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Self-Organized Beam Scheduling as an Enabler for Coexistence in 5G Unlicensed Bands

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SUMMARY In order to support user data rates of Gbps and above in the fifth generation (5G) communication systems, millimeter wave (mm-wave) communication is proposed as one of the most important enabling technologies. In this paper, we consider the spectrum bands shared by 5G cellular base stations (BS) and some existing networks, such as WiGig and proposed a method for spectrally efficient coexistence of multiple interfering BSs through adaptive self-organized beam scheduling. These BSs might use multiple radio access technologies belonging to multiple operators and are deployed in the unlicensed bands, such as 60 GHz. Different from the recently emerging coexistence scenarios in the unlicensed 5 GHz band, where the proposed methods are based on omni-directional transmission, beam-forming needs to be employed in mm-wave bands to combat the high path loss problem. The proposed method is concerned with this new scenario of communication in the unlicensed bands where (a) beam-forming is mandatory to combat severe path loss, (b) without optimal scheduling of beams mutual interference could be severe due to the possibility of beam-collisions, (c) unlike LTE which users time-frequency resource blocks, a new resource, i.e., the beam direction, is used as mandatory feature. We propose in this paper a novel multi-RAT coexistence mechanism where neighbouring 5G BSs, each serving their own associated users, schedule their beam configurations in a self-organized manner such that their own utility function, e.g. spectral efficiency, is maximized. The problem is formulated as a combinatorial optimization problem and it is shown via simulations that our proposed distributed algorithms yield a comparable spectral efficiency for the entire networks as that using an exhaustive search, which requires global coordination among coexisting RATs and also has a much higher algorithmic complexity.
key words: *millimeter-wave, 5G, licensed and unlicensed bands, coexistence, spectrum sharing*

1. Introduction

The astronomical growth in mobile data traffic volume is making it increasingly difficult for operators to meet the traffic demands with the available resources and network architecture. It is reported that over half a billion (526 million) mobile devices and connections were added in 2013 and the overall mobile data traffic is expected to grow to 15.9 exabytes per month by 2018, nearly an 11-fold increase over 2013 [1]. The global mobile traffic growth has imposed one of the primary challenges to the available resources such as spectrum bands.

Currently, the 4G system, e.g., LTE, specifies its operating frequency bands and some of them are assigned to cellular operators [2]. These deployments can be beneficial since the existing 4G system will not interfere with other radio access technologies (RATs). Also the 4G system can provide robust communication service. In the conventional cellular scenarios, such as LTE, the base stations belonging to a given operator have exclusive access to a given licensed spectrum band [3]. Therefore within that exclusively assigned band they could coordinate their operations, either through centralized planning of resources or through signalling in order to minimize mutual interference.

However, obtaining the licensed spectrums requires not only considerable investment, but also a significantly long period of time spent on regulatory process. More importantly, a substantial portion of the licensed spectrums around 5 GHz is already being used [4]. In this context, a recent trend in 3GPPP is to utilize the licensed and unlicensed spectrums simultaneously for extending available system bandwidth. The licensed spectrum is used for maintaining the connection between the device and the network infrastructure, and for transmitting the user data. The unlicensed spectrum is used only for the high data rate service. In this context, LTE in unlicensed spectrum, referred to as LTE-U, is proposed to enable mobile operators to offload data traffic onto unlicensed frequencies more efficiently and effectively, and provides high performance and seamless user experience [5].

With the 5G research well underway in many parts of the world, researchers are looking at spectrum options to meet the user data traffic requirements that will underpin future 5G services. The mm-wave spectrum (denoted as 6–100 GHz for convenience) looks increasingly likely to play a major role in 5G operations since this spectrum offers unprecedented bandwidth potentially for mobile communications [6]. Integration of unlicensed bands is also considered as one of the key enablers for 5G cellular systems [7]. In the context of 5G systems the unlicensed spectrum already have plenty of bandwidth, especially approximately 8 GHz bandwidth is available in 60 GHz unlicensed band and this could be used for cellular systems.

As aforementioned multi-standard and multi-operator unlicensed spectrum sharing scenario imposes significant challenges on coexistence in terms of interference mitigation. In the recently emerging coexistence scenarios in the unlicensed 5 GHz band, cellular base stations belonging to a given operator system may need to coexist with WiFi access points or cellular base stations belonging to other operators.

For coexistence in 5G mm-wave systems, one of the

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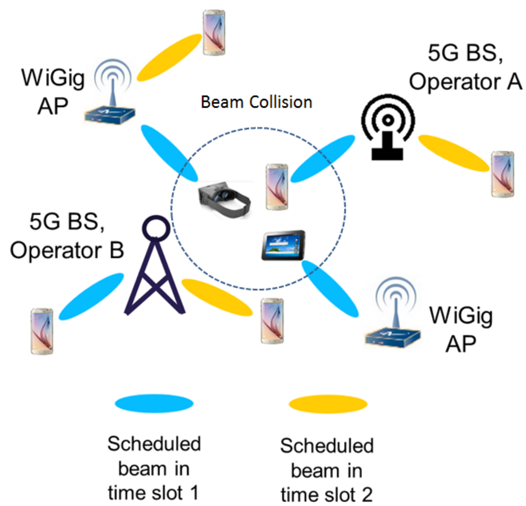

Fig. 1 Coexistence scenario in 60 GHz deployment with beamforming.

major issues is that the use of highly directional antennas as one of the key enablers for 5G networks [8], [9] becomes problematic for the current coexistence mechanisms where omni-directional antennas were mostly assumed. For example, transmission by a different nearby 5G BS or WiGig access Point (AP) may not be detected due to the narrow beam that has been used, resulting a transmission that causes excessive interference to the victim user equipment (UE), e.g., UEs in the central area as illustrated in Fig. 1. In this regard, the simultaneous transmission should be coordinated and exploited fully to greatly enhance the network capacity. It is noted from Fig. 1 that in such a system where multiple beams transmitting to different associated users, it is possible to schedule the beams in a way such that at a given time slot, the beams targeting at different UEs are not transmitting to the same UE as any other beams, therefore avoid causing interference to each other. Such a mechanism is referred as beam scheduling.

