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Chao Zhang
École Supérieure d'Electricité

Bhanukiran Perabathini
Alcatel Lucent

Samson Lasaulce
French National Centre for Scientific Research

Cooperative Energy Efficient Resource Allocation in Fast Fading Interference Networks

Achal AGRAWAL*, Sivasriprasanna MADDILA*, Chao ZHANG†,
Bhanukiran PERABATHINI‡, Samson LASAULCE†

* Mahindra École Centrale, Hyderabad, India, † L2S (CNRS-CentraleSupelec-Univ. Paris Sud), France,
‡ SRMAP, Amravati, India
email: *{firstname.lastname@mechyd.ac.in}, †{firstname.lastname@lss.supelec.fr}
, ‡{bhanukiran.p@srmap.edu.in}

***Abstract*—Cooperative schemes for energy efficient resource allocation usually require certain forms of communication (implicit or explicit) among the cooperating transmitters. These solutions are therefore impractical in the fast fading scenario where the channel gains change very quickly and there is no time for communication. Inspired by previous information theoretical results, in this paper we propose a heuristic resource allocation function which achieves cooperation without mutual communication among the transmitters. This function is a one shot decision function whose parameters are tuned offline for given channel statistics. It can be used online in a fast fading scenario as given the local channel state information (CSI), we can instantaneously find an energy efficient power allocation in a distributed manner. We compare the performance of the proposed function with other state of the art distributed power allocation schemes requiring communication. While some communicating schemes achieve better performances than the one proposed herein, it must be noted that they do so by using up timeslots for communication. By the virtue of not requiring communication, the proposed algorithm is superior for fast fading scenarios where communication might not be feasible as the coherence time of channels is only a few timeslots which will be used up for communication.**

I. Introduction

Energy-efficiency of wireless communications is becoming an increasingly important problem due to the exponential increase in data flux and the energy required to sustain it. Also, given the battery-constraints for mobile devices, energy efficiency of the communications is of paramount importance. Lately, energy efficiency has also become an important criterion for radio base stations and telecommunication operators due to their large share in the operational costs [1]. Techniques for energy efficient wireless systems are discussed in [2] for numerous scenarios. In this paper, we consider the specific problem of energy efficient power allocation in a multi-carrier interference network.

A multi-carrier interference network is a network of a few Transmitter-Receiver pairs trying to communicate between each other over different orthogonal frequencies. The communications interfere with other pairs who might be using the same carrier frequency to pass their messages. The aim is to allocate power for each transmitter across all the bands so as to maximize the sum-energy efficiency of the system.

In order to perform *socially optimal* power allocation, the global channel state information (CSI) must be known. One of the ways of exchanging the global CSI is through the inter-transmitter signaling channels [3]. Another technique involves implicit signalling through the interference channel [4]. Doing this one can achieve near optimal coordination schemes albeit at the cost of timeslots for communication between the transmitters for exchanging information [5]. Opportunistic carrier-sense multiple access (CSMA) has also been proposed as a protocol to perform auctions for the various frequency bands [6] in a distributed manner. However, all of these works require the channels to have a long coherence time. In the case of fast-fading channels, these algorithms perform badly due to the time lost in convergence to a good solution. Furthermore, increasing the number of transmitters increases the time taken to converge, leading to higher opportunity costs.

One of the important early works treating the power allocation problem in multi-carrier interference networks is [7]. Therein, the authors develop an algorithm based on best response dynamics (BRD) to reach Nash Equilibrium (NE) whenever it exists. However, it is well known that Nash Equilibria are bad operating points in terms of sum-energy efficiency for the entire system due to high interference from competing transmitters. To mitigate the interference amongst various users, a distributed auction scheme was proposed in [8] building upon the centralized auction scheme proposed in [9]. This scheme performs very well for resource allocation as every band is allotted to only one user (the

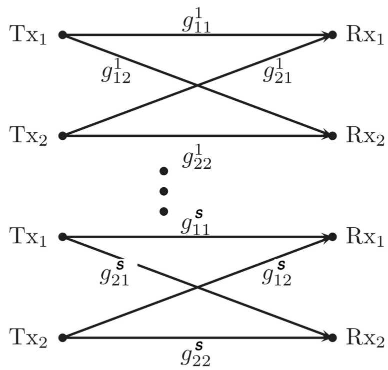

Fig. 1: Schema of the multi-carrier interference network discussed in Sec. II with 2 transmitters (Txs), 2 receivers (Rxs), and $S \geqslant 1$ non-overlapping frequency bands.

highest bidder). Thus there is no interference caused. The auction scheme was made better by using bipartite graphs to find optimal matching in [10]. Even though this improved the auction algorithm in terms of faster convergence, the distributed auction algorithm still performed better in terms of absolute performance.

