Multi-scale Spectrum Sensing in Millimeter Wave Cognitive Networks

Nicolo Michelusi, Matthew Nokleby, Urbashi Mitra, and Robert Calderbank

***Abstract*—In this paper, a multi-scale approach to spectrum sensing and information exchange in millimeter wave cognitive cellular networks is proposed. In order to overcome the huge energy cost of acquiring full network state information on the occupancy of each cell over the network, secondary users acquire local state estimates, which are aggregated up the hierarchy to produce multi-scale estimates of spectrum occupancy. The proposed design accounts for local estimation errors and the *irregular* interference patterns arising due to sensitivity to blockages, high attenuation, and high directionality at millimeter wave. A greedy algorithm based on agglomerative clustering is proposed to design an *interference-based tree* (IBT), matched to the interference pattern of the network. The proposed aggregation algorithm over IBT is shown to be much more cost efficient than acquiring full network state information from the neighboring cells, requiring as little as 1/5th of the energy cost.**

I. Introduction

To satisfy increasing throughput demands, 5G cellular networks will employ techniques such as millimeter wave (mm-wave), massive MIMO, cell densification, and cognitive radio [1]–[3]. A challenge in deploying these technologies is the high attenuation and sensitivity to *blockage* of mm-wave transmissions. Attenuation in mm-wave is not solely defined by the distance between transmitter and receiver, which cases irregular interference patterns. Techniques for managing interference in mm-wave networks must account for these irregularities. Furthermore, the acquisition of network state information (NSI) becomes more challenging as cell density increases. A scalable approach for NSI is required.

In this paper, we consider a cognitive mm-wave cellular network with a set of primary users (PUs), licensed to access the spectrum, and a set of opportunistic secondary users (SUs), which seek access to unoccupied spectrum. In each cell, PUs join and leave the channel at random times. In order to utilize the unoccupied spectrum, the SUs require accurate estimates of spectrum occupancies throughout the cellular network. In principle, channel occupancies can be estimated locally and collected at a fusion center; in practice, such centralized estimation is too costly in terms of transmit energy and delay. Furthermore, due to path loss, shadowing, and blockage, SUs may cause significant interference in some cells, but negligible interference elsewhere in the network. Each SU needs precise information about the occupancies *only of cells at which it is likely to cause interference.*

To this end, we present a *cost effective* approach to NSI estimation and interference management that is tailored to irregular interference patterns. We propose a *hierarchical* spectrum sensing scheme, based on [4], by which local estimates of spectrum occupancy are aggregated efficiently at multiple layers. As a result, SUs estimate accurately the spectrum occupancy of cells to which they cause strong interference, and estimate coarsely the spectrum occupancy otherwise. This allows an effective trade-off between SU network throughput and interference to PUs.

The main ingredients of this approach are (1) a cellular hierarchy that determines the aggregation of measurements and is matched to the irregular interference pattern of the network based on *agglomerative clustering* [5, Ch. 14], and (2) a derivation of the Bayes-optimum estimate of the spectrum occupancy from the aggregated measurements. In terms of the trade-off between SU network throughput, interference to the PUs, and the energy expended in collecting spectrum information, we observe a 10% cost reduction over the regular tree construction proposed in our previous work [6], and up to 1/5th of the cost of exchanging full NSI within neighboring cells.

Previous work includes consensus-based schemes for spectrum estimation in static networks [7], [8], whereas here we focus on a *dynamic* setting due to the high susceptibility to the mobility of users and blockages at mm-wave. A framework for joint spectrum sensing and scheduling in wireless networks has been proposed in [9] for the case of a single cell; here we consider a network composed of multiple cells.

The rest of this paper is organized as follows. In Section II, we present the system model. In Section III, we introduce the hierarchical spectrum sensing protocol, which is then analyzed in Section IV. In Section V, we present the tree design and some numerical results, followed by concluding remarks in Section VI. Proofs, as well as analysis that considers the impact of aggregation delays, are provided in [10].

