Good Neighbor Distributed Beam Scheduling in Coexisting Multi-RAT Networks

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Abstract—Spectrum sharing and employing highly directional antennas in the mm-wave bands are considered among the key enablers for 5G networks. Conventional interference avoidance techniques like listen-before-talk (LBT) may not be efficient for such coexisting networks. In this paper, we address a coexistence mechanism by means of distributed beam scheduling with minimum cooperation between spectrum sharing subsystems without any direct data exchange between them. We extend a “Good Neighbor” (GN) principle initially developed for decentralized spectrum allocation to the distributed beam scheduling problem. To do that, we introduce relative performance targets, develop a GN beam scheduling algorithm, and demonstrate its efficiency in terms of performance/complexity trade off compared to that of the conventional selfish (SLF) and recently proposed distributed learning scheduling (DLS) solutions by means of simulations in highly directional antenna mm-wave scenarios.

Keywords— 5G, mm-wave, coexisting networks, distributed beamforming scheduling, selfish and good neighbor algorithms.

I. INTRODUCTION

A current vision of future wireless networks is that integration of mm-wave bands and using highly directional antennas are among the key enablers for 5G networks [1], [2]. Particularly, in mm-wave spectrum, the short wavelengths allow for hundreds of antenna elements to be placed in an array on a relatively small physical platform at the base station or access point [3].

Interference avoidance and/or mitigation for coexistence of multi radio access technologies (multi-RAT) systems equipped with highly directional antennas may be challenging. First of all, this is because centralized coordination by means of direct signaling exchange may be problematic between multi-RAT systems. Secondly, conventional interference avoidance techniques like LBT that is currently exploited in the industrial, scientific, and medical (ISM) band and proposed for the coexistence mechanisms in unlicensed LTE [4], become inefficient for networks with highly directional antennas because interference may not be reliably detected at LBT nodes leading to the well known hidden terminal problem.

Decentralized beamforming scheduling is a well known topic in multi-cell networks, e.g., [5] - [7]. A typical assumption for such schemes is that distributed beam scheduling requires local message passing at least between neighboring BSs. For multi-RAT networks, this assumption may be too restrictive.

Consequently, new multi-RAT coexistence mechanisms are needed for wireless networks with highly directional

antennas. The main requirement for such techniques is to keep minimum level of cooperation between spectrum sharing subsystems strictly without direct data exchange between them and/or any central controller.

One scenario of such cooperation is addressed in [8], [9] for distributed beam scheduling for multi-RAT mm-wave 5G networks. In particular, it assumes:

- downlink beamforming with preselected beams;
- coordinated transmissions and sequential scheduling
- adaptation for coexisting subsystems;
- given number of iterations for scheduling adaptation for each subsystem;
- locally estimated utility at each node;
- no data exchange between subsystems.

The corresponding interference scenario is non-reciprocal, which means that the known decentralized solutions like selfish (greedy) algorithm or computationally simplified DLS proposed in [8], may demonstrate slow convergence or high probability of non-convergence to some equilibrium. Slow or even non-convergent algorithms still can be applied in the partially coordinated scenario with the given number of iterations and demonstrate some performance improvement compared to random allocations as shown in [8] for relatively low directivity antennas of 8 elements and 16 pre-defined beams. In the most interesting highly directional antenna mm-wave scenarios, faster convergent scheduling adaptation algorithms with higher convergence probability would be more efficient compared to the selfish and computationally simplified algorithms.

In this paper we address a similar to [8], [9] scenario and demonstrate how the GN approach to decentralized resource allocation introduced in [10] can be effectively extended to the distributed beam scheduling problem. According to the GN principle, the achievable performance targets for each coexisting subsystem should be reached with minimum changes to the current resource allocation. It is shown in [10] that the GN based distributed resource allocation allows controllable trade off between equilibrium and transient performance in rule regulated networks without any data exchange between coexisting subsystems. The critical GN requirement is availability of adequate to the actual interference scenario performance targets. In [11], such targets are developed by means of the decentralized occupation control based on the receive antenna array interference mitigation diversity in a dynamic uplink spectrum allocation scenario. However, extension of the GN principle to the considered mm-wave downlink scenario is

not trivial because the absolute performance targets are not known in realistic environments and occupation control similar to [11] is not directly applicable for the considered transmit beamforming problem. We propose another GN solution based on the relative performance targets compared to the best locally achievable performance over some dynamically selected user subsets at the current iteration. Although it cannot guarantee convergence to some equilibrium, in the scenario with the fixed number of adaptation iterations, it allows significant performance improvements over the SLF and DLS algorithms with controllable complexity trade off, especially in the most interesting highly directional antenna scenarios.

