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Secure mmWave Spectrum Sharing with Autonomous Beam Scheduling for 5G and Beyond

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***Abstract*—Spectrum Sharing (SS) has seen a renewed set of initiatives in 5G with the availability of shared and unlicensed spectrum bands that can be used by multiple cellular service providers and private cellular networks. Beam based transmission, instead of the traditional sector based transmission in conjunction with the spectrum agility of the 5G New Radio (NR) has brought new opportunities to optimized sharing of spectrum. Currently in the U.S., a centralized Spectrum Access Server (SAS) is used to co-ordinate spectrum sharing among networks sharing the same spectrum band. However, SAS becomes a focal point for security attacks and a performance bottleneck. In addition, SAS relies on an Environmental Sensor Network (ESN), separate from the 5G network. Without trusted spectral occupancy information, false reporting of spectrum sensing data can create sub-optimal and unfair spectrum usage. This paper summarizes our recent research findings in using a decentralized scheme for multiple networks to securely share spectrum with autonomous beam scheduling : 1) A new stochastic network framework based on Lyapunov Optimization approach is developed to optimize scheduling at the base stations; 2) Game theoretic (GT) approach is used to formulate the distributed scheduler; 3) Another distributed scheduler with Q-learning is presented that utilizes the Reinforcement Learning (RL) approach; 4) The performance and convergence rate of these distributed solutions to use shared and unlicensed spectrum are compared with existing solutions. Conditions under which the performance of these schedulers approach the theoretical upper bound, which is the performance possible with no interference among the operators sharing the spectrum, are presented; 5) The ability of a base station to use its own user equipment as sensors, for optimal spectrum sharing with base stations in other operator networks, is demonstrated to be an effective approach.**

I. Introduction

Spectrum sharing (SS) was identified as a major area of importance with research gap by National Institute of Standards and Technology (NIST) [1]. Need to increase spectrum efficiency and effectiveness through secure autonomous spectrum was identified as a national spectrum research priority in [2] with recommendation to increase decentralized spectrum decision making and spectrum sharing. SS has seen a renewed set of initiatives in 5G with the potential of harvesting all of the spectrum available to use across multiple cellular service providers and private cellular networks. The FCC has been making new bands in both sub 6 GHz and mmWave available for spectrum sharing. Beam based transmission, instead of the traditional sector based radio frequency (RF) transmission, with mMIMO (massive MIMO) in sub 6 GHz and mmWave beams, in conjunction with the spectrum agility of the 5G New Radio (NR) has brought new opportunities for spatial spectrum sharing (See Fig. 1). 3GPP introduced New Radio-Unlicensed (NR-U) specifications in Release 16 for 5G use of unlicensed bands in various configurations. We would like to note that the term SS used in this paper, sharing of the same spectrum by several 5G networks, does not include the Dynamic Spectrum Sharing (DSS) capability also defined in the 3GPP Specifications for use of the same frequency band across LTE and 5G networks.

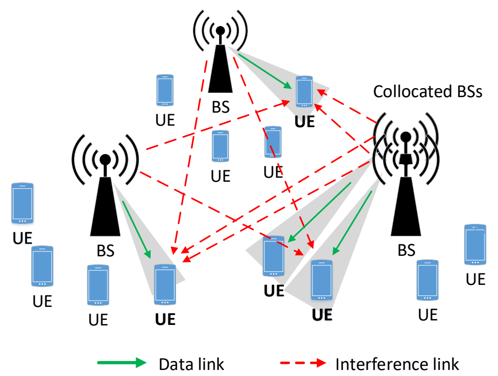


Fig. 1. Cellular mmWave network with co-located BSs and UEs.

Currently, spectrum sharing among multiple networks in the U.S. uses a centralized architecture, similar to Licensed Spectrum Access (LSA) in Europe, which depends on the enforcement of access rules and arbitration of spectrum access by the SAS database [3]. SAS depends on the Environment Sensing Capability (ESC) which is not inherent in the cellular network and needs additional sensor deployment. Without trusted spectral occupancy information, falsification of spectrum sensing data [4] can create sub-optimal and unfair spectrum usage. In addition, SAS can become a focal point for security attacks and a performance bottleneck. Use of distributed scheduling where each base station (BS) has the ability to autonomously share spectrum with its user equipment as sensors is an effective as well as secure solution. Work in [5]–[9] discuss various approaches and challenges in beam based spectrum sharing among multiple networks.