II. System model

A. Network Model

We consider a cognitive network, depicted in Fig. 1, composed of a cellular network of PUs with N_C cells, and an opportunistic network of SUs. We denote the set of cells by $\mathcal{C} \equiv \{1, 2, \dots, N_C\}$. Transmissions are slotted and occur over frames, indexed by t. Let $b_{i,t} \in \{0, 1\}$ be the PU spectrum occupancy of cell $i \in \mathcal{C}$ at time t; i.e. $b_{i,t} = 1$ if the channel is occupied by PUs in cell i at time t, and $b_{i,t} = 0$ if it is idle. We suppose that $\{b_{i,t}, t \geq 0, i \in \mathcal{C}\}$ are i.i.d. across cells and

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N. Michelusi is with the School of Electrical and Computer Engineering, Purdue University. email: michelus@purdue.edu.

M. Nokleby is with the Dept. of Electrical and Computer Engineering, Wayne State University. email: matthew.nokleby@wayne.edu

U. Mitra is with the Dept. of Electrical Engineering, University of Southern California. email: ubli@usc.edu.

R. Calderbank is with the Dept. of Electrical Engineering, Duke University. email: robert.calderbank@duke.edu.

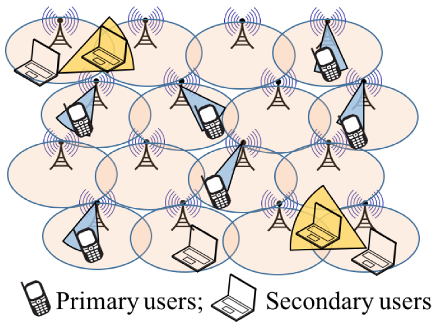

Fig. 1: System Model.

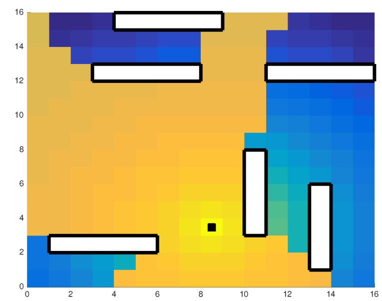

Fig. 2: Blockage Model.

evolve according to a two-state Markov chain, as a result of PUs joining and leaving the network at random times. Let

$$\nu_1 \triangleq \mathbb{P}(b_{i,t+1}{=}1|b_{i,t}{=}0),\ \ \nu_0 \triangleq \mathbb{P}(b_{i,t+1}{=}0|b_{i,t}{=}1), \quad (1)$$

denote the transition probabilities of the Markov chain from "0" to "1" and from "1" to "0", respectively. At steady-state, $b_{i,t} = 1$ with probability

$$\pi_B \triangleq \frac{\nu_1}{\nu_1 + \nu_0}. \quad (2)$$

We denote the state of the network at time t as $\mathbf{b}_t = (b_{1,t}, b_{2,t}, \ldots, b_{N_C,t})$.

The SUs opportunistically access the spectrum to maximize their own throughput, subject to a constraint on the interference caused to the PUs. The *SU access decisions* are denoted as $a_{i,t} \in \{0, 1\}$, where $a_{i,t} = 1$ if the SUs operating in cell i access the channel at time t, and $a_{i,t} = 0$ otherwise. Let the network-wide SU access decision be denoted by $\mathbf{a}_t = (a_{1,t}, a_{2,t}, \ldots, a_{N_C,t})$ at time t. Let $\phi_{i,j} \geq 0$ denote the interference strength generated by the SUs in cell i to the primary network in cell j. We assume that interference is symmetric, so that $\phi_{i,j} = \phi_{j,i}, \forall i, j \in \mathcal{C}$. While this assumption relies on channel reciprocity, we note that our analysis extends readily to asymmetric interference. We collect the interference strength values into the matrix $\mathbf{\Phi} \in \mathbb{R}^{N_C \times N_C}$.

