Shared Spectrum Allocation via Pathloss Estimation in Crowdsensed Shared Spectrum Systems

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***Abstract*—The RF spectrum is a natural resource in great demand. The research community has addressed this unabated increase in demand via development of shared spectrum paradigms, wherein the spectrum is made available to unlicensed users (secondaries) as long as they do not interfere with the transmission of licensed incumbents (primaries). In this paradigm, typically a centralized entity (spectrum manager) is responsible for allocation of spectrum bands to a requesting SU, based on known parameters of the primaries and channel state. Optimal power allocation is important for efficient management of spectrum.**

In this work, we consider a crowdsourced architecture of the shared spectrum paradigm, wherein the spectrum is monitored by a large number of inexpensive spectrum sensors deployed in the area of interest. In this context, we propose a spectrum allocation algorithm that is based on estimation of path loss from the sensing reports of these spectrum sensors. Such an architecture obviates the need to assume a propagation model, but requires design of accurate estimation techniques. We consider various possible estimation schemes involving splitting of aggregate power received at each sensor and multiple interpolation schemes. We evaluate the performance of our proposed schemes with respect to the optimal allocation, and observe that allocation using the best of our methods is close to the optimal.

I. Introduction

The RF spectrum is a natural resource in great demand due to the unabated increase in mobile (and hence, wireless) data consumption [3]. The research community has addressed this capacity crunch via development of *shared spectrum paradigms*, wherein the spectrum is made available to unlicensed users as long as they do not interfere with the transmission of licensed incumbents (primaries). Effective management of spectrum in such systems is challenging, and several different spectrum sharing or spectrum management architectures have been proposed over the years [16]. A significant inefficiency in such architectures is that the spectrum availability is estimated by imperfect propagation modeling [12], [11], [5] or via spectrum sensing that has poor spatial granularity. Our work makes use of an alternative *crowdsourced* sensing architecture of such shared spectrum paradigms, where relatively low-cost, independently deployed spectrum sensors (see Figure 1) are deployed [6] for real-time spectrum monitoring and spectrum allocation is done based on the real-time sensing reports of such deployed spectrum sensors. In this context, we develop accurate spectrum allocation strategies based on real-time path loss estimation from the sensing reports.

II. Spectrum Allocation in a Crowdsourced Architecture

Related Work. Spectrum allocation in shared spectrum systems has been studied extensively (see [16] for a survey). In the centralized spectrum manager (SM) architecture, it is generally assumed that the SM has complete knowledge of the PUs' parameters (i.e., locations, transmit powers, and "coverage regions"). Most prior works assume a propagation model which allows spectrum allocation power to be computed via linear programming [16] or other techniques for common optimization objectives. However, in practice, since even the best-known propagation models [15], [12], [11] have unsatisfactory accuracy, spectrum allocation must be done overly conservatively for correctness. A crowdsourced architecture for spectrum allocation has a potential to eliminate this limitation. In our concurrent work [9], we develop an efficient secured protocol for spectrum allocation; in this work, we focus on evaluation of schemes involving various interpolation schemes.

Crowdsourced Sensing Architecture. A crowdsourced architecture setup for shared spectrum allocation involves four independent entities: (i) primary users (PU) (ii) secondary users (SU), (iii) spectrum sensors (SS), and (iv) central spectrum manager (SM). For a spectrum allocation *query* from the SU, the spectrum manager (SM) first estimates appropriate signal path-loss values from known PUs' parameters and real-time sensing reports of crowdsourced spectrum sensors (SS), and then use the estimated path-loss values to allocate spectrum to the SU. See details below. Crowdsources thus allows high granularity spectrum data collection via relatively inexpensive means. This model facilitates spectrum allocation based on real-time SS sensing reports, and thus, obviates the need to assume a propagation model. Allocation based on real-time channel conditions is also important for accurate power allocation, as the conditions affecting signal attenuation (e.g., air, rain, vehicular traffic) may change over time. However, spectrum allocation based on sensing reports can be challenging, due to need for accurate path-loss estimation techniques from relatively inexpensive sensors–but the challenge can be mitigated with the availability of a large number of sensing reports via crowdsourced spectrum sensing [6], [14]. The practicality of crowdsourced sensing architectures has been demonstrated in research projects [6], [17], [4] as well as commercial ventures such as Flightaware [2]. Note that the