In this paper, we consider a multi-RAT deployment where 5G BSs and other APs deployed in unlicensed bands, e.g., WiGig APs at 60 GHz, co-exist and transmit via beamforming. We form a scheduled beam sequence containing the indices of the beams used at different time slots, and formulate an optimization problem to find the optimal scheduled beam sequence to maximize the spectral efficiency of the entire network. It is known that such a combinatorial problem is NP-hard and highly computationally costly when using exhaustive search [10]. We therefore further propose a novel self-organized learning algorithm where different BSs cooperatively and iteratively update the beam sequences such that near maximum spectral efficiency is achieved. It is shown that the proposed algorithm almost achieves comparable spectral efficiency to that using the exhaustive search, while at the same time having a much reduced complexity and signaling overhead. It should be noted that the proposed algorithm and analysis are general and can be easily applied to other unlicensed bands. The rest of the paper is organized as follows. Related works will be introduced in the next section. Section 3 describes the system model and the optimization problem is formulated in Sect. 4. In Sect. 5, we detail the proposed self-organized distributed learning algorithm and compare its complexity with that using exhaustive search and distributed greedy scheduling. Simulation results are presented in Sect. 6 and Sect. 7 concludes the paper.

2. Related Works and Standardization Activities

Licensed Assisted Access (LAA) with listen-before-talk (LBT) protocol has been proposed for the current coexistence mechanism of LTE-U [11] and work on LAA is addressed in 3GPP. Specifically, 3GPP Release 13 has included support for LTE operation on the unlicensed 5 GHz band. The 3GPP study also covers the mechanisms for co-existence in 5GHz band. In LBT, an LTE BS attempts to access channel only at pre-assigned time instants denoted as “transmission opportunities” [12]. At a transmission opportunity, if it has to send data and it is not already transmitting, sensing takes place which is based on the detection of energy in the channel at a predefined time interval. If energy is below threshold, the channel is available and transmission takes place. If energy is above threshold, the channel is busy and no transmission occurs. The coexistence gap provides opportunities to other secondary networks operating in the same band using gaps in LTE transmission. Coexistence gaps are silent gaps i.e. LTE “OFF” periods. eNB resumes transmission at the end of each coexistence gap without assessing the availability of channel. However, the LBT method proposed for coexistence between LTE and WiFi proposed in this scenario has the following shortcomings (a) it does not work in mm-wave band since it relies on omnidirectional/sectorial transmissions and (b) is not spectrally efficient.

Various access networks operating in unlicensed bands, e.g., 60 GHz, may use different resource allocation strategies for multi-user access. For example, 60 GHz cellular systems may use time-frequency resource blocks similar to LTE, where the available spectrum bandwidth is divided into a number of frequency and time slots and users are then served through scheduling of resource blocks. The IEEE 802.11ad standard uses a contention based approach where at any given time the entire channel is allocated to a single user, but users content for time-slots to be served using hybrid TDMA- CSMA scheme based on IEEE 802.11 enhance distributed channel access (EDCA) [13], [14]. A common characteristic of all systems operating in 60 GHz band is that beam-forming is mandatory to compensate for the significantly higher pathloss in mmWave frequencies. For example the IEEE 802.11ad standard supports up to four transmitter antennas, four receiver antennas, and 128 sectors. Beam forming is mandatory in 802.11ad, and both transmitter-side and receiver-side beamforming are supported.

For coexistence in 5G, there has been some related work on beam scheduling based on TDMA [15], [16] and a concept of exclusive region is introduced in [17] to enable concurrent transmission with significant interference reduction. However, the effect of interference aggregation is not

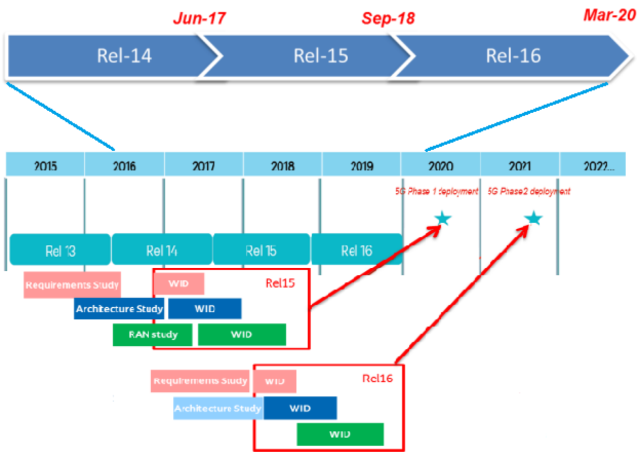

Fig. 2 3GPP timeline [21].

captured. Other approaches are proposed based on centralized coordination in [18]–[20], where the access points are coordinated in a centralized manner to reduce interferences and improve network capacity. Centralized beam scheduling/coordination is normally with high complexity and requires global channel state information to be collected at the central coordinator, which will significantly increase the signalling overhead.