B. Propagation Model

We suppose that nodes transmit and receive in the mm-wave band and employ directional antenna arrays [1], [11]. Mm-wave transmissions tend to be absorbed by objects, resulting in *blockages* [12] that severely attenuate the wireless signal. At the same time, the reduced wavelength of mm-wave transmission permits more antennas to fit onto devices, resulting in higher directivity [2], [13].

These two factors result in an irregular interference pattern. To model this, we adopt a variation of the stochastic blockage and sectored beamforming model of [14]–[17]. Rectangular blockages of fixed height and width are placed randomly on cell *boundaries*, as shown in Fig. 2. We say that links between cells i, j are *line of sight* (LOS) if the line segment connecting the centers of cells i and j does not intersect any blockage object. Otherwise, such links are said to be *non-LOS* (NLOS). Accordingly, we define LOS and NLOS path loss exponents, denoted α_L and α_N, respectively. Experimentally-derived values are published in [1], [13], with $\alpha_L \approx 2$ and $\alpha_N \approx 3-4$ as typical values.

Let $G_t(\theta_t)$ and $G_r(\theta_r)$ denote the antenna array gains of the SUs and PUs along the directions θ_t and θ_r, respectively. Let G_t, g_t (with $g_t < G_t$) and ω_t denote the main lobe gain, side lobe gain, and half-beamwidth of the main lobe of the transmit SU array, and let G_r, g_r (with $g_r < G_r$) and ω_r denote the same quantities related to the receiver's array. Then, the antenna array gains are

$$G_i(\theta_i) = \begin{cases} \frac{G_i}{2\omega_i G_i + 2(\pi-\omega_i)g_i} & |\theta_i| \leq \omega_i, \\ \frac{g_i}{2\omega_i G_i + 2(\pi-\omega)g_i} & |\theta_i| > \omega_i, \end{cases} \quad (3)$$

where the denominator ensures that the total radiated power is constant regardless of directivity.

The interference caused by the SUs depends on the orientation of the users, which, due to mobility, will vary across time slots. Rather than calculate a new interference matrix in every time slot, we define the interference in an *average* sense, supposing that θ_t, θ_r are uniformly distributed across $(-\pi, \pi]$. More precisely, we define Φ as

$$\phi_{i,j} = \begin{cases} \frac{P_t d(i,j)^{-\alpha_L}}{4\pi^2} \int G_t(\theta_t) G_r(\theta_r) d\theta_t \theta_r, & (i,j) \text{ is LOS}, \\ \frac{P_t d(i,j)^{-\alpha_N}}{4\pi^2} \int G_t(\theta_t) G_r(\theta_r) d\theta_t \theta_r, & (i,j) \text{ is NLOS}, \end{cases} \quad (4)$$

where P_t is a reference transmit power and $d(i, j)$ is the distance between cells i and j. The higher the blockage density, the smaller the beamwidths ω_t, ω_r, and the greater the difference between gains G_i and g_i, the less the interference and the better the performance of the network.

C. Network Performance Metrics

Given the NSI $\mathbf{b}_t \in \{0, 1\}^{N_C}$ and the SU access decision $\mathbf{a}_t \in \{0, 1\}^{N_C}$, we define the local expected reward for the SUs in cell i and the interference to the PUs caused by the activity of the SUs in cell i as

$$r_{S,i}(a_{i,t}, \mathbf{b}_t) = a_{i,t}\big[\rho_I(1 - b_{i,t}) + \rho_B b_{i,t}\big], \quad (5)$$

$$\iota_{P,i}(a_{i,t}, \mathbf{b}_t) = a_{i,t} \sum_{j=1}^{N_C} \phi_{i,j} b_{j,t}. \quad (6)$$

The first term in (5) indicates the reward if the SUs in cell i access the channel when the PU is idle, where $\rho_I \geq 0$ is the expected throughput per frame. The second term is the reward if the SUs in cell i access the channel when the PU is active, where $0 \leq \rho_B \leq \rho_I$ is the instantaneous expected throughput in this case. The term (6) indicates the total interference generated by SUs in cell i to the rest of the primary network.

