Spectrum Sharing Efficiency Analysis in Rule Regulated Networks with Decentralized Occupation Control

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Abstract— Decentralized dynamic spectrum allocation (DSA) that exploit adaptive antenna array interference mitigation (IM) diversity at the receiver, is studied for interference-limited environments with high level of frequency reuse. The system consists of base stations (BSs) that can optimize uplink frequency allocation to their user equipments (UEs) to minimize impact of interference on the useful signal, assuming no control over band allocation of other BSs sharing the same bands. To this end, “good neighbor” (GN) rules allow effective trade off between the equilibrium and transient decentralized DSA behavior if the performance targets are adequate to the interference scenario. In this paper, we extend the GN rules by including a spectrum occupation control that allows adaptive selection of the performance targets corresponding to the potentially “interference free” DSA; define the semi-analytic absorbing Markov chain model for the GN DSA with occupation control and study the convergence properties including effects of possible breaks of the GN rules; and for higher-dimension networks, develop the simplified search GN algorithms with occupation and power control (PC) and demonstrate their efficiency by means of simulations in the scenario with unlimited requested network occupation.

Keywords— Spectrum sharing, interference mitigation, “selfish” and “good neighbor” rules, performance target, occupation control, absorbing Markov chain.

I. INTRODUCTION

A current vision of spectrum utilization for future networks is that shared spectrum may be a useful supplement for 5G, [1], [2]. Dynamic spectrum allocation is an effective way to increase the spectral efficiency of wireless communications systems [3]. DSA can be implemented using explicit coordination between access nodes, which is mostly suitable for cellular systems in a licensed spectrum. In license-exempt spectrum sharing scenarios, frequency band allocation has to be performed by each provider in a decentralized autonomous way. In the most challenging interference-limited scenario joint DSA and multiple-antenna interference mitigation may be beneficial [4].

We consider DSA in the uplink interference-limited wireless systems consisting of multiple-antenna BSs and single-antenna UEs. These systems are not synchronized and they do not explicitly cooperate in a centralized fashion. Frequency channels in this case can be formed in an OFDM-based system with guard bands for preventing energy leakage between channels allocated to unsynchronized users [5] or in spectrally efficient multicarrier systems by using frequency selective filters for adjacent channels [6].

Since the number of available bands may be less than

the total number of UEs, some of these UEs belonging to the same or different sub-systems have to share the same frequency. Antenna array interference mitigation based DSA at each sub-system should allocate bands to its users, such that the propagation channels from the users to their BSs are as orthogonal as possible to the active interference propagation channels. In [7], this type of allocation is referred to as an antenna array interference mitigation diversity and a rule regulated “good neighbor” approach to decentralized DSA is proposed that may be treated as useful, despite the fact that convergence with probability one to certain stationary (equilibrium) points cannot be guaranteed. Instead, a trade off between the equilibrium and transient performance is introduced, which allows a controllable convergence behavior without any explicit communications between spectrum sharing sub-systems. The main GN idea is that the controllable performance targets should be reached with minimum changes to the current band allocations. Efficiency of the GN DSA is established in [7] subject to the performance targets for the given number of BS antennas that are adequate to the existing interference scenario. Particularly, two scenarios were considered: the number of degrees of freedom (antenna elements) is high enough and not high enough for rejection of all interference sources at all BSs in the network. In both scenarios, the desired convergence and equilibrium properties of the GN algorithms are demonstrated for the corresponding performance targets. In the realistic spectrum sharing scenarios, the UE numbers for different BSs with the given number of antennas may be variable leading to unpredicted interference environment for different sub-systems. In the case of the performance targets mismatch, the overall network performance may be significantly degraded. For example, if the performance targets are defined under the wrong assumption that the overall number of degrees of freedom for interference mitigation allows a possibility of “interference free” DSA, then the GN algorithms actually become selfish with the corresponding negative consequences. This means that to give a practical perspective for the GN algorithms, an adaptive selection of the reliable performance targets needs to be addressed.