In this paper, we summarize our ongoing research with the following approach in [10] and additional details in [11]–[16]:

- Spectrum sensing at the user equipment (UE) by the base station of an operator for carrier sensing at the receiver (CSR) as opposed to carrier sensing at the transmitter (CST).
- Fair sharing of spectrum is accomplished by the operators with a distributed scheduler at their base stations without any communication among the operators or without the use of a centralized server to facilitate the sharing.
- This distributed scheduler that guarantees fair sharing is designed to maximize the total throughput with constraints on the output power of the base stations that need to operate under the sharing mode while utilizing CSR performed through the UE.
- Spatial concentration of RF coverage with beam based transmission is exploited to maximize spectrum sharing. The mmWave bands are used to demonstrate the feasibility and effectiveness for this approach. However, the solutions can in general be applied to beams in non mmWave bands.

The resulting decentralized and autonomous spectrum sharing solution is applicable also to the real world scenario of multiple operators sharing the same tower for the base station antennas. The rest of this paper is organized as follows. Section II formulates optimal spectrum sharing using the Lyapunov framework. Section III describes solutions to achieve spectrum sharing with an autonomous beam scheduler independently utilized by the operators sharing the spectrum. Section IV presents numerical evaluation of these solutions to demonstrate their effectiveness. Finally, section V includes concluding remarks based on our work so far, and plans for future work.

II. Spectrum Sharing Optimization Formulation with the Lyapunov Framework

We have proposed a novel problem formulation based on the Lyapunov stochastic optimization framework [17] with optimization of parameters such as the BS transmit powers. The optimization objective uses a log-fairness function to ensure fair sharing among BSs and UEs. Given the average and peak power constraints of the BSs, the proposed network utility optimization problem was decomposed into two sub-optimization problems. Solving the two sub-problems in each time frame yields a network utility within an additive gap to that obtained by solving the original optimization problem. The first sub-problem is convex and involves a set of auxiliary variables which can be solved distributively. The second sub-problem involves the power allocation for the UEs associated with each BS, and is stochastic and non-convex. Two virtual queues, the transmit power queue and the auxiliary variable queue, which are updated in each time frame using the solutions of the sub-problems, ensure the satisfaction of the average power constraint of the BSs in the long run. The use of the Lyapunov optimization framework guarantees that if the sub-problems can be solved within accuracy ε, then this gap can be reduced to ε/V (V is the Lyapunov constant and can be tuned manually to find a desirable trade-off between convergence speed and optimality gap) when

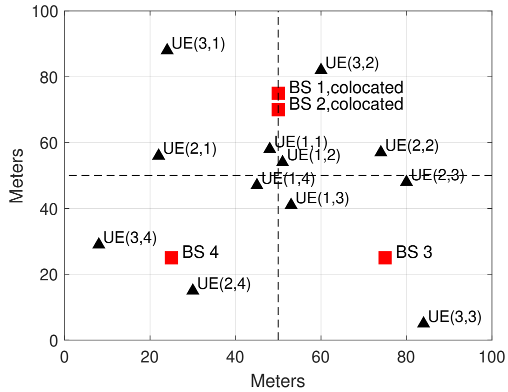


Fig. 2. Simulation network. UE (j, i) refers to the j^{th} UE of BS i.

translating back to the original network utility optimization problem. We have proposed two different approaches to solve the second sub-problem, including a Game Theoretic (GT) approach [11] where the beam scheduling and power allocation are formulated as a non-cooperative game, and a Q-learning based approach [12] where the BSs are modeled as Q-learning agents that make autonomous decisions.

III. Development of the Autonomous Scheduler Solution

To solve the second sub-problem that involves optimal power allocation by each base station, including zero power, i.e. no transmission, two approaches are pursued.

A. Game Theoretic Approach

In the first approach, the beam scheduling problem is formulated as a non-cooperative game in which the BSs are the players which do not cooperate with each other. Each BS has its own payoff function which is defined as a weighted sum of the total throughput achieved by the UEs associated with that BS, plus a power consumption penalization term. The weights in the payoff function are optimally determined by the virtual queues which are derived from the Lyapunov optimization and used in the sub-problems. Under this formulation, the second sub-problem can be approximately solved in a distributed manner by solving the Nash Equilibrium (NE) of the corresponding non-cooperative game. A parallel updating algorithm was proposed and performed periodically to provide approximate solutions to the second sub-problem in each scheduling interval. In particular, based on the measured interference at their scheduled UEs, the BSs update their transmit powers simultaneously and generate beams from slot to slot. The parallel updating algorithm was proven to converge and sufficient conditions were identified to guarantee the uniqueness of NE.