We define the SU network reward and the total interference to PUs as the sum of local rewards and interferences over the entire network:

$$R_S(\mathbf{a}_t, \mathbf{b}_t) = \sum_{i \in \mathcal{C}} r_{S,i}(a_{i,t}, \mathbf{b}_t), \tag{7}$$

$$I_P(\mathbf{a}_t, \mathbf{b}_t) = \sum_{i \in \mathcal{C}} \iota_{P,i}(a_{i,t}, \mathbf{b}_t). \tag{8}$$

The SUs in cell i select $a_{i,t}$ to optimize a trade-off between $R_S(\mathbf{a}_t, \mathbf{b}_t)$ and $I_P(\mathbf{a}_t, \mathbf{b}_t)$ based on partial NSI, denoted by the belief $\pi_{i,t}(\mathbf{b})$ that the NSI takes value $\mathbf{b}_t = \mathbf{b}$ at time t. We use a Lagrangian formulation to capture such trade-off, denoting the expected utility by

$$u_i(a_{i,t}, \pi_{i,t}) \triangleq \sum_{\mathbf{b} \in \{0,1\}^{N_C}} \pi_{i,t}(\mathbf{b}) \big[r_{S,i}(a_{i,t}, \mathbf{b}) - \lambda \iota_{P,i}(a_{i,t}, \mathbf{b}) \big], \tag{9}$$

where $\lambda \geq 0$ is a Lagrangian multiplier term.[1] Thus,

$$a^*_{i,t} = \arg \max_{a \in \{0,1\}} u_i(a, \pi_{i,t}), \tag{10}$$

yielding the optimal expected local utility

$$u^*_i(\pi_{i,t}) = \max\big\{ u_i(0, \pi_{i,t}), u_i(1, \pi_{i,t}) \big\} = \big(u_i(1, \pi_{i,t}) \big)^+,$$

where $(\cdot)^+ = \max\{\cdot, 0\}$ and $u_i(0, \pi_{i,t}) = 0$ from (5)-(6).

Given the belief $\boldsymbol{\pi}_t = (\pi_{1,t}, \pi_{2,t}, \ldots, \pi_{N_C,t})$ across the network, under the optimal SU access decisions $\mathbf{a}^*_t$ given by (10), the optimal network utility is thus given by

$$U^*(\boldsymbol{\pi}_t) = \sum_{i \in \mathcal{C}} u^*_i(\pi_{i,t}). \tag{11}$$

The belief $\boldsymbol{\pi}_t$ is computed based on *noisy, and aggregate* (noise-free and fine-grained) spectrum measurements performed over the network, as described in the next section.

III. Hierarchical Spectrum Sensing

In order to reduce the cost of acquisition of NSI and account for errors in spectrum measurements and delay incurred during information exchange, we propose a *multi-scale* approach to spectrum sensing. To this end, we partition the cellular grid into a tree-based hierarchical structure. We will design an algorithm for the construction of this tree in Section V.

We associate a tree to the cell grid. At level-0, we have the leaves, represented by the cells $\mathcal{C}$. We let $\mathcal{C}_0^{(i)} \equiv \{i\}$ for $i \in \mathcal{C}$. At level-1, let $\mathcal{C}_1^{(k)}$ be a partition of the cells into n_1 non-empty subsets, where $1 \leq k \leq n_1 \leq |\mathcal{C}|$. We associate a cluster head to each subset $\mathcal{C}_1^{(k)}$; the set of n_1 level-1 cluster heads is denoted as $\mathcal{H}_1$. Hence, $\mathcal{C}_1^{(k)}$ is the set of cells associated to the level-1 cluster head $k \in \mathcal{H}_1$.