Generally, for the requested network occupation (number of UEs) per spectrum sharing sub-system and the available resources (number of bands and BS antennas) a potential performance should be estimated leading to the re-

quired performance targets, which may be a difficult problem. To simplify this situation, we note that any limited resources cannot serve an arbitrary network occupation. Thus, it is natural to assume availability of other recourses, e.g. groups of bands or radio access networks (RAT), and possibility of user reallocation between them leading to a possible difference between the requested and achievable network occupation. Thus, we consider application of the GN DSA to the specific spectrum sharing problem, where the performance targets can be easily established. Particularly, we extend the GN rules by means of including a spectrum occupation control that allows adaptive selection of the performance targets corresponding to the potentially “interference free” DSA. The idea is that spectrum sharing sub-systems should agree to change the number of their UEs following some fairness restrictions including a possibility to relocate some of the UEs to be served by other resources in the “no room” case for the considered group of available bands. Then, the performance targets can be locally estimated at each sensing interval assuming the noise limited scenario.

The usual assumption for rule regulated networks is that all spectrum sharing nodes follow some rules, for example, the GN ones. Generally, a problem of incentives and regulations is under discussion in cognitive radio literature, e.g., [8]. For that, it is critically important to study consequences of possible undesirable behavior of some spectrum sharing nodes. We investigate the effects of possible breaks of the GN and occupation control rules by means the absorbing Markov chain analysis.

The contribution of this paper compared to [7] is three-fold: 1) we extend the GN rules by including a spectrum occupation control that allows adaptive selection of the performance targets corresponding to the potentially “interference free” DSA; 2) we define the semi-analytic (analytic for the given channel realizations) absorbing Markov chain model for the GN DSA with occupation control and study the convergence properties including effects of possible breaks of the GN and occupation control rules; 3) for higher-dimension networks, we develop the simplified search GN algorithms with occupation and power control and demonstrate their efficiency by means of simulations in the scenario with unlimited requested network occupation.

II. SYSTEM MODEL AND PROBLEM FORMULATION

The considered system consists of N independent sub-systems containing base stations BS_n , $n = 1, \dots, N$ and corresponding UE_{nm} , $m = 1, \dots, M_n$, where M_n is the number of users per BS_n .

Users transmit data to their BSs using one of F , possibly $F < M_n$, available frequency channels (bands). BSs have full information and control of their own users. In particular, they can estimate propagation channels in all the available bands and assign the individual bands and transmit powers to their own users. Assuming for simplicity narrowband channels, the signal received by an antenna

array of K elements can be expressed as follows:

$$\mathbf{x}_{nf}(t) = \sum_{l=1}^N \sum_{m=1}^{M_l} \delta_{fd_{lm}} q_{lm} \mathbf{h}_{d_{lm}mln} s_{lm}(t) + \mathbf{z}_{nf}(t), \quad (1)$$

where $\mathbf{x}_{nf}(t)$ is a $K \times 1$ vector of the signal received at BS_n in the f th band at the t th time instant, $\mathbf{h}_{fmln}$ is a $K \times 1$ vector of the propagation channel to BS_n in the f th band from the m th user of the l th sub-system including $l = n$ for the local UEs, $s_{nm}(t)$ is the transmitted signal from UE_{nm} with $\text{E}\{|s_{nm}(t)|^2\} = 1$ and q_{nm}^2 is its constrained power $\sum_{m=1}^{M_n} q_{nm}^2 = M_n$, $n = 1, \dots, N$, $\mathbf{z}_{nf}(t)$ is a $K \times 1$ vector of AWGN with $\text{E}\{\mathbf{z}_{nf}(t)\mathbf{z}_{nf}(t)^*\} = \sigma^2 \mathbf{I}_K$, d_{nm} is the nm th element of the $1 \times M_n$ decision vector $\mathbf{d}_n$ denoting the frequency band assigned to UE_{nm} , $\text{E}\{\cdot\}$ is the averaging operator, $(\cdot)^*$ is the conjugate transpose operation, $\mathbf{I}_K$ is the $K \times K$ unity matrix, and δ_{ij} is the Kronecker function.