Given that the topic of LAA is generating a lot of interest, a particular focus is on the work of coexistence in unlicensed spectrum. 3GPP work will carry on and 5G RAT features will be divided into two phases as shown in Fig. 2. Basically, phase 1 will be completed by Sep 2018 in 3GPP Rel-15 to address a more urgent subset of the commercial needs with focus on enhanced mobile broadband use case [21]. Study items for New Radio of 5G (NR) such as waveform, channel coding, inter-networking between NR and LTE and other non-3GPP systems have been approved in phase 1 with focusing on below 30 GHz [22]. Phase 2 will be completed by Mar. 2020 in Rel-16 to address all identified use cases & requirements and extend the studied frequency to above 30 GHz. Coexistence in unlicensed spectrum bands, in particular 60GHz mm-wave bands, is envisioned to be one of the important research topics.

3. System Model

In this paper, we assume that both 5G BSs and co-existing APs employ beamforming to tackle the increased path loss in 60 GHz band. From now on, we do not differentiate 5G BS and co-existing AP and refer to them as 5G AP for simplicity. We also assume that each 5G AP is only able to transmit data using a single beam at a time for simplicity and the mechanism considered here can be extended to the multi-beam case.

We assume a coexistence deployment scenario with N 5G APs, which could either be 5G BSs or co-existing APs or a mixture of both, and M associated UEs for every AP. Each 5G AP has N_t transmit antennas, whilst each UE has one receive antenna. At a given time, the nth ($n = 1, \ldots, N$) 5G AP transmits to the mth ($m = 1, \cdots, M$) UE using a beam $\mathbf{w}_{nm}$, where $\mathbf{w}_{nm}$ is vector with length N_t. To obtain the beamforming vector $\mathbf{w}_{nm}$, we assume that the 5G AP selects the beam configuration within a predefined beam codebook with cardinality C that uniformly covers the azimuth directions around the AP. In particular, the codebooks at the transmitter are formed by vectors $\{\mathbf{v}_1, \cdots, \mathbf{v}_C\}$, with the ith length-N_t vector $\mathbf{v}_i$ denoting the beam for the ith codebook entry. The nth AP selects the $\hat{i}$th entry in the codebook according to

$$\hat{i} = \arg \max_{i=1,\cdots,C} \left|\mathbf{v}_i^T \mathbf{h}_{mn}\right|^2 \tag{1}$$

and

$$\mathbf{w}_{nm} = \mathbf{v}_{\hat{i}}. \tag{2}$$

We define a scheduling cycle with duration of M time slots. Within each scheduling cycle, we consider scheduling the beams for M UEs associated with a particular 5G AP, for example, the nth AP. Suppose at a given time slot m ($m = 1, \cdots, M$), this AP is transmitting to only one of the UEs via one beam in a round robin manner, which could be any one of the beams from $\mathbf{w}_{n1}, \cdots, \mathbf{w}_{nM}$, indexed as beam $1, \cdots, M$. During one scheduling cycle, the indices of the transmitted beams therefore form a beam sequence vector with a length M, denoted as $\mathbf{b}_n(t) = [b_{n1}(t), \cdots, b_{nM}(t)]^T$, where $b_{nm}(t) \in [1, \cdots, M]$.

It is known that there are $\prod_{m=1}^{M} m = M!$ permutations of such beam sequences, whereas there may exist only one optimal sequence given particular network criterion. This paper therefore aims at finding an optimal $\mathbf{b}_n(t)$ for the nth 5G AP, such that certain utility function is optimized in every scheduling cycle. In particular, we consider using the spectral efficiency as the utility function and aim to find an optimal beam sequence that maximizes the spectral efficiency.

4. Problem Formulation

Let $\mathcal{B}$ denote the set that contains all $M!$ possible beam sequences. The mathematical description of the problem is given by

$$\hat{\mathbf{b}}_n = \arg \max_{\mathbf{b}_n \in \mathcal{B}} U(\mathbf{b}_n) \tag{3}$$

where $U(\mathbf{b}_n)$ is a utility function obtained when the sequence $\mathbf{b}_n$ is chosen as the beam sequence within one scheduling cycle with duration of M time slot. When spectral efficiency is considered, the utility function for the entire scheduling cycle is given by

$$U(\mathbf{b}_n) = \frac{1}{M} \sum_{m=1}^{M} U(b_{nm}) \tag{4}$$

where $U(b_{nm})$ is the utility function for the mth user. We then consider the problem of finding the optimal $\hat{\mathbf{b}}_n$ such that the average spectral efficiency is maximized.

4.1 Derivation of Spectral Efficiency

We now show the derivation of spectral efficiency $U(b_{nm})$. Suppose at a given time slot, the mth UE is scheduled and the 5G AP is transmitting via beam $\mathbf{w}_{nm}$. The spectral efficiency for the given time slot can be expressed as [23]

$$U(b_{nm}) = \log_2\left(1 + \frac{P_r(n,m)}{I(m) + N(m)}\right) \tag{5}$$

where $P_r(n,m)$ is the received signal power at the scheduled UE m, and $I(m)$ and $N(m)$ are the interference and noise term, respectively.

The received signal power is given by

$$P_r(n,m)(dB) = P_n + G_n(m) - PL(d) \tag{6}$$

where P_n and $G_n(m)$ are the transmission power and beamforming gain at the nth 5G AP. In this paper we consider a constant transmission power, given by $P_n = \frac{P_{total}}{B}$, where P_{total} is the total transmission power and B is the bandwidth.