The 3-fold novelty of this work is as follows: We show that the rule regulated Good Neighbor network coexistence proposed in [10] for the particular dynamic spectrum allocation scenario is actually a more general tool that can be modified for other important scenarios. We introduce the GN with relative targets and demonstrate its applicability and efficiency for decentralized beamforming scheduling in coexisting mm-wave networks. We introduce subset versions of the SLF and GN algorithms and demonstrate a trade off between performance and complexity.

The rest of the paper is organized as follows. The system model and problem formulation are presented in Section II. In Section III, we introduce the basic selfish algorithm and develop the distributed GN scheduling beamforming algorithm with the relative performance targets. Section IV presents the simulation results in the stationary and dynamic scenarios. Finally, Section V concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

The considered coexistence deployment scenario consists of N BSs equipped with K transmit antennas and M single antenna UEs for every BS. At a given time, the n th BS ($n = 1, \dots, N$) transmits to its m th UE, $m = 1, \dots, M$ using a beam with a $(K \times 1)$ vector of antenna coefficients $\mathbf{w}_{nm}$. Each BS selects the beamforming vector $\mathbf{w}_{nm}$ from a predefined codebook of C vectors that uniformly cover the azimuth directions around the BS. Particularly, the transmit codebooks are formed by the $(K \times 1)$ vectors $\{\mathbf{v}_1, \dots, \mathbf{v}_C\}$, $|\mathbf{v}_i|^2 = 1$. The n th BS selects the $\hat{i}$ th vector from the codebook according to

$$\hat{i} = \arg \max_{i=1, \dots, C} |\mathbf{v}_i^* \mathbf{h}_{nmn}|^2, \quad (1)$$

where $\mathbf{h}_{nmq}$ is the $(K \times 1)$ channel vector from the q th BS to the m th UE associated with the n th BS, and $(\cdot)^*$ is the conjugate transpose operation. Then,

$$\mathbf{w}_{nm} = \mathbf{v}_{\hat{i}}. \quad (2)$$

A scheduling cycle of M time slots is defined to serve UEs for each BS assuming synchronization of the scheduling cycles for the coexisting subsystems. At the t th time slot each BS transmits to only one m_{nt} th of its UEs using only one beamforming vector $\mathbf{w}_{nm_{nt}}$. During one scheduling cycle, a scheduling sequence is defined as $\mathcal{M}_n^j = \{m_{nm_{nt}}^j, t = 1, \dots, M\}$, where $j = 1, \dots, M!$ for all possible sequences for

each BS. An example of the presented coexisting network is plotted in Fig. 1 for $N = 2$ and $M = 5$ illustrating the main difficulty with this scenario: possible beam collisions from different BSs, which may lead to uncontrollable performance degradation for the whole network.

Global (centralized) scheduling optimization solutions for the local utility function $U(m_{nm_{nt}}^j)$ can be formulated for the total spectrum efficiency

$$\{\hat{\mathcal{M}}_1, \dots, \hat{\mathcal{M}}_N\} = \arg \max_{\{\mathcal{M}_1^j, \dots, \mathcal{M}_N^j\}, j=1, \dots, (M!)^N} \sum_{n=1}^N \sum_{t=1}^M U(m_{nm_{nt}}^j) \quad (3)$$

or for the maximum efficiency of the weakest UE in the network

$$\{\hat{\mathcal{M}}_1, \dots, \hat{\mathcal{M}}_N\} = \arg \max_{\{\mathcal{M}_1^j, \dots, \mathcal{M}_N^j\}, j=1, \dots, (M!)^N} \left[\min_{m_{nm_{nt}}^j, t=1, \dots, M, n=1, \dots, N} U(m_{nm_{nt}}^j) \right]. \quad (4)$$

The local utility function can be defined as the potential data rate

$$U(m_{nm_{nt}}^j) = \log_2 \left(1 + \frac{P |\mathbf{w}_{nm_{nt}}^* \mathbf{h}_{nm_{nt}n}|^2}{P \sum_{q=1, q \neq n}^N |\mathbf{w}_{qm_{nt}}^* \mathbf{h}_{nm_{nt}q}|^2 + \sigma^2} \right), \quad (5)$$

where P is the transmit power, which is the same for all BSs, and σ^2 is the noise power.