We use the data rate for the weakest link in the system as a global performance metric

$$\gamma = \min_{m=1, \dots, M_n, n=1, \dots, N} \log_2 [1 + \text{SINR}(\mathbf{d}_n)], \quad (2)$$

where $\text{SINR}(\mathbf{d}_n) = q_{nm}^2 \mathbf{h}_{d_{nm}mnn}^* \mathbf{R}_{d_{nm}n}^{-1} \mathbf{h}_{d_{nm}mnn}$ is the SINR at the output of the optimal spatial filter for the nm th user and

$$\mathbf{R}_{d_{nm}n} = \tilde{\mathbf{R}}_{d_{nm}n} + \sum_{p=1}^{M_n} \delta_{d_{nm}f_p} q_{np}^2 \mathbf{h}_{f_p pnn} \mathbf{h}_{f_p pnn}^* \quad (3)$$

$$\tilde{\mathbf{R}}_{d_{nm}n} = \sum_{i=1, i \neq n}^N \sum_{j=1}^{M_i} \delta_{d_{nm}d_{ij}} q_{nm}^2 \mathbf{h}_{d_{ij}jin} \mathbf{h}_{d_{ij}jin}^* + \sigma^2 \mathbf{I}_K \quad (4)$$

where $\mathbf{R}_{d_{nm}n}$ is a $K \times K$ interference plus noise covariance matrix at BS_n in the band occupied by UE_{nm} including the inter system interference plus noise matrix $\tilde{\mathbf{R}}_{d_{nm}n}$, which can be estimated at the sensing interval with the paused local UEs, and the intra system interference matrix if a number of local UEs occupy the same band as UE_{nm} for $F < M_n$.

The power constraint of $\sum_{m=1}^{M_n} q_{nm}^2 = M_n$ is assumed for all spectrum sharing nodes $n = 1, \dots, N$. For the beginning, in Sections 3 and 4, we assume the constant power $q_{nm}^2 = 1$ for all users in the system. Power control in the IM-based DSA with occupation control is addressed in Section 5.

In this paper, we concentrate on the DSA related issues rather than on the non-stationary propagation channels and finite amount of data effects. Thus, the propagation channels for all users in all bands are assumed to be stationary and known at the corresponding BS, i.e., BS_n knows $\mathbf{h}_{fmln}$ for $f = 1, \dots, F$, $m = 1, \dots, M_n$. Space-time spectrum sensing is required at each BS_n to obtain the interference plus noise covariance matrices (4) in all the available bands. To this end, we assume that all users can transmit data signals or stay silent during data and sensing intervals controlled by the BSs. Furthermore, focusing on the spectrum sharing effects, we assume that the sensing

intervals for different sub-systems do not overlap and the interference covariance matrices are estimated accurately during corresponding sensing intervals. This system model is a generalization of the model in [7] regarding variable M_n for different BS_{*n*} and arbitrary F and M_n relations including $F < M_n$.

The problem is to develop and analyze decentralized algorithms for selection of the number of locally served users M_n and decision vectors $\mathbf{d}_n$ that with high probability achieve reasonably fast convergence to acceptable/controllable equilibrium performance (2) for the given number of bands F and BS receive antennas K .

