40)

20: **end for**

21: The MBS updates θ using (39) and broadcasts the updated value to all FAPs via a common control channel.

22: $\ell = \ell + 1$

23: **Repeat**

24: until convergence $\ell = \ell^{max}$

3. SIMULATION RESULTS AND DISCUSSIONS

3.1 Simulation Environment

The simulation parameters are set according to the 3GPP evolved universal terrestrial radio access standard [42]. The radius of the MBS is set to 500m while that of the FAP is set to 10m. The path loss model from an FAP PL_{FAP} to an FUE/MUE is expressed as [36], [42]:

$$PL_{FAP} = 38.46 + 20\log_{10}R + 0.7d + \Xi L_{iw} + 18.3\Psi\left(\frac{\Xi+2}{\Xi+1}\right)^{-0.46}, \quad (42)$$

where d is the distance between the FAP and inside FUE, while R is the distance between the FAP and outside FUE. L_{ow} is the penetration loss in the internal walls of a building, which is 5dB. Ξ and Ψ represent the number of penetrated walls

and floors respectively. The path loss model from an MBS PL_{MBS} to MUE/FUE is expressed as [36],[42]:

$$PL_{MBS} = 15.3 + 37.6 \log_{10} R + L_{ow}, \quad (43)$$

where R is the distance between the MBS and the MUE/FUE. L_{ow} is the penetration loss in the external walls of a building, which is 10dB. The standard deviation of log-normal shadowing between MBS and UEs is 8dB, while that between an FAP and UEs is 10dB. The fast fading channel gains are modelled as independent and identically distributed (i.i.d.) random variables with unit mean. The probabilities of MUE's occupation, mis-detection and false-alarm are uniformly distributed over [0,1], [0.01, 0.05], and [0.05, 0.1] respectively. We assume K_p and K_o to be $\{1, 3, \dots, 99\}$ and $\{2, 4, \dots, 100\}$ respectively. The carrier frequency is set to 2.6GHz. The channel bandwidth is set to 20 MHz and it is divided into 100 subchannels. The thermal noise density is -174dBm/Hz. The maximum transmit power for an MBS is 46dBm. We set the lower bound and the upper bound on the number of subchannel assignment for all UEs to 2 and 20 per femtocell respectively

3.2 Performance Evaluation

The proposed QRR algorithm is compared with the existing algorithm in [25] termed dynamic spectrum allocation for hybrid access (DSA-HA) in which the spectrum sensing error is not considered. In the algorithm, the MBS in the network assigns a portion of subchannels to the FAP to serve its associated users while the FAP allocates the subchannels and power to maximize its network utility. We included our power allocation method (lines 17-20) of QRR to the DSA-HA for fair comparison and referred to it as modified DSA-HA (MDSA-HA). In Fig. 2, we investigate the effect of varying the P_{max} and the interference thresholds $I_{th} = I_{th,k}^{MF} = I_{th,k}^{FF}$ on the femtocell network downlink throughput. We set $R_u^{min} = 8 \text{ bits/s/Hz}$, $P_{max} = 30 \text{ dBm}$ and $I_{th} = I_{th,k}^{MF} = I_{th,k}^{FF} = 20 \text{ dBm}$ as the benchmark case.

We notice that higher values of interference threshold and transmit power give higher throughput. Moreover, the values of the achievable network throughputs are different for different P_{max} and I_{th} . This is due to different channel conditions, the location of users and the requested application of users. Therefore, we carefully selected the P_{max} and I_{th} that will limit the amount of cross-tier and co-tier interference introduced into a subchannel. It was observed from the figure that the achieved total throughput for $P_{max} = 5 \text{ dBm}$ to 30 dBm are marginally close to each other when I_{th} are set to 5 dBm and 10 dBm . Also, there is an appreciable increase in the overall throughput when P_{max} is increased from 15 dBm to 20 dBm as compared to when the values of P_{max} is increased from 10 dBm to 15 dBm . Also, we notice a steady increase in the total throughput from $P_{max} = 15 \text{ dBm}$ to 30 dBm . This shows that the proposed algorithm achieves stable power saving for interference mitigation especially in the event of the ultra-dense deployment of femtocells, which will involve much higher total transmit power.