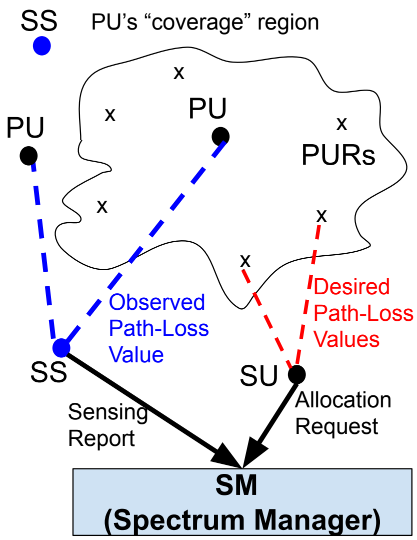

Fig. 1. Primary user (PU), its "coverage" region with potential receivers (PURs), a secondary user (SU), spectrum sensors (SSs), and the spectrum manager (SM). The figures shows the *observed channel-gain* by the PU-signal measured by the SSs, and the *desired channel-gains* for determine spectrum allocation the to SU.

challenge of malicious behavior of some SS nodes (faulty sensing reports) can be handled by appropriate fault-tolerance strategies [10].

Spectrum Allocation Problem. For a given query from a single SU (we discuss multiple SUs later), the goal of the spectrum allocation algorithm is to allocate maximum possible power to the SU such that its transmission at the allocated power would not interfere with PU's reception at any of its receivers. There are many ways to model PU receivers, e.g., a coverage region around PU. As in [13], we assume a finite set of representative receivers called PURs around a PU. Each PUR is associated with an *initial threshold*, which is continually updated, to signify the maximum additional interference it can tolerate from the SUs. At a high-level, for a single SU request (we discuss multiple SUs briefly in §III), the spectrum allocation algorithm consists of the following steps: (i) compute the path loss between the SU and each of the PURs, (ii) allocate spectrum as below, (iii) update the PURs' thresholds. See Figure 1. More formally, let us denote the path loss function by $P\left(,\right)$; we discuss estimation of this function in more detail in the next section.

If an SU S_i at location l_i is allowed to transmit at power t_i, then the signal power received at PUR R_j at location l_j is given by $p_{ij} = t_i \cdot P\left(l_i, l_j\right)$. To ensure that p_{ij} is less than each R_j's current threshold τ_j, the maximum power that can be allocated to S_i is:

$$\min_j \frac{\tau_j}{P\left(l_i, l_j\right)}. \tag{1}$$

Once a certain transmit power has been allocated to an SU S_i, the second step for the SM is to update the thresholds for each PUR location l_j to account for the interference caused by S_i due to the newly assigned power, i.e.,:

$$\tau_j = \tau_j - t_i \times P\left(l_i, l_j\right). \tag{2}$$

Case Against Simple Solutions/Approaches. We examine a couple of simple spectrum allocation approaches, and presents arguments against their viability. Note that the approach that estimates path-loss between an SU and an PUR by actually having the SU transmit to the PUR is not feasible, as such "test" transmission by SU may cause interference to the PU's communication with the PUR. Another simple approach could be to allocate spectrum to an SU if there is no spectrum power sensed at its location. Such a scheme is overly conservative, and implicitly assumes PURs to be co-located with their PU.

III. Path-Loss Estimation via Spectrum Sensors

As per the previous section, for a new (single) SU request, the overall spectrum allocation algorithm can be described as a sequence of the following steps: (i) compute the path loss between the SU and each of the PURs, (ii) allocate spectrum as per Eqn. 1, and (iii) update the thresholds of the PURs based on the allocation to the SU. We describe the first step in detail below; the other two steps are just straightforward assignment of values to appropriate variables.

Path Loss Estimation. As per Eqn 1, we need to compute the path loss between the requesting SU S_i and each of the PUs' receivers (i.e., PURs). For a given PUR R_{jk} of a PU P_j, we compute the path loss $P\left(S_i, R_{jk}\right)$ between R_{jk} and S_i as follows. See Figure 2. Essentially, we first compute the path loss $P\left(S_i, P_j\right)$ between the SU S_i and PU P_j using the first two steps below, and then estimate the desired path losses between the given SU and PURs.