III. IM-BASED DSA WITH OCCUPATION CONTROL

A general IM-based DSA structure at BS_{*n*} for UE_{*nm*}, $m = 1, \dots, M_n$ can be summarized as follows:

Sensing interval:

- Step 1: Estimate $\tilde{\mathbf{R}}_{fn}$, $\mathbf{h}_{f_mnn}$, $f = 1, \dots, F$;
- Step 2: Find $\mathbf{d}_n$ and assign bands d_{nm} to UE_{*nm*};

Data interval:

- UE_{*nm*} transmit data in the bands assigned in $\mathbf{d}_n$;
- BS_{*n*} receives data with the optimal weight vectors

$$\mathbf{w}_{nm} = \frac{\mathbf{R}_{d_{nm}n}^{-1} \mathbf{h}_{d_{nm}nn}}{\mathbf{h}_{d_{nm}nn}^* \mathbf{R}_{d_{nm}n}^{-1} \mathbf{h}_{d_{nm}nn}}. \quad (5)$$

A basic element of this algorithm is a local search of the band assignment $\mathbf{d}_n$. Following [7] we consider the conventional “selfish” and two versions of the GN search for some given performance target γ_{0n} :

- Selfish (MaxMin):

$$\mathbf{d}_n^{\text{MaxMin}} = \arg \max_{m \in \mathcal{M}_n, f_m \in \mathcal{F}} \min_{f_m \in \mathcal{F}} \mathbf{h}_{f_mnn}^* \mathbf{R}_{f_mnn}^{-1} \mathbf{h}_{f_mnn}. \quad (6)$$

- GN-MaxMin:

$$\mathbf{d}_n^{\text{GN-MaxMin}} = \begin{cases} \mathbf{d}_n^{(0)}, & \gamma_n \geq \gamma_{0n} \\ \mathbf{d}_n^{\text{MaxMin}}, & \gamma_n < \gamma_{0n} \end{cases}, \quad (7)$$

- GN-MinSwitch:

$$\mathbf{d}_n^{\text{GN-MinSwitch}} = \begin{cases} \mathbf{d}_n^{(0)}, & \gamma_n \geq \gamma_{0n} \\ \tilde{\mathbf{d}}_n, & \gamma_n < \gamma_{0n} \end{cases}, \quad (8)$$

where $\mathbf{d}_n^{(0)}$ is the current band allocation,

$$\gamma_n = \log_2 \left(1 + \min_{m=1, \dots, M_n} \mathbf{h}_{d_{nm}nn}^* \mathbf{R}_{d_{nm}nn}^{-1} \mathbf{h}_{d_{nm}nn} \right) \quad (9)$$

is the minimum data rate for the sensing sub-system for the current band allocation, and

$$\tilde{\mathbf{d}}_n = \arg \min_{m \in \mathcal{M}_n, f_m \in \mathcal{F}} \sum_{m=1}^{M_n} |\text{sign}(f_m - d_{nm}^{(0)})|, \quad (10)$$

subject to $\log_2 \left(1 + \mathbf{h}_{f_mnn}^* \mathbf{R}_{f_mnn}^{-1} \mathbf{h}_{f_mnn} \right) \geq \gamma_{0n}$, where $\text{sign}(a) = \{-1, 0, 1\}$ is the sign function. If solution (8), (10) does not exist, then $\tilde{\mathbf{d}}_n = \mathbf{d}_n^{\text{GN-MaxMin}}$.

As mentioned in Section 1, selection of the target thresholds γ_{0n} is critical for the GN algorithms. If the whole network may be potentially “interference free”, i.e., the total number of degrees of freedom available at BS_{*n*} exceeds the total number of signals

$$KF > \sum_{n=1}^N M_n, \quad (11)$$

then, γ_{0n} could be estimated assuming no inter-system interference with the removed diversity gain assuming that the “spare” degrees of freedom actually may be needed for IM:

$$\gamma_{0n} = \log_2 \left(1 + \frac{\alpha}{K_d} \max_{m \in \mathcal{M}_n} \min_{f_m \in \mathcal{F}} \mathbf{h}_{f_mnn}^* \mathbf{R}_{f_mnn}^{-1} \mathbf{h}_{f_mnn} \right) \quad (12)$$

for $\tilde{\mathbf{R}}_{f_mnn} = \sigma^2 \mathbf{I}_K$, where α is a parameter to control trade off between the equilibrium and convergence properties of the algorithm, and K_d is the expected diversity gain because of the no interference assumption averaged per band.