Fig. 2. Total throughput versus interference threshold.

Fig. 3 shows the performance of QRR for different number of UEs from 1 to 8 in a femtocell. We set $R_u^{min} = 8 \text{ bits/s/Hz}$, and vary the values of P_{max} , $I_{th,k}^{MF}$ and $I_{th,k}^{FF}$. It was observed from the plot that there is an appreciable increase in the total throughput when $P_{max} = 30 \text{ dBm}$ and $I_{th,k}^{MF} = I_{th,k}^{FF} = 20 \text{ dBm}$. This is because more users in the

network increases the total capacity of the network thereby increases the total throughput of the network. Moreover, this indicates that there is a high level of satisfaction for all users in the network

Fig. 4 shows the amount of cross-tier interference power introduced into the MUE's subchannel for different values of FAP transmit power from 0dBm to 40dBm with 8 users in a femtocell for QRRA and MDSA-HA. QRRA considers the case of spectrum sensing error while MDSA-HA has considered perfect spectrum sensing. We notice that when we considered the mis-detection and false alarm errors in the proposed QRRA, the cross-tier interference is kept below 20dBm as the transmit power reaches 30dBm. This shows that the cross-tier interference suffered by an MUE in a subchannel can be limited to a particular pre-determined value. Also, this will enhance the performance of the network and will not cause any throughput degradation whereas in MDSA-HA, the cross-tier interference for different values of transmit power keeps increasing. This shows that each MUE in a subchannel will experience more interference and this will result in lower achievable throughput.

Fig.3. Total Throughput versus Number of FUEs for different values of maximum transmit power and interference thresholds.

Fig. 4. The amount of cross-tier interference power introduced into the MUE's subchannel versus different values of FAP transmit power for QRRA and MDSA-HA.

Fig. 5 shows the effect of co-tier interference power to the neighboring FUEs on each subchannel against different values of FAP transmit power for QRRA and MDSA-HA. For QRRA, it was observed that the co-tier interference is kept below 20dBm as the transmit power reaches 20dBm, whereas for MDSA-HA, the interference power keeps increasing. This shows that if the issue of spectrum sensing error is not considered the neighboring cognitive femtocell users can experience more co-tier interference from each other and hence, this will result in low throughput performance in the network.

Fig. 6 shows the overall throughput of all the cognitive FAPs when the P_{max} increases from 5dBm to 25dBm for different ratios of FUEs with heterogeneous services. We set $I_{th} = I_{th,k}^{MF} = I_{th,k}^{FF} = 20\text{dBm}$. We consider $U_1 = 5$ RT FUEs and $U_2 = 3$ NRT and BE FUEs in each FAPs. The minimum rate is fixed to 8bits/s/Hz for all RT FUEs. We also vary the rate of NRT and BE FUEs between 2bits/s/Hz and 8bits/s/Hz.

We notice that the overall throughput increases when the ratio of U_1/U_2 increases. This means that the network performance is better with more RT FUEs in the network. We also observe that the overall throughput of all FUEs increases gradually with increase in transmit power from 20dBm to 25dBm. This is because the interference threshold is kept below a particular level in each subchannel.

Fig. 5. The co-tier interference introduces to each neighbouring FUE on each subchannel against different values of transmit power for QRRA and MDSA-HA.

Fig. 6. Overall throughput versus maximum power constraint.

Fig.7 shows the overall throughput of our proposed algorithm with different value of maximum power and interference thresholds. We considered different numbers of FAPs from 10 to 100. It is clear from the figure that the overall throughput is gradually decreasing as more FAPs are being added. The rate at which the overall throughput is decreasing is not significant from 60 to 100 FAPs. This is because mis-detection and false-alarm error have been considered, if more FAPs are deployed in the network, the cross-tier and co-tier interference as well as transmit power will be limited to a particular predetermined value. This has greatly improved the performance of the overall network throughput.