1) *Splitting Aggregate Received Power.* Compute path loss $P\left(P_j, C_l\right)$ from PU P_j to each of the spectrum sensors C_l. Since a spectrum sensor C_l only senses the *aggregate* power received from all PUs, computing path loss from PU P_j to C_l requires splitting the sensed power across the PUs.
2) *Estimate PU-SU Path-loss.* Use interpolation to compute the path loss $P\left(S_i, P_j\right)$.
3) *Estimate SU-PUR Path-loss.* Then, we compute the desired path loss $P\left(S_i, R_{jk}\right)$ from the above computed $P\left(S_i, P_j\right)$.

We now describe each of the above steps in the below subsections.

A. Splitting Aggregate Power Received at SS

The first step of estimating path loss between an SU and a PUR is to split the aggregate power received from the PUs at each SS into power received from individual PUs. In general, this blind source separation is a very challenging problem, and only very limited settings allow for known techniques using sophisticated receivers. In our context, we take advantage of the fact that we know the actual locations of the various transmitters i.e., the PUs, and thus, employ a simple distance-based strategy. In particular, we split the received aggregate

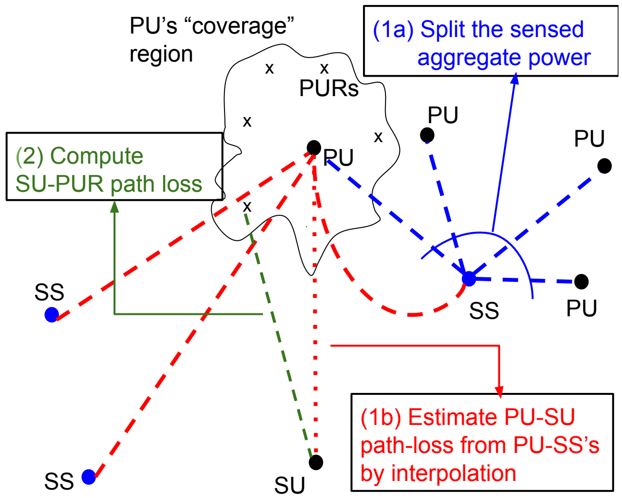

Fig. 2. Path Loss Estimation Steps

power into components due to individual PUs based on the ratio of their distances from the SS node. Formally,

$$R(P_j, C_l) = R(*, C_l) \frac{T(P_j)/|P_j - C_l|^{\alpha}}{\sum_{k=1}^{m} T(P_k)/|P_k - C_l|^{\alpha}} \quad (3)$$

where $R(*, C_l)$ is the total power received at the SS node C_l, where $R(P_j, C_l)$ is the power received at C_l due to the PU P_j, α is a pathloss exponent, $|.|$ is the distance between the locations of the two entities, $T(P_k)$ is the transmission power of a PU P_k. Instead of considering all the PUs, we propose to consider only the nearest m PUs from C_l in the above equation. In most cases, due to PUs having disjoint coverage regions (so that they don't interfere with each other at their intended receivers), we do not expect a spectrum sensor to receive non-negligible power from many PUs, and hence, a small value of m (2-4) may suffice. In our experiments, we vary m and evaluate the performance of the resulting spectrum allocation algorithm. Based on the above, the pathloss value between the sensor C_l and a near-by PU P_j can be computed as $P(C_l, P_j) = T(P_j)/R(C_l, P_j)$.

B. PU-SU Pathloss Estimation:

In the second step, we use interpolation techniques to estimate the pathloss between a PU P_j and the requesting SU S_i, $P(P_j, S_i)$, based on the pathloss values between the PUs and SSs estimated in the above step. In particular, we consider the simple Inverse Distance Weighting (IDW) as well as Ordinary Kriging (OK) method. We briefly describe them below.