One way to introduce the occupation control based on the locally estimated total dimension of the noise subspace D_{nf} of the interference-plus-noise covariance matrices in all F bands can be summarized as modification of the Sensing interval above:

Sensing interval:

- Step 1a: Find D_{nf} , $f = 1, \dots, F$ for $\lambda_{nfD_{nf}}/\sigma^2 \leq \delta$, where λ_{nfk} , $k = 1, \dots, K$ are increasingly ranked eigenvalues of $\tilde{\mathbf{R}}_{fn}$ and $\delta > 1$ is the interference level threshold;
- Step 1b: Calculate the “interference free” room for the BS_{*n*} UEs

$$M_{0n} = \sum_{f=1}^F D_{nf}; \quad (13)$$

- Step 1c: Update M_n if needed

$$M_n = \begin{cases} M_n, & \text{if } M_n \leq M_{0n} + \beta, \quad M_n = \tilde{M}_n \\ M_n = M_n + \Delta, & \text{if } M_n < M_{0n} + \beta, \quad M_n < \tilde{M}_n \\ M_n = M_n - \Delta, & \text{if } M_n > M_{0n} + \beta \end{cases}, \quad (14)$$

where $\tilde{M}_n$ is the requested number of UEs for BS_{*n*}, $\beta \geq 0$ is the caution parameter to control network occupation, and $\Delta \geq 1$ is the number of UEs that can be relocated at each sensing interval, then go to Step 2.

Then, the average diversity gain in target threshold (12) could be estimated as $K_d = K - (M_n + \beta)/F$.

IV. ABSORBING MARKOV CHAINS FOR ANALYSIS OF THE IM-BASED DSA WITH OCCUPATION CONTROL

A. Markov Chain Modeling

To formulate a Markov model we assume that all possible I different allocation matrices $\mathbf{D}_i = [\mathbf{d}_{1i}; \dots; \mathbf{d}_{Ni}]$, $i = 1, \dots, I$ form states of the Markov chain. To take into account the occupation control we introduce one more state in the each element of the decision vector that reflects activation of the corresponding UE $d_{nm} = \{0, 1, \dots, F\}$, where “0” corresponds to the non-activated state. Also,

for simplicity we assume $M_n \geq 1$, $\tilde{M}_n = \tilde{M}$ and place all non-activated UEs at the end of the UE list. For example, vector $\mathbf{d}_{ni} = [f_{1i}, f_{2i}, 0, 0]$ indicates that $\tilde{M} = 4$, $M_n = 2$, and bands $f_{1i}, f_{2i} \in \mathcal{F}$ are used for activated UE $_{n1}$ and UE $_{n2}$ correspondingly for the i th Markov chain state. Also, we assume that UEs activation/deactivation just follows the fixed list of UEs for each sub-system without any optimization according to some selection criteria. This simplification reduces the total dimension of the model from $I = (F + 1)^{\tilde{M}N}$ in the general case with occupation control to the significantly lower number of $I = \left(\sum_{m=0}^{\tilde{M}-1} F^{\tilde{M}-m}\right)^N$.

For a given state $\mathbf{D}_i$, sensing of the n th sub-system transfers the system to state $\mathbf{D}_{j_n}$ depending on the given channel realization and DSA algorithm, where $j_n \in [1, I]$, including $j_n = i$. Repeating this procedure for $n = 1, \dots, N$, a set of $\mathbf{D}_{j_n}$ can be found, where not all j_n may be different.