Fig. 8 shows the average throughput of the proposed QRRA with consideration for spectrum sensing error and perfect spectrum sensing as well as the modified DSA-HA (MDSA-HA). The maximum transmit power is set to 25dBm. We considered different sizes of FAPs from 10 to 100. We set $I_{th}^{MF} = I_{th,k}^{FF} = 20dBm$ for all subchannel. The proposed algorithm with consideration for spectrum sensing error outperforms the proposed algorithm without consideration for spectrum sensing error and the modified existing algorithm (MDSA-HA). This is because QRRA ensures that the QoS requirements of RT FUEs are satisfied first and also all the threshold values are carefully selected to achieve high throughput. This enhances the achieved throughput by 14.7% and 32.5% as compared to QRRA without consideration for spectrum sensing error and MDSA- HA respectively. We also noticed that there is a little decrease in the average throughput as we add more FAPs, which shows a high level of satisfaction for all UEs in the network. From the graph, we can conclude that our proposed algorithm has potential for ultra-dense small cell deployments in 5G networks.

Fig. 7. Overall network throughput versus number of FAPs..

Fig. 8. Average throughput versus number of FAPs

Fig. 9 shows the convergence of QRRA and MDSA-HA in terms of average network throughput versus the number of iterations for a minimum of 80 FAPs and maximum of 100 FAPs. We set $R_u^{min} = 8bits/s/Hz$ for all RT

FUEs, $P_{max} = 20dBm$, $I_{th} = I_{th,k}^{MF} = I_{th,k}^{FF} = 20dBm$ for all subchannels. The location of the considered 8 UEs per femtocell were kept fixed throughout each simulation. It is observed from the figure that, the average throughput for 80 FAPs is higher than that of 100 FAPs, this is because co-tier interference increases with the number of femto-cells. Additionally, the difference in the performance of the achievable average throughput for 80 and 100 FAPs is not much, this is because co-tier interference has been suppressed to a particular pre-determined value. Also, from the graph, we can observe that the proposed algorithm outperforms the MDSA-HA in terms of the average throughput, this is because the QRRR has taken into consideration the spectrum sensing error and given priority to users with real time application, this has improved the network throughput performance. Moreover, QRRR takes only ten iterations to converge to an optimal point. This reveals that the proposed algorithm is appropriate for real implementation of ultra-dense deployment of FAPs.

Fig. 9. Convergence of different algorithms.

Fig. 10. The effect of different number of FAPs on the running time for QRRR and MDSA-HA.

Fig. 10 shows the running time of the proposed QRRR and MDSA-HA for different number of FAPs from 10 to 100. The computer used for running the simulation is Intel(R) Core (TM) i7-7500U CPU with 8GB RAM. We set $R_u^{min} =$

8bits/s/Hz for all RT FUEs, $P_{max} = 20\text{dBm}$, $I_{th} = I_{th,k}^{MF} = I_{th,k}^{FF} = 20\text{dBm}$ for all subchannels. It is observed that QRRRA takes 30s to run when 100FAPs are considered in the simulation while it took the exhaustive search method 70s to run the simulation. As shown in the figure, there is significant reduction in the running time improvement as compared with the exhaustive search method.

4. CONCLUSION

In this paper, we have proposed a QoS-aware radio resource allocation (QRRRA) algorithm for a cognitive femtocell to reduce cross-tier and co-tier interference and to ensure adequate QoS provisioning for different users with heterogeneous services. We have considered imperfect spectrum sensing in our problem formulation. The QRRRA problem is a mixed integer non-linear programming (MINLP), which is very hard to solve. The problem has been reformulated and solved using the method of Lagrangian dual decomposition. The performance of the proposed algorithm has been evaluated using MATLAB and compared with an existing algorithm. The simulation results show that the effectiveness of the proposed algorithm, which can greatly reduce cross-tier and co-tier interference in the overall network and improve the overall network throughput in the downlink transmission. The proposed algorithm can be implemented in femtocell for ultra-dense small cell deployments in 5G networks.

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