In addition, the beamforming gain at the nth 5G AP $G_n(m)$ is calculated as

$$G_n(m) = \left|\mathbf{w}_{nm}^H \mathbf{h}_{nm}\right|^2 \tag{7}$$

where $\mathbf{h}_{nm}$ is the channel between the nth base station to the scheduled UE given in [23] as

$$\mathbf{h}_{nm} = \sqrt{\frac{N}{L}} \sum_{l=1}^{L} \alpha_l \mathbf{a}_{UE}\left(\gamma_l^{UE}\right) \mathbf{a}_{AP}^{*}\left(\gamma_l^{AP}\right). \tag{8}$$

In (8), α_l is the complex gain of the lth path, γ_l^{UE} and $\gamma_l^{AP} \in [0, 2\pi]$ are the uniformly distributed random variables representing the angles of arrival and departure, respectively, and $\mathbf{a}_{UE}$ and $\mathbf{a}_{AP}$ are the antenna array responses at the UEs and 5G APs, respectively. Assuming uniform linear arrays, $\mathbf{a}_{AP}$ can be written as

$$\mathbf{a}_{AP} = \frac{1}{\sqrt{N_{AP}}}\left[1, \cdots, e^{j(N_{AP}-1)\frac{2\pi}{\lambda} D \sin(\gamma_l^{AP})}\right]^T.$$

For single antenna UE, we have

$$\mathbf{a}_{UE} = 1.$$

Lastly, $PL(d)$ is the path loss component between the nth 5G AP and the mth user, which is a function of the distance d between two nodes. We now look at the interference term given in (5), which is given by

$$I(m) = \sum_{\substack{n'=1 \\ n' \neq n}}^{N} P_r(n', m) \tag{9}$$

where $P_r(n',m)$ is calculated in the same manner as $P_r(n,m)$. The noise term $N(m)$ in (5) is simply white Gaussian noise, given by

$$N(m) = K_B T B \tag{10}$$

where K_B is the Boltzmann constant and T is the noise temperature.

Having obtained the spectral efficiency, the optimization problem given in (3) can then be solved and the optimal beam sequence can be found. One could perform an exhaustive search in the finite set of possible beam sequences, known to yield a high computational complexity. In the following section, we propose a novel distributed learning algorithm to solve the optimization problem, which is shown to yield comparable performance than that using exhaustive search, while achieving a much reduced complexity.

5. Beam Scheduling Algorithms

As identified in the previous sections, without joint coordination between different 5G APs, it is possible that a beam from one 5G AP points at a UE associated with a different 5G AP thereby generating interference to the victim UE. In this regard, a proper beam scheduling algorithm is needed to avoid such situations. In addition, it is possible that the optimal beam sequence obtained for one scheduling cycle with a duration of time M would not be optimal any longer due to the changes of the channel, or entry or movement of the terminals within the small cell range. Therefore, in this section, we propose a learning algorithm where the base stations can determine the optimal sequences as an accumulated statistic function from the UEs. We first present a distributed greedy scheduling mechanism, followed by a detailed description of the self-organized distributed learning algorithm.

5.1 Distributed Greedy Scheduling

In the distributed greedy scheduling algorithm, at the beginning of each scheduling cycle, $\mathbf{b}_n$ is randomly chosen from the $M!$ possible permutation sequences for each 5G AP. A block-coordinate optimization algorithm is then applied to maximize the individual utility function of each 5G AP sequentially [24]. Different from exhaustive search, where a global optimization is reached and maximum spectral efficiency is achieved for all BSs, the distributed greedy scheduling mechanism maximizes the utility function with respect to $\mathbf{b}_n$ while keeping other $\mathbf{b}_i (i \neq n)$ unchanged. In other words, the nth 5G AP computes the utility functions for all possible permutations of $\mathbf{b}_n$, and then greedily selects the sequence that yields the maximum utility value, i.e., spectrum efficiency, for itself, assuming the first $(n-1)$ 5G APs are using the optimal sequences obtained in the previous selection process. The process continues until it reaches the last 5G AP, which completes one iteration of greedy selection. The same iteration will be repeated N_{DG} times until a scheduling decision is made, where N_{DG} is the maximum iteration number.

5.2 Self-Organized Distributed Learning Scheduling

In this section, we propose a self-organized distributed learning algorithm for beam scheduling. In the proposed learning algorithm, we allocate each sequence a probability at the beginning of each scheduling cycle and then update the probability and utility functions of the sequences iteratively. The optimal beam sequence is then selected at the end of the learning procedure according to such a probability. Such a learning algorithm is detailed as follows.