In this work, we develop a one-shot decision function, which gives good performance right from the start. Moreover, to ensure the completely distributed nature of our solution, the decision function for a transmitter depends only on the individual CSI. No live communication between transmitters is therefore required in our framework. It was shown in [11] that knowing global CSI does not help perform much better than when one knows only local CSI. We compare the performance of our algorithm with the distributed auction algorithm [8] after it has converged. The distributed auction scheme uses opportunistic CSMA protocol for performing the auction in a completely distributed manner, i.e. without an auctioneer. However, opportunistic CSMA requires defining a backoff period where transmitters need to wait and sense if other transmitters are on the same channel. This induces performance loss due to potentially long bidding times. This work is a natural extension of [12] wherein a continuous power control function was devised for the single carrier case. The current study generalizes this approach to the multi-carrier scenario.

This paper is organized as follows: In Section II, we formulate the system model and define the problem under consideration more precisely. We motivate the one-shot decision function in Section III. To find the function parameters, we develop a distributed algorithm in Section IV. We compare the performance of our scheme with state of the art power allocation schemes for interference networks in Section V. We conclude in Section VI.

II. Problem formulation

Consider K transmitter-receiver pairs in a wireless network, each choosing their individual power emitted in each channel $p_i^s \in \mathcal{P}_i^s$, where $i \in \mathcal{K} = \{1, ..., K\}$ denotes the transmitter index and $s \in \mathcal{S} = \{1, ..., S\}$ denotes the bands. The total power chosen by any transmitter summed over all the channels should not exceed the maximum power $P_{\max}$ available to any transmitter, i.e. $\sum_{s=1}^{S} p_i^s \leqslant P_{\max}, \forall i$.

All transmitters emitting on the same band create interference for each other. We denote the signal to interference plus noise ratio (SINR) for transmitter i in band s as γ_i^s, and can be written as

$$\gamma_i^s = \frac{{p_i}^s g_{ii}^s}{\sigma^2 + \sum_{j=1, j \neq i}^{K} {p_j}^s g_{ji}^s} \quad (1)$$

where $g_{ji}^s \in \mathbb{R}_{\geqslant 0}$ is the channel gain coefficient for the transmission between transmitter j and the receiver i in the band s. The variance of noise is denoted by σ^2. The collection of all the individual CSIs is the global channel state $G = (g_{11}^s, ..., g_{KK}^s) \in \mathbb{R}^{K^2}$. The global channel state is a random variable, and its realizations directly affect the common payoff. Indeed, the challenge for the transmitters lies in being able to choose the power levels for a given global channel realization. Each global channel gain realization g_{ji}^s is taken to be independent and identically distributed (i.i.d.). We consider the Rayleigh fading model, i.e. the random variable G_{ji}^s is assumed to follow an exponential distribution ρ.

The metric we choose to optimize is the *Average-Energy efficiency (AEE)*, i.e. average of energy efficiency of all the Tx-Rx pairs. Note that this is the same as optimizing sum-energy efficiency as it is just a division by a constant. The energy efficiency for a Tx-Rx pair is defined as the total efficiency obtained over all the bands over the combined power spent by the transmitter over all the bands. The instantaneous average energy efficiency can be written as:

$$AEE(G, \vec{p_1}, \ldots, \vec{p_K}) = \frac{1}{K} \sum_{i=1}^{K} \frac{\sum_{s=1}^{S} \psi(\gamma_i^s)}{\sum_{s=1}^{S} {p_i}^s} \quad (2)$$

where $\vec{p_i}$ denotes the S-dimensional power vector emitted by transmitter i. The function ψ represents the efficiency function for a given SINR value. Some typical efficiency functions are packet success rate, throughtput and goodput.

Since the global CSI G is a random variable, we aim to maximize the expected AEE over all the possible realizations of G and their associated probabilities. More precisely, we aim to maximize the following quantity:

$$\mathbb{E}_G[AEE(G, \mathbf{P})] = \int_{G \in \mathcal{G}} AEE(G, \mathbf{P}) \rho(G) \mathrm{d}G \quad (3)$$

where $\mathbf{P}$ denotes $(\vec{p_1}, \ldots, \vec{p_K})$ for conciseness.