B. Reinforced Learning Approach

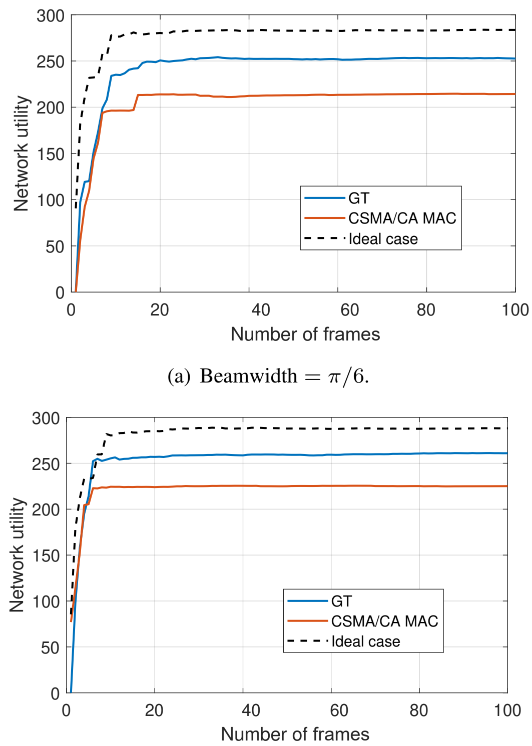
As an alternate approach, we proposed an autonomous power allocation algorithm using Q-learning, which is a classical reinforcement learning algorithm. In particular, we model each BS as an independent Q-learning agent which decides the transmit powers to its scheduled UEs from slot to slot based on the measurement of interference from other BSs. A percentile-based interference quantization method was proposed to map the continuous interference experienced by the scheduled UEs to discrete *states*. This quantization process is adaptive as it does not specify the absolute value of the interference corresponding to each state for all UEs. Therefore, the same state may imply different measured interference for different UEs. A tabular representation of the Q-table was used to store the action-state values for each UE. The ϵ-greedy action selection algorithm was used in each slot to determine the transmit powers which provides solutions to the second sub-problem decomposed from the Lyapunov optimization. The Q-learning approach adopts a storage complexity of $O\big(\frac{P_q I_q K}{M}\big)$ and a per-slot implementation complexity of $O\big(\max\{P_q, I_q\}\big)$ at each BS (with K, M, P_q and I_q being the number of UEs, BSs, discrete power levels and interference states respectively). The storage and implementation complexity are both linear in the number of UEs, demonstrating its applicability to large networks.

The Q-learning based approach can outperform the GT approach in the high interference regime thanks to its active exploration of non-greedy actions and the ability to learn from experience formalized in the action-state values. One important scenario is the case of co-located BSs with possible overlapped beams. The GT approach can perform poorly in such a scenario due to its selfish nature, which leads each BS to transmit with full power in order to maximize its own payoff while causing strong interference to other UEs which compromises the overall network-level performance. Q-learning based agents can avoid such bad decisions by observing the small reward emitted from choosing large powers. In addition, by active exploration, there is a higher chance of finding the optimal transmit power in the long run.

IV. Numerical Evaluation

We present the performance evaluation of the GT approach and Q-learning approach in this section. A simulation network with four BSs, with co-located BS 1 and BS 2, are used where each BS is associated with three UEs as shown in Fig. 2. The UEs are classified as cell-edge and cell-center UEs. Cell-edge UEs, such as the 1^{st} UE of each BS, located near the BS coverage boundary, are likely to experience interference from neighboring BSs. In contrast, cell-center UEs such as the 3^{rd} UEs of each BS, located close to the cell center, are less likely to be interfered by other BSs. The main-lobe and side-lobe have constant radiation gains in the antenna model and the *antenna gain* is defined as the ratio of the main-lobe gain to the side-lobe gain. The Nakagami-m distribution is used to model the small-scale fading.

For each BS, different UEs are scheduled randomly from block to block. Each time frame contains 8 blocks while each block contains 50 slots. As a baseline, the GT approach is compared with the CSMA/CA MAC protocol. The ideal case refers to a scenario where we assume no interference among BSs and therefore it serves as a performance upper bound. Fig 3(a) shows the achieved network utility with BS



(a) Beamwidth $= \pi/6$.

(b) Beamwidth $= \pi/18$.