Suppose the kth ($k \in [1, \cdots, M!]$) beam sequence is selected for 5G AP n at iteration t, which we denote as $\mathbf{b}_{nk}^{(t)} \in \mathcal{B}$, where $\mathcal{B}$ is the set consisting of all possible beam sequences. At the beginning, i.e., $t = 1$, each sequence is assigned with the same probability $p(U(\mathbf{b}_{nk}^{(1)})) = \frac{1}{M!}$, and one sequence $\mathbf{b}_{nk}^{(1)} \in \mathcal{B}$ is randomly selected for the nth 5G AP according to this probability. The utility functions are then calculated for each 5G AP. At the end of the tth iteration, the probability $p(U(\mathbf{b}_{ni}^{(t+1)}))$ ($1 \leqslant i \leqslant M!$) is updated for the nth 5G AP according to [25] as

$$p(U(\mathbf{b}_{ni}^{(t+1)})) = p(U(\mathbf{b}_{ni}^{(t)})) - w\frac{U(\mathbf{b}_{ni}^{(t)})}{U^{max}(t)}p(U(\mathbf{b}_{ni}^{(t)})) \tag{11}$$

subject to $\sum_{i=1}^{M!} p(U(\mathbf{b}_{ni}^{(t+1)})) = 1$, where $i \neq k$, w is a weighting factor, and $U^{max}(t)$ is the maximum utility function obtained up to iteration t, given by

$$U^{max}(t) = \max\{U(\mathbf{b}_n^{(1)}), \cdots, U(\mathbf{b}_n^{(t)})\}. \tag{12}$$

For $i = k$, $p(U(\mathbf{b}_{nk}^{(t+1)}))$ is updated as

$$p(U(\mathbf{b}_{nk}^{(t+1)})) = p(U(\mathbf{b}_{nk}^{(t)})) + w\frac{U(\mathbf{b}_{nk}^{(t)})}{U^{max}(t)}P_n^{sum} \tag{13}$$

where

$$P_n^{sum} = \sum_{i=1, i\neq k}^{M!} p(U(\mathbf{b}_{ni}^{(t)})) \tag{14}$$

The similar learning procedure is applied to the next 5G AP until it reaches the last one and then the $(t+1)$th iteration starts. Such a learning process continues until the maximum number of iteration T is hit and then the training phase stops. The final probabilities used to choose the optimal sequence for the nth 5G AP among all permutations is given by

$$\hat{k}_n(M) = \arg\max_{k\in\{1,\cdots,M!\}}\{p(U(\mathbf{b}_n^{(1)})), \cdots, p(U(\mathbf{b}_n^{(M!)}))\}. \tag{15}$$

A flow chart of the distributed learning scheduling algorithm is given in Fig. 3.

5.3 Complexity and Signaling Overhead Analysis

It is known that for exhaustive search, the statistical utility functions need to be computed for all APs and all possible beam sequences, yielding a complexity of $O((M!)^N)$, which becomes prohibitive especially with a large number

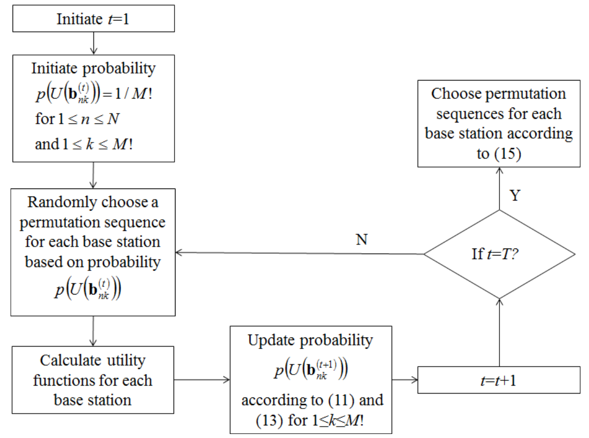

Fig. 3 Flow chart of the distributed learning scheduling algorithm.

of APs. For the distributed greedy scheduling algorithm, for N APs and N_{DG} iterations, we need to calculate $N_{DG}NM!$ utility functions in total, having a computational complexity of $O(N_{DG}NM!)$. The proposed distributed learning algorithm, on the contrary, assuming maximum number of iterations for the learning algorithm is N_{LE}, computes only one utility function for each 5G AP at a given iteration, yielding a complexity of $O(N_{LE}N)$, which is much smaller than the exhaustive search as well as the distributed greedy scheduling. In addition, as illustrated in the next section, the number of iterations required by the proposed leaning algorithm is also less than that of the greedy ones, i.e., $N_{LE} < N_{DG}$, leading to even less calculations.

In terms of signaling overhead, exhaustive search requires global utility function information to be exchanged among all 5G APs, whilst the signaling overhead of the proposed distributed learning scheduling algorithm is similar to the distributed greedy scheduling algorithm since there is no need for exchanging utility function globally.

6. Simulations

In this section, we present simulation results obtained based on the scheduling algorithms proposed in the previous section. We assume a total transmission power of 30 dBm and a total bandwidth of 500 MHz and the 5G APs distribute the power uniformly over the entire bandwidth. The pathloss model used here is given in [8]. The noise temperature T is taken as the room temperature of 300K. The detailed system parameters are presented in Table 1.

Figure 4 shows an example of a deployment scenario with 2 5G APs, each covering 5 UEs. In the figure, UE_{ij} denotes the jth UE associated with the ith 5G AP. It can be seen that if UE_{13} and UE_{22} are scheduled at the same time, the transmission beam of AP_1 to UE_{13} will cause interference to UE_{22}. Figure 5 illustrates the fluctuation of the utility functions of two APs obtained during the entire learning procedure with weighting factor chosen as $w = 0.15$ to maintain appropriate converging speed ($w = 0.15$ is used for the rest of the simulation results). As illustrated, the utility

Table 1 Main system parameters.