Recursively, at level-L, let $\mathcal{H}_L$ be the set level-L cluster heads, with $L \geq 1$. If $|\mathcal{H}_L| = 1$, then we have defined a tree with depth $D = L$. Otherwise, we define a partition of $\mathcal{H}_L$ into n_{L+1} non-empty subsets $\mathcal{H}_L^{(m)}$, where $1 \leq m \leq n_{L+1} \leq |\mathcal{H}_L|$, and we associate to each subset a level-$(L+1)$ cluster head (specifically, $\mathcal{H}_L^{(m)}$ is associated to level-$(L+1)$ cluster head m); the set of n_{L+1} level-$(L+1)$ cluster heads is denoted as $\mathcal{H}_{L+1}$. Let $\mathcal{C}_{L+1}^{(m)}, m = 1, 2, \ldots, n_{L+1}$ be the set of cells associated to level-$(L+1)$ cluster head $m \in \mathcal{H}_{L+1}$. This is obtained recursively as

$$\mathcal{C}_{L+1}^{(m)} = \bigcup_{k \in \mathcal{H}_L^{(m)}} \mathcal{C}_L^{(k)}. \tag{12}$$

Let $H_L(i) \in \mathcal{H}_L$ be the level-L parent of cell $i \in \mathcal{C}$, *i.e.*, $H_0(i) = i$, and $H_L(i) = k$ for $L \geq 1$ if and only if $i \in \mathcal{C}_L^{(k)}$, for some $k \in \mathcal{H}_L$. We make the following definitions.

Definition 1. We define the *hierarchical distance* between cells $i \in \mathcal{C}$ and $j \in \mathcal{C}$ as

$$\Lambda(i,j) \triangleq \min\{L \geq 0 : H_L(i) = H_L(j)\}.$$

In other words, $\Lambda(i,j)$ is the lowest level L such that cells i and j belong to the same level-L cluster. It follows that $\Lambda(i,i) = 0$ and $\Lambda(i,j) = \Lambda(j,i)$, *i.e.*, the hierarchical distance between cell i and itself is 0, and it is symmetric.

Definition 2. We let $\mathcal{C}_\Lambda^{(i)}(L)$ be the set of cells at hierarchical distance L from cell $i \in \mathcal{C}$. That is, $\mathcal{C}_\Lambda^{(i)}(0) \equiv \{i\}$, and

$$\mathcal{C}_\Lambda^{(i)}(L) \equiv \mathcal{C}_L^{(H_L(i))} \setminus \mathcal{C}_{L-1}^{(H_{L-1}(i))}, \ L > 0. \tag{13}$$

In fact, $\mathcal{C}_L^{(H_L(i))}$ contains all cells at hierarchical distance (from cell i) less than L (or equal to it). Thus, $\mathcal{C}_\Lambda^{(i)}(L)$ is obtained by removing from $\mathcal{C}_L^{(H_L(i))}$ all cells at hierarchical distance less than (or equal to) $L-1$, $\mathcal{C}_{L-1}^{(H_{L-1}(i))}$ (note that this is a subset of $\mathcal{C}_{L-1}^{(H_{L-1}(i))}$, since $H_{L-1}(i) \in \mathcal{H}_{L-1}^{(H_L(i))}$).

In order to collect NSI, the SUs exchange local estimates over the tree. In particular, we propose a scheme in which the SUs carry out a *hierarchical* fusion of local estimates. This fusion is patterned after *hierarchical averaging*, a technique for scalar average consensus in wireless sensor networks [4].

At frame t, the SUs in each cell i obtain a noisy measurement of $b_{i,t}$. The SUs transmit their estimates to a single SU, designated the *cluster head* for cell i. The cluster head forms the aggregate estimate $\hat{b}_{i,t}$ of the spectrum occupancy.