We are looking for power allocation policies which maximize the expected payoff. In general, these policies could use the past channel realizations. However, if one assumes the channel realizations to be i.i.d., then past channel realizations bring no extra information for taking the decision. Thus, we shall only be considering stationary, i.e. time independent strategies. Another restriction that can be put on the policies is that they should depend solely on the individual CSI available at the transmitter. More precisely, we assume that the decision function of transmitter i can be written as $f_i(\vec{g_{ii}})\mathbb{R}_{\geqslant 0} \rightarrow \vec{p_i}$ where $\vec{g_{ii}}$ is the S-dimensional vector of the individual CSIs for transmitter i.

Having restricted the space of possible functions, our aim will be to find the joint decision function $f := (f_1(\cdot), \ldots, f_K(\cdot))$ that maximizes the the Average-Energy Efficiency (AEE) of the system. The optimization problem can formally stated as:

$$\underset{f \in \mathcal{F}}{\text{Maximize}} \quad \mathbb{E}_G[AEE(G, \mathbf{P})]. \tag{4}$$

In the next section, we shall introduce a heuristic power allocation function to help maximize the expected payoff.

III. Continuous Power Allocation function

Performing the functional optimization problem (4) is nonetheless a difficult proposition. In [13], we proposed a locally optimal solution which did an exhaustive search to find the best output for every possible function input. The complexity of this approach was prohibitive even in the single-carrier case. However, the toy simulations performed using the algorithm did give us insights about the characteristics of the decision function. In [12], we used some of the insights to design scalable one-shot decision functions in the single carrier case, i.e. when $S = 1$.

In the multi-carrier case ($S > 1$), the complexity of the algorithm developed in [13] further increases exponentially with the number of bands. This is because one has to consider all permutations and combinations of the different channel realizations, making an exhaustive approach unfeasible. In this paper, we propose a heuristic power allocation function based on exhaustive simulation results for two bands and three Tx-Rx pairs. The following intuitions were gained from these simulations for the characteristics of the good decision functions:

- Channel Inversion - It is well known that channel inversion is an optimal strategy in case of only 1 user [14]. We propose that whenever a user chooses to emit over a band, it uses power which maximizes its utility on a given band assuming no interference from other users. The probability of interference is reduced by using the thresholding policy.
- Thresholding Policy - In this policy, a transmitter does not emit any power on a channel until the channel gain is above a certain threshold. It was shown that in the case of single-band Interference Channel (IC), thresholding can be an effective way of reducing interference by other users [12]. For the multi-band case, we propose a similar policy with every user i having a different threshold $\lambda_i^s \in \Lambda$ for each band s based on the global channel statistics, where Λ denotes the set of all possible λ_i^s.
- Channel Selection - Channel selection also helps in reducing the interference caused. It has also been proposed as solutions for power allocation in various works [7] . The channel selection is achieved through a weight vector $\alpha_i^s \in \mathcal{A}$, with $\sum_s \alpha_i^s = 1$, which again depends on the global channel statistics.

Combining these three policies we propose the function defined in equation 5. This function first evaluates the set $S_i^\lambda = \{s \in S | g_{ii}^s > \lambda_i^s\}$. If the set is empty, the user chooses to emit P_{min} in every band. If the set has only one element, then the user chooses the channel inversion power on that channel. In the event of more than one bands satisfying the thresholding condition, we evaluate the product of the weights α_i^s and the individual direct channels g_{ii}^s for all the bands $s \in S_\lambda$. User chooses the band with the highest product $s^\star = \arg\max_{s \in \mathcal{S}_\lambda} \alpha_i^s g_{ii}^s$. In the highly unlikely event of the non-unicity of $s^\star$, we randomly choose one of the bands.

In the following definition for the function, we assume the S-dimensional weight vector $\vec{\alpha_i} \quad \forall i$ and threshold vector $\vec{\lambda_i} \quad \forall i$ have already been calculated. In the next section, we describe an algorithm which can help us find these quantities.

$$f_i^{\vec{\lambda_i}, \vec{\alpha_i}}(\vec{g}_{ii}) = \begin{cases} 0 & \text{if } |S_i^\lambda| = 0 \\ \\ +(\frac{\gamma^\star \sigma^2}{\vec{g}_{ii}})\mathbb{1}_s & \text{if } |S_i^\lambda| = 1, s \in S_i^\lambda \\ \\ (\frac{\gamma^\star \sigma^2}{\vec{g}_{ii}^s})\mathbb{1}_{s^\star} & \text{if } |S_i^\lambda| > 1 \\ & s^\star = \underset{s \in S_i^\lambda}{\text{argmax}}\, \alpha_i^s g_{ii}^s \end{cases} \tag{5}$$

where $\mathbb{1}_s$ is the vector with s^{th} component being 1 and other components 0. The optimal single player SINR $\gamma^\star$ can be gotten by solving $\gamma\psi'(\gamma) = \psi(\gamma)$, where $\psi(.)$ is the efficiency function.