Parameter	Value
Carrier frequency	60 GHz
Total bandwidth	500MHz
Base station Tx power	30dBm
Inter-cell distance	200 or 400m
Number of base station antenna	8
Beam codebook size of base stations	16
Number of base stations	2 or 10
Number of UEs per base station	3 or 5
Number of UE antennas	1
Number of scatters	3
Noise temperature	300 K

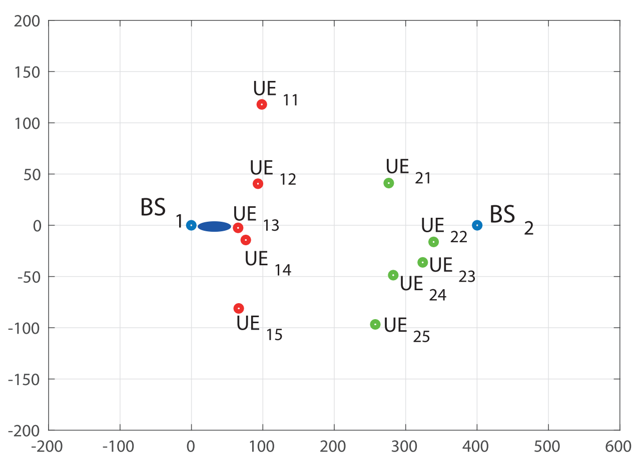

Fig. 4 Deployment of 2 5G APs (5 UEs per AP).

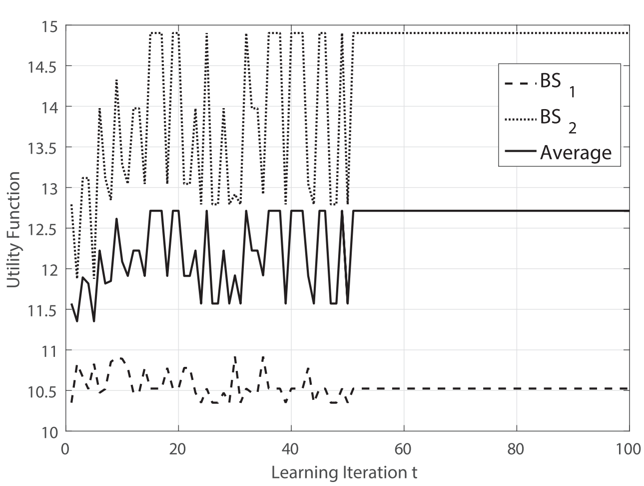

Fig. 5 Convergence behavior of the distributed learning scheduling algorithm.

functions rapidly converge to the optimal values in less than 55 learning iterations. The average utility function of two also converges to the maximum at the same pace.

The 95% available spectrum efficiency, average spectrum efficiency and 5% spectrum efficiency for different

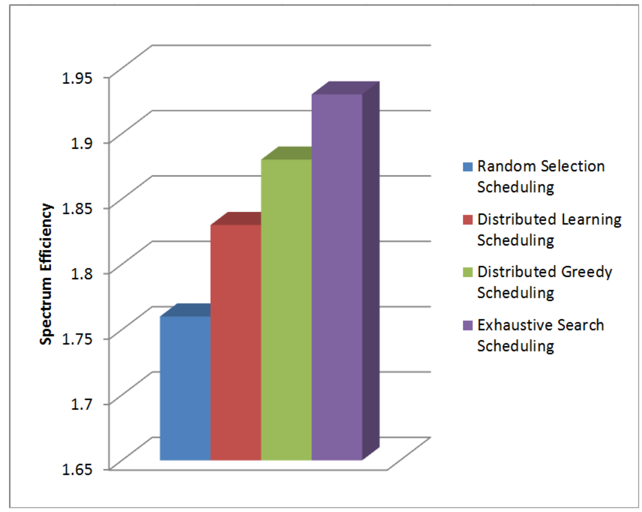

Fig. 6 95% avaialbe spectrum efficiency (cell size = 400 m).

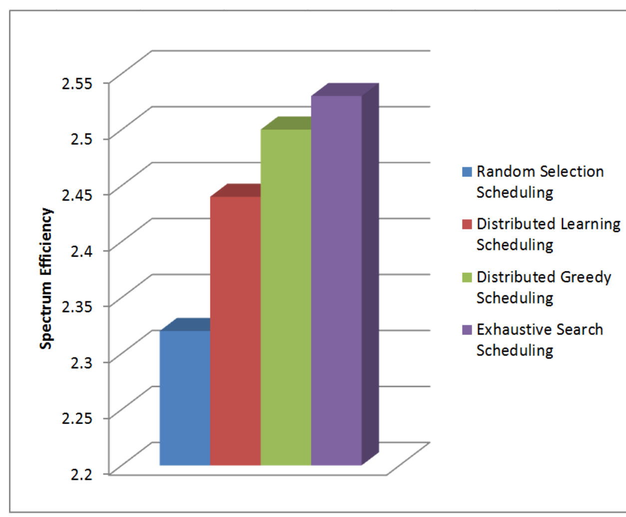

Fig. 7 Average spectrum efficiency (cell size = 400 m).

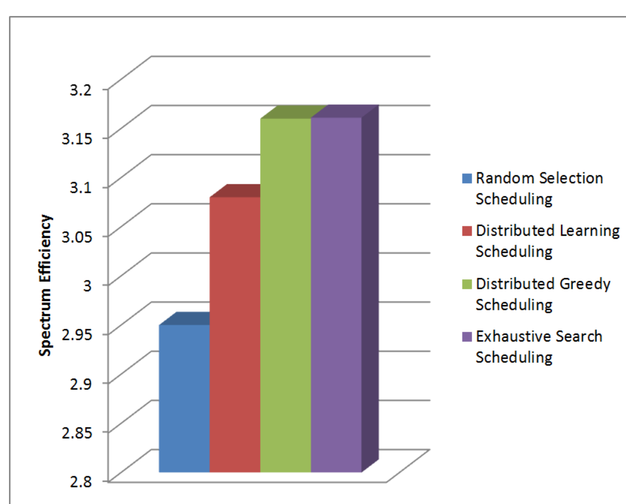

Fig. 8 5% peak spectrum efficiency (cell size = 400 m).