Next, these estimates are fused up the hierarchy.[2] By the end of the spectrum sensing phase in frame t, the level-1 cluster head $m \in \mathcal{H}_1$ receives the spectrum estimates from its cluster $\mathcal{C}_1^{(m)}$, that is $\hat{b}_{i,t}$ from cells $i \in \mathcal{C}_1^{(m)}$. These estimates are aggregated at the level-1 cluster head as

$$S_{m,t}^{(1)} \triangleq \sum_{i \in \mathcal{C}_1^{(m)}} \hat{b}_{i,t}, \ \forall m \in \mathcal{H}_1, \tag{14}$$

which estimates the number of PUs occupying the spectrum in cell $C_1^{(m)}$ at time t.

This process continues up the hierarchy: the level-L cluster head $m \in \mathcal{H}_L$ receives the *aggregate* spectrum estimate

[1] In principle, different cells may employ different values of λ. We ignore this case for simplicity.

[2] Typically, this fusion incurs delay. Due to space constraint, herein we consider no delay; the case with aggregation delays is investigated in [10].

$S_{k,t}^{(L-1)}$ from the level-$(L-1)$ cluster head $k \in \mathcal{H}_{L-1}^{(m)}$ connected to it. These are aggregated as

$$S_{m,t}^{(L)} = \sum_{k \in \mathcal{H}_{L-1}^{(m)}} S_{k,t}^{(L-1)}. \tag{15}$$

Thus, $S_{m,t}^{(L)}$ represents the *aggregate* spectrum estimate at the level L cluster head m. Finally, the aggregate spectrum measurements are fused at the root (level D) as

$$S_{1,t}^{(D)} = \sum_{k \in \mathcal{H}_{D-1}^{(1)}} S_{k,t}^{(D-1)} = \sum_{j \in \mathcal{C}} \hat{b}_{j,t}. \tag{16}$$

After reaching the final level of the hierarchy, the aggregated measurements are propagated down to the individual cells $i \in \mathcal{C}$, following the tree. At frame t, SUs operating in cell i receive from their level-L cluster heads:

$$\begin{cases} S_{H_0(i),t}^{(0)} &= \hat{b}_{i,t}, \\ S_{H_L(i),t}^{(L)} &= \sum_{j \in \mathcal{C}_L^{(H_L(i))}} \hat{b}_{j,t},\ 1 \leq L < D, \end{cases}$$

recalling that $H_L(i)$ is the level-L parent of cell i, $\mathcal{C}_L^{(H_L(i))}$ is the set of cells associated to $H_L(i)$. From these measurements, cell i can compute the aggregate spectrum estimate of the cells at all hierarchical distances from itself:

$$\begin{cases} \sigma_{i,t}^{(0)} \triangleq \hat{b}_{i,t}, \\ \sigma_{i,t}^{(L)} \triangleq S_{H_L(i),t}^{(L)} - S_{H_{L-1}(i),t}^{(L-1)},\ 1 \leq L \leq D. \end{cases} \tag{17}$$

Thus, the SUs operating in cell i can compute the *aggregate* spectrum estimate at multiple scales corresponding to different hierarchical distances L, for $L = 0, 1, \ldots, D$. Importantly, only an estimate of the aggregate spectrum is available, rather than the current state of a specific cell $b_{j,t}, \forall j \neq i$. These aggregate spectrum estimates are used to update the belief $\pi_{i,t}$ in the next section.

IV. Analysis

Using the aggregate estimates at each scale, the SUs in each cell i update the belief $\pi_{i,t}$ based on the following theorem.

Theorem 1. *Given* $\boldsymbol{\sigma}_i^t = (\mathbf{o}_0^t, \mathbf{o}_1^t, \ldots, \mathbf{o}_D^t)$, *where* $\mathbf{o}_L^t = (o_{L,0}, o_{L,1}, \ldots, o_{L,t})$, *we have*

$$\pi_{i,t}(\mathbf{b}) = \prod_{L=0}^{D} \mathbb{P}\left(b_{j,t} = b_j, \forall j \in \mathcal{C}_\Lambda^{(i)}(L) | \boldsymbol{\sigma}_i^{(L,t)} = o_L^t\right), \tag{18}$$