The above function structure reduces the search space for power allocation functions to a search over parameters $\vec{\lambda_i} \in \Lambda^S$ and $\vec{\alpha}_i \in \mathcal{A}^S$, where $\Lambda^S, \mathcal{A}^S$ denote the cartesian product of alphabets S times. While this is a considerable reduction in search space, a joint-exhaustive search for finding the optimal parameters is still computationally demanding.

In the next section, we describe a distributed algorithm to find the aforementioned parameters $\Lambda^S, \mathcal{A}^S$. In Algorithm 1, we use sequential global best response dynamics, to find these parameters offline. The computational complexity is thus only linear in $|\Lambda||\mathcal{A}|$ as opposed to $|\Lambda^S||\mathcal{A}^S|$ for the joint exhaustive search.

IV. Offline Distributed Algorithm

Here, we develop an algorithm to find the function parameters λ_i^s, α_i^s for all Tx-Rx pairs and all the bands. Finding these in a joint manner quickly becomes computationally prohibitive beyond two Tx-Rx pairs and two bands. We develop an algorithm where each transmitter i sequentially learns and updates its own function parameters which maximize the ecpected AEE. Other transmitters are assumed to keep their parameters fixed till it is not their turn to update. This procedure is known as sequential Best Response Dynamics (BRD).

However, there are two major differences with our implementation when compared to BRD: 1) The procedure is performed offline and can thus be used to generate decision functions that can be exploited immediately 2) Instead of each transmitter maximizing its own energy efficiency, it chooses the parameters that maximize the average energy efficiency (AEE), thus learning how to coordinate.

Since we are doing best response dynamics for a common 'team' payoff $AEE(G, \mathbf{P})\rho(G)$, the convergence of best-response dynamics is guaranteed [15].

Proposition IV.1. *Algorithm 1 converges for a common team payoff* $AEE(G, \mathbf{P})\rho(G)$.

Proof. The result can be proved by calling for an exact potential game property [15]. Since the common payoff function itself satisfies all the properties of a potential function, it is trivially an exact potential game. Note that his argument holds for all common payoffs, i.e. sum or average of any performance criteria. □

Due to the iterative nature of the algorithm, there is no guarantee of achieving the global maxima. However, through simulations we show that for the smaller cases where an exhaustive search is feasible, our distributed iterative algorithm achieves performance comparable to joint optimization of the individual function parameters. Also, quite like gradient descent, the approach is sensitive to the initialization. We propose a no-preference initialization, with the channel weights $\alpha_i^s = 1/S, \forall i, s$, and the channel thresholds $\lambda_i^s = 0, \forall i, s$. The pseudo-code for the algorithm is provided in Algorithm 1.

Algorithm 1 Proposed distributed Algorithm for finding thresholds λ_i^s and channel selection weights α_i^s offline

inputs: $\rho(G)$

output: $\lambda_i^s, \forall(i, s) \in \{1, ..., K\} \times \{1, ..., S\}$,
$\alpha_i^s, \forall(i, s) \in \{1, ..., K\} \times \{1, ..., S\}$

initialization: $(\lambda_i^s, \alpha_i^s) = (0, 1/S)\forall i, s, \quad iter = 0$, $iter_{max} = 100$

while $\exists \; i, s : (\lambda_i^s, \alpha_i^s)_{\text{iter}} - (\lambda_i^s, \alpha_i^s)_{\text{iter}-1} \geqslant \epsilon$ *AND* $\text{iter} \leqslant \text{iter}_{max}$ *OR* $\text{iter} = 0$ **do**
- $\text{iter} = \text{iter} + 1$
- **foreach** $i \in \{1, \ldots, K\}$ **do**
  - **foreach** $(\vec{\lambda}_i, \vec{\alpha}_i) \in \Lambda^s \times \mathcal{A}^s$ **do**
    - Find $\overline{AEE}_{\vec{\lambda}_i, \vec{\alpha}_i} = \sum_G \rho(G) AEE(G, \mathbf{P})$
    - where $\mathbf{P} : (\vec{p_1}, \ldots, \vec{p_K})$ and $\vec{p_i} = f_i^{\vec{\lambda}_i, \vec{\alpha}_i}(G)$
    - Store $\overline{AEE}_{\vec{\lambda}_i, \vec{\alpha}_i}$
  - **end**
  - Update the thresholds and weights $(\vec{\lambda}_i, \vec{\alpha}_i) = \underset{(\vec{\lambda}_i, \vec{\alpha}_i) \in \Lambda^s \times \mathcal{A}^s}{\text{argmax}} \overline{AEE}_{\vec{\lambda}_i, \vec{\alpha}_i}$
- **end**

end

In the next section we analyze the performance of the proposed algorithm, and compare it with other distributed power allocation schemes.