Assuming that, at each sensing interval, one randomly selected sub-system is sensed with the uniform probability of N^{-1} , the nonzero elements of the $I \times I$ transition probability matrix $\mathbf{P} = \{p_{ij}\}$ can be defined as $p_{ij} = g_j/N$, $i = 1, \dots, I$, where $1 \leq g_j \leq N$ is the number of sensing trials at BS $_n$, $n = 1, \dots, N$, leading to $\mathbf{D}_{j_n} = \mathbf{D}_j$.

The transition probability matrix $\mathbf{P} = \{p_{ij}\}$ is a sparse stochastic matrix with maximum N nonzero elements in a row, such that $\sum_{j=1}^I p_{ij} = 1$ for $i = 1, \dots, I$, which completely defines the Markov model of the considered spectrum sharing network with the IM-based DSA and occupation control. To apply the theory of absorbing Markov chains to the modified problem, we need the following: calculate a transition probability matrix for the given channel realization and algorithms; classify all the states into three groups: transient, absorbing, and ergodic, e.g., as in [9]; estimate the equilibrium performance for the absorbing states; if ergodic subchains are found, then transform the initial Markov chain to the reduced size absorbing Markov chain by means of replacing the ergodic subchains with the corresponding absorbing states; calculate probabilities of absorption by the absorbing states (convergence) and ergodic subchains (non-convergence) and average convergence rate.

The difference of this model compared to the model in [7] for the known target thresholds and no occupation control is the extended dimension of the decision vectors and the corresponding extension of the total number of Markov model states, which is $I = F^{\tilde{M}N}$ in the case of no occupation control. Now, each absorbing point may have different numbers of the activated UEs for different BSs corresponding to the target performance threshold for the particular interference scenario observed at the sensing intervals.

The absorption (convergence) probabilities from each transient state to each absorbing point $\mathbf{E}$ and the average number of sensing intervals before absorption $\mathbf{t}$ can be calculated as follows [10]: $\mathbf{E} = \mathbf{C}\mathbf{B}$, $\mathbf{t} = \mathbf{C}\mathbf{1}$, where $\mathbf{C} = (\mathbf{I}_t - \mathbf{A})^{-1}$ is the fundamental matrix of the canonical form $\bar{\mathbf{P}}_a$ of the absorbing transition probability matrix $\mathbf{P}_a$ found after replacement of all ergodic subchains in matrix

$\mathbf{P}$, if they exist, with the corresponding absorbing points

$$\bar{\mathbf{P}}_a = \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{0} & \mathbf{I}_{I_a} \end{bmatrix}, \quad (15)$$

$\mathbf{1}$ is the vector of all ones, I_t and I_a are the numbers of the transient and absorbing states, including the collapsed ergodic subchains in $\mathbf{P}_a$ if they exist, and $I_t + I_a \leq I$.

Now, generating channel realizations for some network configuration, we can analytically study the equilibrium and convergence/non-convergence probabilities and convergence rates for different spectrum sharing algorithms with and without occupation control.

B. Semi-analytic study

First of all, let us study the GN behavior with the target threshold defined in (12) without occupation control when the “interference free” condition (11) is satisfied or may be violated. We assume $M_n = 4$, $F = 2$, $N = 3$, $K = \{5, 7\}$, $\sigma^2 = 10^{-2}$, and independent random Gaussian vectors $\mathbf{h}_{fmln} \sim \mathcal{CW}(0, \mathbf{I}_K)$ as stationary propagation channels without pathloss modeling, which means that all BSs are affected by all UEs in the whole network activated in the given frequency bands. One can see that (11) is satisfied for $K = 7$ and violated for $K = 5$. Total number of states for such network without occupation control is $I = F^{NM_n} = 4096$. The non-convergence probabilities are presented in Table 1 and convergence equilibrium and transient results are shown in Fig. 1 in 100 channel realizations. Target scaling parameter α in (12) is used for trade off control between the equilibrium and convergence performance. Exhaustive local search is used for all algorithms. One can see that for $K = 7$, the GN algorithms demonstrate the desirable controllable behavior, but for $K = 5$, the GN algorithms actually collapse to the selfish case, and the performance degrades accordingly as expected. The globally optimum performance is also shown in Fig. 1a for comparison.