where, letting $\sum_{j \in \mathcal{C}_\Lambda^{(i)}(L)} b_j = x$,

$$\begin{aligned} &\mathbb{P}\left(b_{j,t} = b_j, \forall j \in \mathcal{C}_\Lambda^{(i)}(L) \middle| \boldsymbol{\sigma}_i^{(L,t)} = o_L^t\right) \\ &= \underbrace{\mathbb{P}\left(\sum_{j \in \mathcal{C}_\Lambda^{(i)}(L)} b_{j,t} = \sum_{j \in \mathcal{C}_\Lambda^{(i)}(L)} b_j \middle| \boldsymbol{\sigma}_i^{(L,t)} = o_L^t\right)}_{A} \\ &\times \underbrace{\frac{\left(\sum_{j \in \mathcal{C}_\Lambda^{(i)}(L)} b_j\right)! \left(|\mathcal{C}_\Lambda^{(i)}(L)| - \sum_{j \in \mathcal{C}_\Lambda^{(i)}(L)} b_j\right)!}{|\mathcal{C}_\Lambda^{(i)}(L)|!}}_{B} \end{aligned} \tag{19}$$

where $\chi(\cdot)$ *is the indicator function. Additionally,*

$$\sum_{x=0}^{|\mathcal{C}_\Lambda^{(i)}(L)|} x \mathbb{P}\left(\sum_{j \in \mathcal{C}_\Lambda^{(i)}(L)} b_{j,t} = x \middle| \boldsymbol{\sigma}_i^{(L,t)} = o_L^t\right) = o_{L,t}. \tag{20}$$

To help unpack Theorem 1, we make the following observations:

1) Equation (18) implies that $\pi_{i,t}$ is statistically independent across the subsets of cells at different hierarchical distances from cell i; this follows from the i.i.d. assumption made in Section II.
2) Equation (19) contains two terms. The term (A) is the probability distribution of the aggregate spectrum occupancy given previous estimates. The term (B) is the probability of a specific realization of $b_{j,t}, j \in \mathcal{C}_\Lambda^{(i)}(L)$, given that its aggregate equals $\sum_{j \in \mathcal{C}_\Lambda^{(i)}(L)} b_j$. This follows from the fact that there are $\binom{|\mathcal{C}_\Lambda^{(i)}(L)|}{x}$ combinations of such spectrum occupancies.
3) Equation (20) states that the expected aggregate occupancy over $\mathcal{C}_\Lambda^{(i)}(L)$, given past estimates, equals $o_{L,t}$, but is independent of past spectrum estimates. However, its probability distribution given by term (A) in (19) *does* depend on past spectrum estimates.
4) In general, the term (A) in (19) cannot be computed in closed form, except in some special cases (*e.g.*, noiseless measurements [18]). However, we will now show that a closed-form expression is not required to compute the expected utility in cell i.

We can use Theorem 1 to compute the expected utility in cell i, given by (9). Using (5)-(6), partitioning the cells $\mathcal{C}$ based on their hierarchical distance from cell i, and letting

$$\begin{cases} \Phi_i(\text{tot}) \triangleq \sum_{j \in \mathcal{C}} \phi_{i,j} \\ \Phi_i(L) \triangleq \sum_{j \in \mathcal{C}_\Lambda^{(i)}(L)} \phi_{i,j}, \end{cases} \tag{21}$$

be the total interference generated by the SUs in cell i to the network, and the *interference* generated to the cells at hierarchical distance L from cell i, we finally obtain the following lemma.