The global solutions (3) and (4) are not practical because they require centralized signaling exchange and exhaustive search over $(M!)^N$ scheduling sequence options. Instead, following [8], we assume that the utility functions can be estimated and the scheduling sequence can be updated at each BS in the coordinated, e.g. sequential order, during the given number of F iterations without any data exchange between different subsystems. For local estimation of the utility function we assume that the propagation channels $\mathbf{h}_{nmn}$ are known at the corresponding BS¹ and the interference plus noise power $P \sum_{q=1, q \neq n}^N |\mathbf{w}_{qm_{nt}}^* \mathbf{h}_{nm_{nt}q}|^2 + \sigma^2$ can be estimated at the n th BS during its adaptation iteration for $t = 1, \dots, M$. This can be done, for example, if all UEs can report their measured power at all time slots to their associated BS during the corresponding iteration of the scheduling adaptation.

Then, the problem is to find distributed scheduling adaptation algorithms that after the given number of iterations exhibit a performance improvement compared to the known solutions such as random, selfish or DLS distributed scheduling optimization. This problem formulation is similar to the one in [8] except of using the maximum of the minimum data rate performance metric (4) instead of the total spectrum efficiency (3) to emphasize the fairness requirements. The presented basic scenario allows flexibility and extensions in terms of complexity and number of simultaneously served users. Particularly, subset versions of SLF and GN (SSLF, SGN) introduced in Section III allow a trade off between performance and complexity. Also, a possibility of simultaneous transmission from one BS to more

¹In the considered scenario, $\mathbf{h}_{nmn}$ are needed only for beam association and calculation of the received power from the serving BS.

than one UEs with different beams without any changes in the scheduling algorithms is demonstrated in Section IV.

III. DISTRIBUTED BEAM SCHEDULING ALGORITHMS

In the beginning, we introduce SLF and GN with complexity proportional to $M!$ for using them as benchmarks and for explanation of the GN solution in the considered application and its difference with the conventional SLF. Then, the subset versions of the algorithms with the limited complexity proportional to $M_{\max}!$ with $M_{\max} \leq M$ are developed as practical alternatives to SLF and GN with investigation of the performance/complexity trade off in Section IV.

A general structure of distributed beam scheduling adaptation can be summarized as follows. At the f th iteration of adaptation ($f = 1, \dots, F$) the n th subsystem ($n = 1, \dots, N$) is sequentially adjusted with the following steps assuming that all $q = 1, \dots, N$, $q \neq n$ BSs transmit data according to their scheduling sequences defined at the previous adaptation iterations:

- Step 1: Measure the received power P_{nmt} at all $t = 1, \dots, M$ time slots for all $m = 1, \dots, M$ UEs associated with the n th BS and report it back to the n th BS;
- Step 2: Calculate the interference plus noise power at the n th BS²

$$I_{nmt} = P_{nmt} - P|\mathbf{w}_{nm_{nt}}^* \mathbf{h}_{nm_{nt}n}|^2; \quad (6)$$

- Step 3: Calculate the optimization metric $\gamma(\mathcal{M}_n^j)$ for the scheduling sequences $\mathcal{M}_n^j$ for $j = 1, \dots, M!$:

$$\gamma(\mathcal{M}_n^j) = \min_{m_{nt}^j, t=1, \dots, M} \frac{P|\mathbf{w}_{nm_{nt}^j}^* \mathbf{h}_{nm_{nt}^j n}|^2}{I_{nm_{nt}^j t}}; \quad (7)$$

- Step 4: Find $\hat{\mathcal{M}}_n$ and update the UEs with the adjusted scheduling sequence.

Step 4 is the main element of this distributed beam scheduling adaptation. Particularly, the conventional selfish algorithm can be formulated as follows:

$$\hat{\mathcal{M}}_n^{\text{SLF}} = \arg \max_{\mathcal{M}_n^j, j=1, \dots, M!} \gamma(\mathcal{M}_n^j). \quad (8)$$