V. Numerical Analysis

In this section, we shall make some choices for the energy efficiency function and parameters discussed heretofore. However, note that our algorithm can be easily adapted for other energy efficiency utility functions involving throughput, goodput or packet success rate. The form of the individual decision functions remain the same. The function parameters will tune themselves according to the utility function as well as the system parameters.

A typical choice for efficiency function is the packet success rate [16]:

$$\psi(\gamma_i) = (1 - e^{-0.5\gamma_i})^M \tag{6}$$

where total number of bits per frame $M = 80$. For this efficiency function and the chosen value for M, we can obtain $\gamma^\star = 12.4$ by solving $\gamma\psi'(\gamma) = \psi(\gamma)$. We choose the Signal to Noise Ratio (SNR) to be 10 dB for the simulations. The Signal to Noise Ratio (SNR) depends on P_{max} in the following way:

$$SNR = 10log_{10}(\frac{P_{max}}{\sigma^2}) \tag{7}$$

Due to the increasing complexity in number of bands, we restrict ourselves to only two bands, i.e. $S = 2$. For every extra band considered, the complexity of the algorithm increases by $|\Lambda| * |\mathcal{A}|$, where $|.|$ denotes the cardinality of the set. In our simulations, we choose the alphabet sizes to be $|\Lambda| = 21, |\mathcal{A}| = 11$. The alphabet for thresholds $|\Lambda|$ goes from 0 to 5 with the stepsize of 0.25. The weights alphabet $|\mathcal{A}|$ need only go from 0 to 1 with the step size of 0.1.

The channel gain statistics are chosen in such a way that half the players have a better channel on band 1 and the remaining half on band 2 to break the symmetry. More specifically $\mathrm{E}(g_{ii}^1) = 2$ for $i \leqslant \frac{K}{2}$ and 1 otherwise. Similarly, $\mathrm{E}(g_{ii}^2) = 2$ for $i > \frac{K}{2}$ and 1 otherwise. Also the channel gain interference coefficients $\mathrm{E}(g_{ij}) = 0.1, i \neq j$, unless stated otherwise.

Firstly, we want to show that the loss incurred due to the iterative procedure described in Algo-1 is minimal. To do so, in Fig. 2, we plot the average energy efficiency for two cases: Algo-1 and joint exhaustive search over all the parameters $(\vec{\lambda}_i, \vec{\alpha}_i) \in \Lambda^s \times \mathcal{A}^s$. We plot it for for the simplified case of $K = 2, S = 2$ due to the computational complexity for the joint exhaustive search. We can see that the performance of both are comparable, although Algo. 1 has a much smaller complexity.

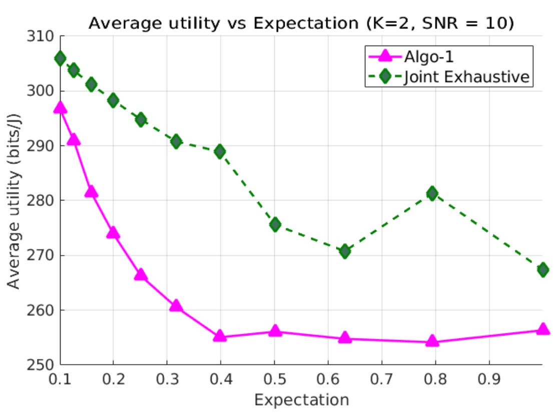

Fig. 2: Comparison of joint exhaustive search and Algo-1. We can see that the performance of Algo-1 is comparable (within 10% of joint exhaustive search. Thus, the distributed algorithm does not incur much loss in terms of optimality

We compare our algorithm with the one proposed in [7]. Therein, Nash equilibrium is achieved by performing channel selection. Every user sequentially chooses his best channel in terms of minimum power required, to achieve $SINR = \gamma^\star$ on that channel. We also compare the performance to a more recent work [8] which explored the use of distributed auction for energy efficient channel allocation. In the auction algorithm, each channel is assigned to only one user. The user is chosen through a bidding process involving several iterations which scales up in number of transmitters.