Lemma 1. The expected utility in cell i is given by $u_i(0, \boldsymbol{\sigma}_{i,t}) = 0$ and

$$\begin{aligned} &u_i(1, \boldsymbol{\sigma}_{i,t}) = \rho_I(1 - \sigma_{i,t}^{(0)}) + \rho_B \sigma_{i,t}^{(0)} \\ &- \lambda \sum_{L=0}^{D} \left(\frac{\sigma_{i,t}^{(L)}}{|\mathcal{C}_\Lambda^{(i)}(L)|} - \pi_B\right) \Phi_i(L) - \lambda \pi_B \Phi_i(\text{tot}). \end{aligned} \tag{22}$$

Note that the utilities, and therefore the aggregate *network utility* (11), depend on the structure of the tree employed for the aggregation of spectrum occupancy estimates. In the next section, we present an algorithm to design the tree so as to maximize the network utility, and we provide some numerical results.

V. Interference-based Tree Design

Network performance depends on the aggregation defined by the sets $\mathcal{C}_L^{(k)}$. Optimizing directly over the aggregation has

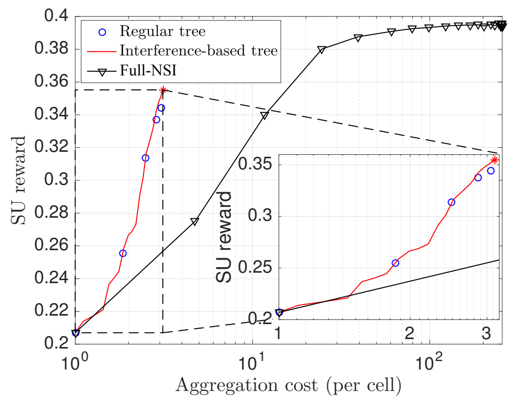

Fig. 3: Reward to SUs for a reference interference to PUs of 0.025 (per cell) as a function of the aggregation cost.

exponential complexity, so we adopt a greedy approach based on agglomerative clustering [5, Ch. 14], which we call the *interference-based tree* (IBT). Define the *similarity* between two macrocells as their total mutual interference, i.e.

$$\gamma_L(k_1,k_2)=\sum_{i\in\mathcal{C}_L^{(k_1)}}\sum_{j\in\mathcal{C}_L^{(k_2)}}\phi_{i,j}. \tag{23}$$

Then, we build the hierarchy by successively merging the macrocells with the highest similarity. This results in the aggregation of cells that have high potential for interference.

We also want to limit the energy expended in aggregating estimates. Define the *aggregation cost per cell*

$$C(k_1,k_2)\ =\frac{1}{N_C}\max_{i\in\mathcal{C}_L^{k_1},j\in\mathcal{C}_L^{k_2}}d(i,j), \tag{24}$$

which supposes that the energy cost is proportional to transmit distance. Each time we combine two macrocells k_1 and k_2, we incur an additional energy cost $C(k_1,k_2)$. Aggregation continues until either the aggregation forms a tree or a maximum aggregation cost is reached. Agglomerative clustering has complexity $O(N_C^2\log(N_C))$, where the N_C^2 term owes to searching over all pairs of clusters.

In Figure 3 we show the trade-off between network reward and per-cell aggregation cost. We simulate a 16×16 rectangular cellular network, with random blockages and $\phi_{i,j}$ calculated according to a path-loss model with exponent $\alpha=2$ for links without blockages (LOS) and $\alpha=4$ for links with blockages (NLOS) [1], [13]. We compare the IBT to two other schemes: a *regular* tree, in which adjacent cells are aggregated together into a tree without regard for $\mathbf{\Phi}$, and *full-NSI*, in which SUs aggregate all of the measurements from cells within a certain radius. Tree-based aggregation substantially improves the reward/cost trade-off, and the IBT outperforms the regular tree by 10%. Importantly, IBT incurs 1/5th of the energy cost of full-NSI to exchange estimates over the network, thus demonstrating a much more efficient use of resources.

VI. Conclusions

To reduce the cost of acquisition of network state information in cognitive mm-wave networks, we have proposed a hierarchical scheme to aggregate estimates at multiple scales. This approach accounts for local estimation errors, the energy cost of aggregation, and irregular interference patterns at mm-wave. Using greedy, agglomerative clustering, we match the aggregation tree to the network interference structure.

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