To formulate the GN solution, the performance targets $\tilde{\gamma}_n$, $n = 1, \dots, N$ need to be available at the BSs. Then, following [10], Step 4 can be formulated as follows:

$$\hat{\mathcal{M}}_n^{\text{GN}} = \begin{cases} \mathcal{M}_n^0, & \gamma(\mathcal{M}_n^0) \geq \tilde{\gamma}_n \\ \tilde{\mathcal{M}}_{n\hat{r}_n}, & \gamma(\mathcal{M}_n^0) < \tilde{\gamma}_n \end{cases}, \quad (9)$$

where

$$\tilde{\mathcal{M}}_{nr_n} = \arg \min_{\mathcal{M}_n^j, j=1, \dots, M!} \nu(\mathcal{M}_n^j) \quad (10)$$

subject to $\gamma(\mathcal{M}_n^j) \geq \tilde{\gamma}_n$, where

$$\nu(\mathcal{M}_n^j) = \sum_{t=1}^M |\text{sign}(m_{nt}^0 - m_{nt}^j)|, \quad (11)$$

²Step 2 could be eliminated if the n th BS stops its transmission at all slots during adaptation iteration. Then, $I_{nmt} = P_{nmt}$ for $\{m, t\} = 1, \dots, M$.

where $\nu(\mathcal{M}_n^j) \in [0, 2, \dots, M]$ is the number of time slots with changes for $\mathcal{M}_n^j$ compared to the current scheduling sequence $\mathcal{M}_n^0$. Index $r_n = 1, \dots, R_n$ in (9) indicates that, generally, $R_n \geq 1$ solutions to the optimization problem (9)-(11) are possible depending on the targets $\tilde{\gamma}_n$. According to the GN principle, any of these solutions could be selected. For simplicity, in this paper we select $\hat{r}_n$ randomly with uniform probability R_n^{-1} .

The absolute targets $\tilde{\gamma}_n$ are generally not available in the considered environment. Indeed, if the potentially interference free environment cannot be guaranteed, e.g., as in [11] by means of decentralized occupation control, then the achievable performance depends on the network geometry, propagation channels, beam number, beam patterns, and other scenario parameters that are normally not known at the coexisting subsystems.

In this paper, we demonstrate that the relative performance targets compared to the selfish scheme can be effectively applied to update subsystem at the given iteration of adaptation if the absolute targets are not available:

$$\tilde{\gamma}_n = \delta \gamma(\hat{\mathcal{M}}_n^{\text{SLF}}), \quad (12)$$

where $0 < \delta < 1$ is the caution parameter controlling a trade off between transient and equilibrium performance. In the boundary cases, if $\delta = 1$ then GN is equivalent to SLF; if $\delta = 0$, then adaptation is not activated and the initial, e.g., random, allocation remains unchanged.

Summarizing, a new version of the GN principle with the relative targets (12) can be formulated as follows:

- Instead of selfishly using the locally best solution in the given interference environment with uncontrollable arbitrary changes to the current interference environment of the coexisting subsystems, define a set of solutions with controllably lower local performance and select allocation with minimum changes to the the current coexisting network interference.

Clearly, a direct SLF or GN application with $M!$ utility function calculations per BS per iteration may be prohibitive in terms of complexity even for modest values of M . To deal with this problem we introduce the subset SSLF and SGN versions of the algorithms assuming that at each iteration only a subset of $M_{\max} < M$ UEs with the lowest utility functions at the current iteration is dynamically selected for optimization keeping the existing allocation for the rest of $M - M_{\max}$ UEs unchanged. For $M_{\max} = M$, SSLF and SGN are back to SLF and GN.

IV. SIMULATION RESULTS

A. Channel model and simulation scenario

Similarly to [8], we assume the following propagation model:

$$\mathbf{h} = \sqrt{\frac{K}{\rho L}} \sum_{l=1}^L \alpha_l \mathbf{a}(\phi_l), \quad (13)$$

where

$$\mathbf{a}(\phi_l) = \frac{1}{\sqrt{K}} \left[1, \dots, e^{j(K-1)\frac{2\pi}{\lambda} D \sin(\phi_l)} \right]^T \quad (14)$$

is the linear antenna array steering vector; $\rho(D) = 64.39 + 24.7\lg(D)$ dB is the pathloss model; D is the distance in meters between transmitter and receiver; α_l is the normally distributed complex gain of the l th path with $E(|\alpha_l|^2) = 1$; $\phi_l \in [0, 2\pi]$ is the uniformly distributed phase of the l th path; and $L = 3$ is the number of paths. Other simulation parameters are:

- 60 GHz carrier frequency;
- 500 MHz bandwidth;
- 8 and 64 BS antennas with 16 and 128 predefined beams correspondingly;
- 5 and 10 BSs randomly located in the area of (600×800) m;
- 100 m minimum distance between BSs;
- 5 and 10 UEs per BS randomly located in the area of ± 50 m around their BSs;
- 30 dBm transmit power;
- 300 K noise temperature.