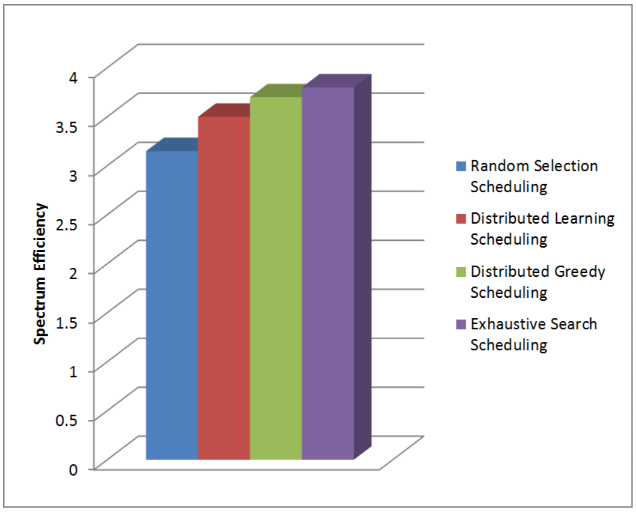

Fig. 9 95% available spectrum efficiency (cell size = 200 m).

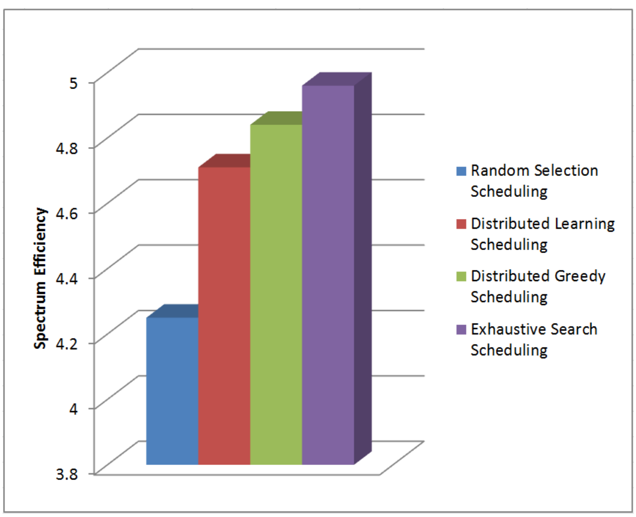

Fig. 10 Average spectrum efficiency (cell size = 200 m).

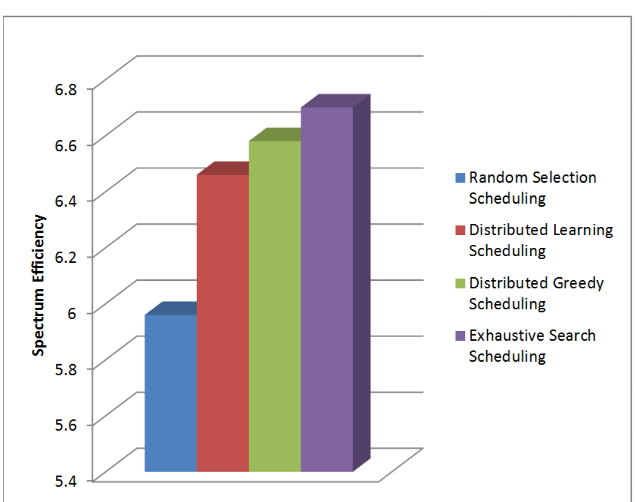

Fig. 11 5% peak spectrum efficiency (cell size = 200 m).

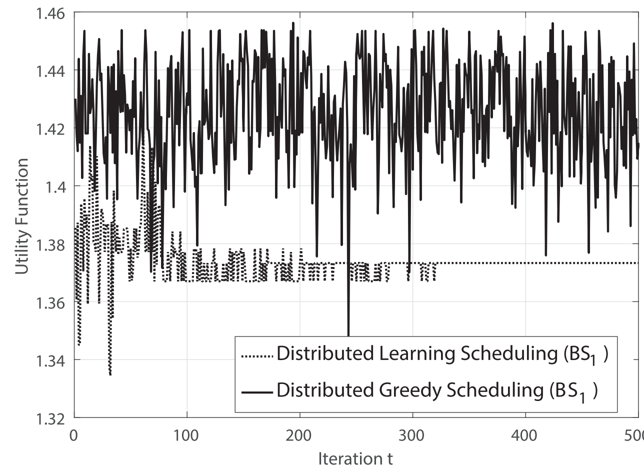

Fig. 12 Convergence behavior of two scheduling schemes.

scheduling algorithms are illustrated in Fig. 6 to Fig. 8. For comparison purpose, we present the results obtained by using random selection of permutation sequences. As expected, the exhaustive search algorithm achieves the maximum overall utility function and the performance of the distributed greedy scheduling algorithm is slightly worse than the exhaustive one, which also serves as a performance boundary for all distributed scheduling algorithms. The performance of the proposed distributed learning algorithm is very close to the greed one but with significantly reduced complexity and signaling overhead as aforementioned while at the same time outperforms random selection scheduling. When the cell deployment is densified with cell size changed from 400 m to 200 m, the performance gap between the distributed greedy scheduling algorithm and the learning algorithm becomes even smaller as shown in Fig. 9 to Fig. 11. The improvement from random selection scheduling is enhanced for peak spectrum efficiency and average spectrum efficiency but the all scheduling methods achieve similar 95% available spectrum efficiency. Another observation is that spectrum efficiency is significantly improved by densifing the APs.