Fig. 3. Effect of BS beamwidth for fixed antenna gain 20 dB.

beamwidth $\pi/6$ (in radius) and antenna gain 20 dB. It can be seen that the GT approach converges in a dozen of frames and achieves higher network utility than the baseline scheme. Comparing Fig 3(a) and Fig 3(b) where the antenna gain is fixed as 20 dB, it can be seen that when the beamwidth is reduced, higher utility can be achieved as narrower beams do not cover undesired UEs and cause less interference. A comparison of the GT approach with the ideal case is shown in Fig. 4 under various beamwidth and antenna gain configurations. It can be seen that the gap between the GT approach and the ideal case becomes smaller when the beams get sharper, implying less interference experienced by each scheduled UE. In an extreme case with beamwidth $\pi/72$ and 40 dB antenna gain, the GT approach has almost identical performance to the ideal case. This demonstrates that the GT approach can achieve near-optimal performance in the high SINR regime.

The effect of the number of discrete power levels P_q, interference states I_q and power penalization factor β are verified for the Q-learning approach. We also verify the performance of both Q-learning and GT approaches under different interference situations. Instead of using random UE scheduling, we consider only one block here to demonstrate the superiority of the Q-learning approach over GT because a better solution to the second sub-problem in each block will naturally yield a better performance when the Lyapunov framework is applied.

In Fig. 5, the effect of P_q is shown under different power

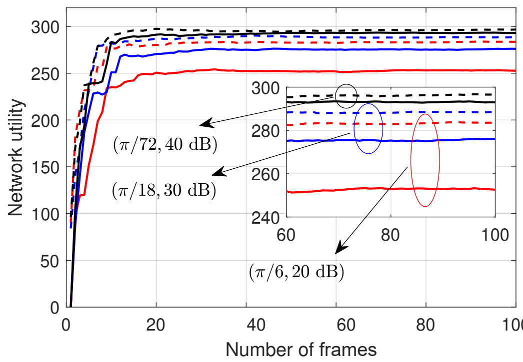
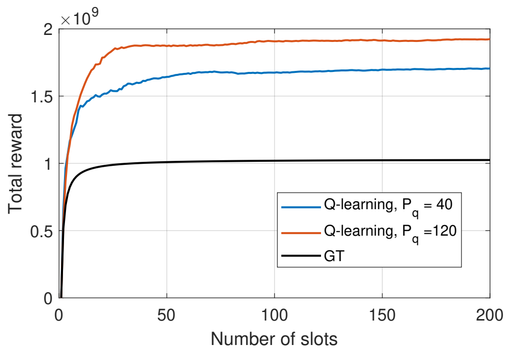
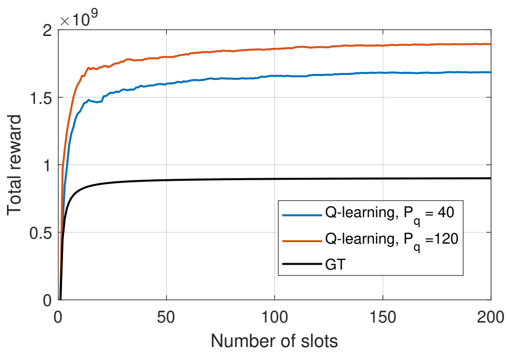


Fig. 4. Comparison of GT with ideal case. Solid lines represent GT and dashed lines represent the ideal case. Lines of the same color are simulated under the same antenna configuration.

penalization factors $\beta = 0$ or $\beta = 0.01BW$ ($BW = 400$ MHz is the total bandwidth). When $\beta = 0$, the objective is equivalent to maximizing the total throughput of the network. Fig. 5(a) shows the case when I_q is fixed to be 40. It can



(a) $\beta = 0$.



(b) $\beta = 0.01BW$.

Fig. 5. Effect of the number of discrete power levels P_q.

be seen that the Q-learning approach achieves much higher reward than GT. Higher reward can also be achieved when P_q is increased from 40 to 120 because larger P_q provides each BS with more decision choices and has the potential to find the optimal power. Similar observation can be obtained from Fig. 5(b) where $\beta = 0.01BW$.

V. Conclusion

We presented results from ongoing research on a distributed solution for spectrum sharing among multiple 5G networks with autonomous beam schedulers in their base stations. Spectrum sensing at the UE is used to adjust the power levels of transmission at the base stations belonging to multiple operators that result in fair sharing of the spectrum. In the future, we intend to use the Platform for Open Wireless Data-driven Experimental Research (POWDER) in the University of Utah for experimental verification of our research.

VI. Acknowledgements

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