A similar network with occupation control is studied for $\tilde{M} = 4$, $\beta = 2$, $\delta = 2$, and $\Delta = 1$ with $I = \left(\sum_{m=0}^{\tilde{M}-1} F^{\tilde{M}-m}\right)^N = 27000$ states. The corresponding results are shown in Table 2 and Fig. 2¹. One can see that the desirable controllable results for $K = 5$ are back and similar to the $K = 7$ performance. The difference is that for $K = 7$ all the actual absorbing points, excluding the collapsed ergodic subchains, contain allocations with all $N\tilde{M} = FK - \beta = 12$ activated UEs, but for $K = 5$ only $FK - \beta = 8$ UEs are activated for each absorbing point.

Now, we study effects of partial breaks of the GN rules. Let us assume the same scenario as in Table 2 and Fig. 2, but BS₁ follows the selfish algorithm with fixed $M_1 = \tilde{M} = 4$, while BS₂ and BS₃ run the GN-MinSwitch algorithm with the occupation control. The total number of Markov chain states is reduced to $I = 14400$ in this case because of

¹The convergence results in Figs. 1, 2 for GN-MinSwitch are similar to GN-MaxMin because of low N and $\tilde{M}$. The GN-MinSwitch advantage becomes significant for higher-dimension networks.

no occupation control for BS₁. The non-convergence probabilities are summarized in Table 3. Comparison of the UE number distributions and the convergence results with the corresponding performance for GN-MinSwitch for all BSs with $K = 5$ antennas are given in Figs. 3, 4. One can see the following consequences of the selfish behavior of BS₁: sub-system 1 always gets the maximum activated UEs and forces other sub-systems to reduce their occupation to maintain the “interference free” spectrum sharing as illustrated in Fig. 3b compared to the full GN network case in Fig. 3a; the steady-state minimum data rate performance in Fig. 4a is slightly increased because of the higher selfish equilibrium results for sub-system 1 if and when it converges; the non-convergence probabilities in Table 3 are significantly higher for the mixed network case compared to the corresponding GN-MinSwitch results in Table 2; the convergence rate results are decreased for the mixed network as one can see in Fig. 4b.

The main observation from the GN rule breaks analysis is that the transient performance degradation in terms of the increased non-convergence probabilities and reduced convergence rate belongs to the whole network including the selfish sub-system.

V. HIGHER-DIMENSION IM-BASED DSA ALGORITHMS WITH OCCUPATION AND POWER CONTROL

An exhaustive search over all M_n^F options in (6)-(11) may not be feasible for higher dimension spectrum sharing networks. One possible simplification can be based on a partial search over some subsets of users $\bar{\mathcal{M}}_n$ and bands $\bar{\mathcal{F}}_n$ with the restricted number of elements $\bar{M}_n \leq M_{max} \leq M_n$ and $\bar{F}_n \leq F_{max} \leq F$ instead of the whole sets $\mathcal{M}_n$ and $\mathcal{F}_n$ in (6)-(10). For our simulations, we collect the UEs with the lowest SINR below γ_{0n} for $\bar{\mathcal{M}}_n$ and use the fixed number of F_{max} bands with the highest dimensions of the noise subspace D_{nfj} , $j = 1, \dots, F_{max}$ for $\bar{\mathcal{F}}_n$ taking into account that D_{nf} needs to be estimated at the sensing interval for the occupation control in any case.

It is well known that power control can significantly improve efficiency of MIMO networks [11]. Generally, in the considered interference limited spectrum sharing case, power adjustments at some sub-systems change interference scenarios for other sub-systems, which may complicate an efficient power control. In [7], it was pointed out that this is actually not the case in the strong interference limited scenario if the number of receive antennas at BSs is high enough for rejection of all interference sources. The main reason for the introduced in Section 3 occupation control is to make sure that for the given number of antennas and available bands, the “interference free” spectrum sharing can be maintained. This means that any local power control should not practically affect other sub-systems.