Then we increase the number of deployed 5G APs to 10, each covering 3 UEs, and clearly such deployment will result in a higher probability for a UE to receive interferences from other 5G APs. In Fig. 12, the convergence speed of the distributed greedy algorithm and the proposed learning algorithm is compared. Even though the greedy algorithm achieves a higher utility value, the convergence speed of the proposed learning algorithm is much higher (more than 150 iterations less), therefore leading to further reduced complexity. The spectrum efficiency is in Fig. 13 to Fig. 15. Generally, the spectrum efficiency is reduced because the increased APs and UEs increase interferences. However, the proposed learning algorithm still outperforms the random one and is close to the greedy one.

7. Conclusion and Future Works

In this paper, we propose a novel multi-RAT coexistence

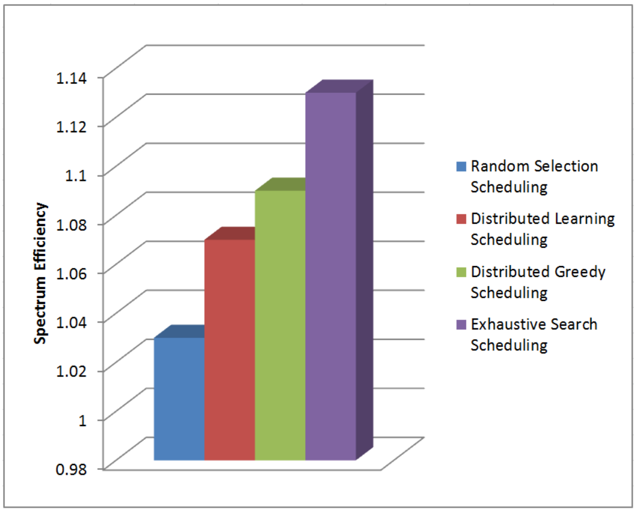

Fig. 13 5% peak spectrum efficiency (10 APs).

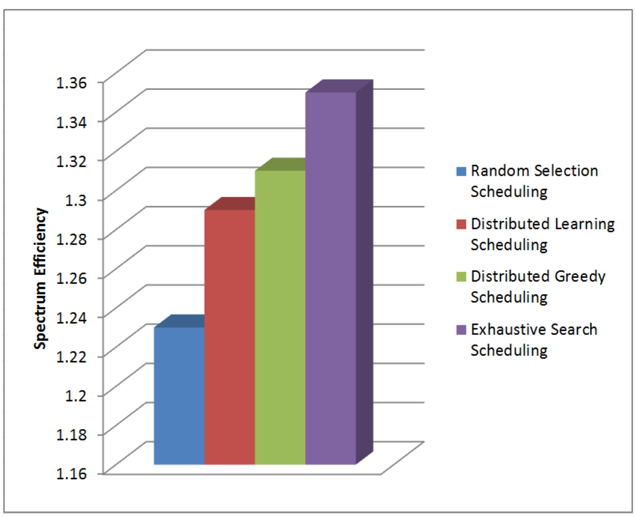

Fig. 14 5% peak spectrum efficiency (10 APs).

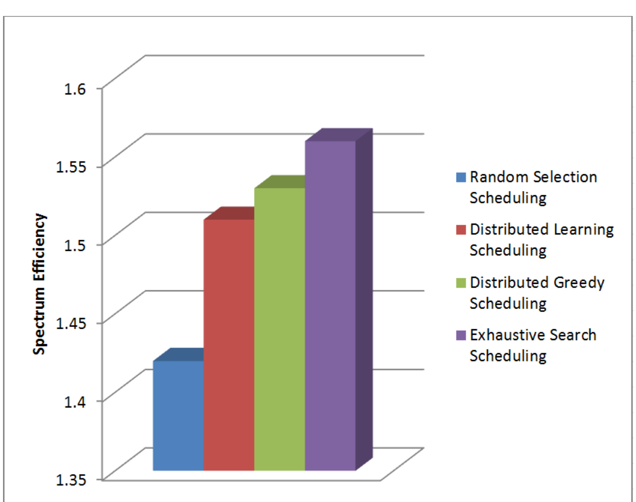

Fig. 15 5% peak spectrum efficiency (10 APs).

mechanism in unlicensed bands, where neighboring 5G APs, each serving their own associated UEs, schedule their beams in a self-organized manner with following advantages:

- Works in multi-standard and multi-operator scenarios, exploiting the common beam-forming feature of any standard that operates in mm-wave bands
- Achieves system spectral efficiency
- Does not require any central controller or scheduler (fully autonomous)
- Does not suffer from the “deafness” problem of listen-before-talk method (inherent to directional transmission scenarios)

The proposed self-organized distributed algorithm yields a comparable spectral efficiency for the entire networks as that using exhaustive search, which requires centralized coordination among multi-RAT networks with much higher algorithmic complexity. Our future work will focus on game theoretical analysis of our proposed algorithm with respect to fairness and its convergence properties.

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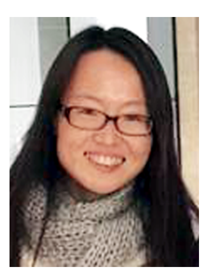

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