Average EE is calculated through 10^6 monte carlo draws for all the algorithms. Instead of plotting the sum-energy efficiency, we will be plotting the energy efficiency per transmitter. This is to ensure a more just comparison even when the number of transmitters are different.

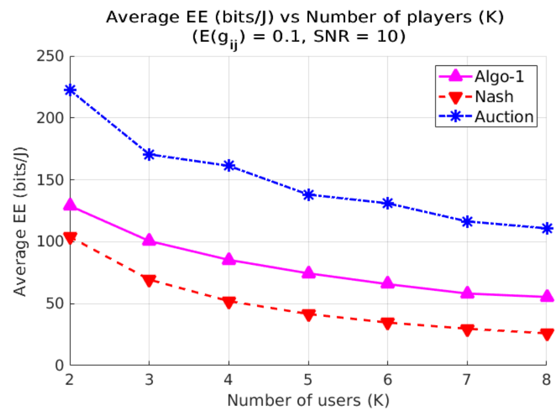

Fig. 3: Comparison of our proposed power allocation policy with Nash policy [7] and auction algorithm [10] for different number of players. We see that the proposed algorithm considerably outperforms [7]. The difference in performance between Algo-1 and the auction algorithm is due to the convergence time available for the auction algorithm which helps transmitters coordinate better. If the channel coherence time is less than twice the convergence time for auction algorithm, then Algo-1 is a better choice.

We can see from Fig. 3 that Nash policy, despite being distributed and of lower complexity, performs very badly in terms of average energy efficiency. Algo-1 brings considerable improvement in performance thanks to the cooperative decision function which reduces the interference between transmitters. Auction algorithm performs almost twice as well as Algo-1. This is not surprising as the auction algorithm relies on implicit communication during the bidding phase, which leads to better channel assignments. Also, a larger number of players increases the bidding phase owing to more possible clashes. In fast-fading or block-fading scenarios where the channel gain coefficients are not constant for many timeslots, our function can help achieve better performance.

Further comparison can be drawn between the two policies over variations in the the expectation of the in-

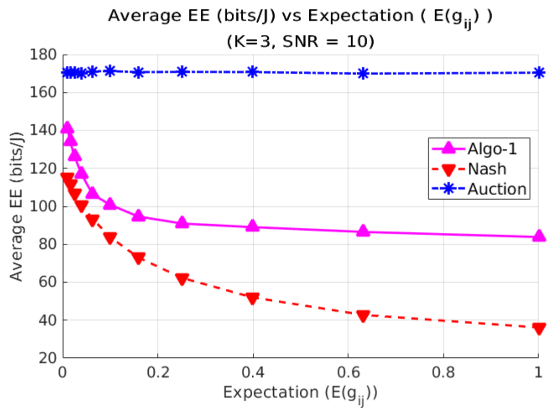

Fig. 4: Comparison of our proposed power control policy with Nash policy and the Auction algorithm as the expectation of the interference channel gain increases. We see that high interference is effectively handled by Algo-1

terference channel gain. Fig. 4 unsurprisingly indicates dropping utilities as the channel interference $E(g_{ij}^s)$ increases for Nash policy and Algo-1. For Auction algorithm, this has no effect as there is no interference to begin with. Indeed, the Nash policy performs badly under high interference due to an increase in emitted power in response to higher interference from other players on their chosen band. The proposed algorithm however adjusts the thresholds and weights to take the higher interference into account. This ensures minimal interference by reducing the number of players per band, explaining the flattening of the curve at higher interference.

VI. Conclusion

While communication has its benefits for achieving better cooperation, in quickly changing environments, the time taken to communicate becomes a significant overhead. One shot decision functions like the one introduced in this study can help with cooperation in such scenarios. The search space for such decision functions is very large. Even after making several assumptions about the functions, the complexity of the algorithm developed here does not scale well in number of bands. Smarter searching methods instead of exhaustively searching over all possible combinations of $(\vec{\lambda}_i, \vec{\alpha}_i) \in \Lambda^s \times \mathcal{A}^s$ could help reduce the search complexity further. One promising direction could be to use our framework and find the optimal parameters using Team Deep Neural Networks (T-DNN) as proposed in [17]. Our framework will help reduce the size of the output layers, with the training required only to find the optimal parameters introduced in our work.

Acknowledgement

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