We simulate higher-dimension network with simplified search algorithms discussed above and the local PC similar to [11] in the no pathloss scenario, where all sub-systems are actually affected by all activated UEs in the spectrum sharing network: $N = 5$, $F = 7$, $K = 15$, $\alpha = 0.5$, $\beta = 3$, $\delta = 3$, $\Delta = 1$, $M_{max} = 4$, and $F_{max} = 3$. Also, we assume

initially 10 UEs per sub-system $M_n = 10$ and unlimited number of requested UEs $\tilde{M}_n$ for $n = 1, \dots, N$.

Taking into account that all sub-systems can sense all activated UEs, the total number of activated UEs for the unlimited $\tilde{M}_n$ should be $KF - \beta = 102$ in the considered scenario. The simulation results in 100 random channels and sensing interval trials are summarized in Figs. 5, 6. Fig. 5 presents the distributions of the steady-stated number of the activated UEs per sub-system for GN-MinSwitch after convergence. The convergence is detected if the occupation and band allocation do not change for all sub-systems in 20 consecutive sensing intervals. Fig. 6 shows CDFs of the minimum data rate and convergence rate for both GN algorithms with and without PC.

The presented simulation results show the following: both GN algorithms converge to the absorbing points in all trials; the selfish algorithm with occupation control do not converge in all 100 trials (the selfish results are not shown because of that); in all trials, the total number of the activated UEs was 102 as expected, but different sub-systems experience different steady state number of the activated UEs, mainly depending of particular sensing interval realizations; the average number of UEs per sub-system is about 20 as one can see in Fig. 5 (higher dimension network because an exhaustive local search over 20^7 options is clearly not feasible) ; PC improves the equilibrium data rate results for both the GN algorithms as shown in Fig. 6a; GN-MinSwitch with PC significantly outperforms GN-MaxMin with PC as illustrated in Fig. 6b.

VI. CONCLUSIONS

A solution for decentralized shared cellular spectrum has been proposed, which is based on extension of the rule regulated GN DSA with the adaptive spectrum occupation control. Semi-analytic absorbing Markov chain model has been extended to the occupation control case and studied to show a possibility of virtually “interference free” spectrum sharing with desired and controllable equilibrium and transient behavior without any explicit communication and cooperation between sub-systems.

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Table 1. IM-based DSA without occupation control

Algorithm	Non-convergence probability, %					
	$K = 5$			$K = 7$		
MaxMin	13.5			15.6		
Target, α	1	0.75	0.5	1	0.75	0.5
GN-MaxMin	13.5	13.5	13.5	0.25	0.16	0.02
GN-MinSwitch	13.5	13.5	13.5	0.17	0.04	0

Table 2. IM-based DSA with occupation control

Algorithm	Non-convergence probability, %					
	$K = 5$			$K = 7$		
MaxMin	12.5			15.9		
Target, α	1	0.75	0.5	1	0.75	0.5
GN-MaxMin	0.24	0.08	0.01	0.23	0.23	0.01
GN-MinSwitch	0.07	0.03	0	0.19	0.05	0

Table 3. Partial GN break: BS₁: MaxMin, BS_{2,3}: GN-MinSwitch

Algorithm	Non-convergence probability, %					
	$K = 5$			$K = 7$		
Target, α	1	0.75	0.5	1	0.75	0.5
Partial GN break	2.35	1.35	0.52	1.94	1.19	0.27

Fig. 1. Convergence results without occupation control

Fig. 2. Convergence results with occupation control

Fig. 3. Distribution of the activated UE numbers

Fig. 4. Convergence results for IM-based DSA with occupation control: partial break of the GN rules

Fig. 5. Distributions of the number of activated UEs per sub-system

Fig. 6. Minimum data and convergence rates distributions