B. Stationary scenario

The convergence behavior of the selfish and GN algorithms for 100 iterations in 1000 realizations of the above scenario is shown in Fig. 2. Particularly, Fig. 2a presents the equilibrium global minimum data results for random initializations for the convergent trials. Figs. 2b and 2c show the convergence rates for 8 and 64 antennas correspondingly for all trials. One can observe the following:

- GN demonstrates much better convergence probability and convergence rate compared to SLF for both antenna configurations.
- For 8 BS antennas and 16 beams, the room for optimization in terms of the equilibrium performance is very limited leading to the similar performance for all solutions including random ones.
- For 64 BS antennas and 128 beams, the room for optimization is significant leading to much better GN equilibrium results compared to the random and SLF solutions.
- Comparison of the GN results for different values of the caution parameter $\delta = [0.25, 0.5, 0.75]$ illustrates the trade off between the equilibrium and transient performance: decreasing δ causes the higher convergence probability with faster convergence rate and lower equilibrium performance.

The simulation results in Fig. 2 suggest that although GN convergence in the given number of iterations cannot be guaranteed, the probability to find an acceptable scheduling sequence is much higher compared to the random and selfish solutions. This is illustrated in the corresponding results for the fixed number of iterations presented in Fig. 3, which gives the global minimum data rates after 10 iterations for the SLF and GN algorithms. The DLS results for 10 and 50 iterations are also shown in Fig. 3. One can observe the following:

- Similarly to Fig. 2a for the convergent trials for high directivity antennas, GN significantly outperforms SLF on average even if convergence is not guaranteed in 10 iterations.

- The performance of computationally simple DLS (only one utility calculation is needed per BS per iteration compared to $M!$ utility calculations for SLF and GN) remains close to the random scheduling in the considered scenario and it can be significantly improved by GN especially in the high directivity antenna case.

Comparison of SLF and GN with their subset versions SSLF and SGN in terms of performance / complexity trade off is given in Fig. 4 for the 64 antenna case. It shows that:

- Counterintuitively, much simpler SSLF significantly outperforms SLF. The reason is that SSLF creates limited changes to the interference scenarios for coexisting subsystems compared to SLF at each iteration. In fact, SSLF can be considered as a non-optimized version of the GN solution.
- For $M_{\max} = 3$, the SSLF and SGN results are similar because of no room for the GN optimization.³
- For $M_{\max} = [4, 5]$ the GN solutions demonstrate much higher performance gain for the given complexity that brings back the normal situation with better performance for higher complexity contradictory to the SLF / SSLF case.

C. Dynamic scenario

The flexibility of the considered scenario is illustrated in Fig. 5, which assumes that each of 5 BSs simultaneously transmits to two groups of 10 UEs at each scheduling cycle, but one iteration still consists of 10 consecutive cycles with only one group of 10 UEs updated at each of them. All the considered algorithms can be directly applied in this scenario, although a joint multiuser processing could be used for further performance improvements. A dynamic scenario is presented in Fig. 5: every 500 scheduling cycles scheduling adaptation activated for 10 iterations and network changes are allowed in the beginning of adaptation intervals. At these moments, up to 2 out of 10 UEs at randomly selected BSs are changed. Fig. 5a shows 20 such intervals. Fig. 5b illustrates network geometries for 3 of them. Again, one can see that in the most situations SGN significantly outperforms SSLF and random scheduling.

V. CONCLUSIONS

In this paper, we have presented a network coexistence mechanism based on distributed beam scheduling with minimum cooperation between spectrum sharing subsystems without any direct data exchange between them. The modified “Good Neighbor” approach with relative performance targets has been proposed. Its performance advantages over the known solutions have been demonstrated by means of simulations in mm-wave scenarios with highly directional BS antennas. Extensions of the basic coexisting scenario and semi-analytic Markov chain analysis can be considered for further investigation.

³The SSLF and SGN results for $M_{\max} = 2$ (not shown) are similar and much worse than for $M_{\max} = 3$ because of the negligible selection room.

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Fig. 1. Network model for $N = 2$ and $M = 5$

Fig. 2. Equilibrium and transient performance: 10 BSs, 5 UEs

Fig. 3. Fixed number of iterations performance: 10 BSs, 5 UEs

Fig. 4. Performance / complexity trade off for SLF and GN with SSLF and SGN: 10 BSs, 5 UEs

Fig. 5. Dynamic scenario: 5 BSs, 20 UEs