Inverse Distance Weighted (IDW) Interpolation. In IDW method, estimate the pathloss $P(P_j, S_i)$ between a given PU P_j and the SU S_i, by weighing the pathlosses $P(P_j, C_l)$'s estimated above by the inverse of their distance from P_j. In particular:

$$P(P_j, S_i) = \frac{\sum_{l=1}^{m} P(P_j, C_l) / |S_i - C_l|^{\alpha}}{\sum_{k=1}^{m} 1/|S_i - C_l|^{\alpha}} \quad (4)$$

Here, α is a parametric exponent (not necessarily equal to the pathloss exponent mentioned above) often chosen to be 2.0. Above, m is the number of nearest (to P_j) SSs involved in the interpolation.

Ordinary Kriging (OK). We briefly introduce the Ordinary Kriging method here. Like IDW, Ordinary Kriging also defines the predicted value as a linear combination of the known neighboring values, but unlike IDW, the weights are computed by minimizing the prediction variance (under certain assumptions). The main advantage of Kriging over other spatial interpolation techniques is that it considers the structure of the spatial correlation (deduced through *semivariograms*), and thus, yielding more reliable predictions. We start with some basic definitions.

Let $s \in \mathbb{R}^d$ be a generic location in a d-dimensional Euclidean space and $\{Z(s), s \in \mathbb{R}^d\}$ be a spatial random function (rf), with Z denoting the attribute/signal of interest. We assume that $Z(s)$ is continuous, i.e., the attribute Z can be observed at any point of the domain.

Semivariogram; Second-order Stationary. *Semivariogram* for a pair of locations (s_i, s_j) is denoted as $\gamma(s_i, s_j)$ and is defined as half of the variance of the difference between the field values at these locations.

A random function $\{Z(s), s \in \mathbb{R}^d\}$ is said to be *second-order stationary*, if the following two conditions hold: (i) the expectation $E[Z(s)]$ is a constant, and (ii) The semivariogram at a pair of locations s and $s + h$ depends only on the vector h (called the *lag*), i.e., $\gamma(s, s + h) = \gamma(h)$ for all s and h.

OK System of Equations. Let $\{Z(s)\}$ be a second-order stationary random function. Given observation values $Z(s_1), Z(s_2), \ldots, Z(s_n)$ at n locations, we wish to find the estimate $\widehat{Z}(s_0)$ of the value $Z(s_0)$ at location s_0. In particular, we seek a linear function predictor $\widehat{Z}(s_0) = \sum_{i=1}^{n} \lambda_i Z(s_i)$ that minimizes $V[\widehat{Z}(s_0) - Z(s_0)]$, the variance of the prediction error, where λ_i are the weights to be derived. With some arithmetic manipulation and writing $\gamma_{ij} = \gamma(s_i, s_j)$, the goal reduces to:

$$\text{Minimize} \;\; 2\sum_{i=1}^{n} \lambda_i \gamma_{i0} - \sum_{i=1}^{n}\sum_{j=1}^{n} \lambda_i \lambda_j \gamma_{ij} \;\; \text{subject to} \;\; \sum_{i=1}^{n} \lambda_i = 1 \quad (5)$$

The above is solved using the Lagrange multiplier method with a multiplier α, and results in the following system of Ordinary

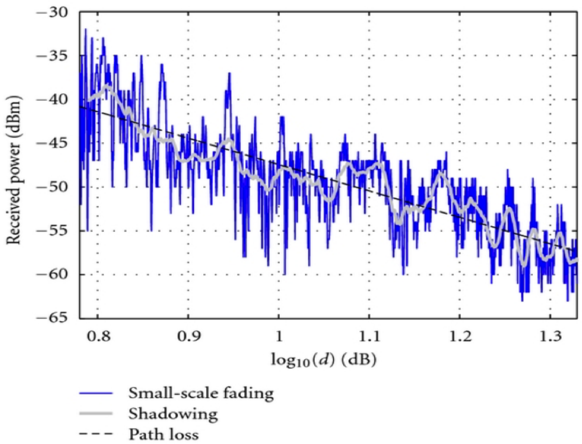

Fig. 3. Decomposing the path-loss function.

Kriging equations:

$$\begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_n \\ \alpha \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1n} & 1 \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2n} & 1 \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ \gamma_{n1} & \gamma_{n2} & \cdots & \gamma_{nn} & 1 \\ 1 & 1 & \cdots & 1 & 0 \end{bmatrix}^{-1} \begin{bmatrix} \gamma_{10} \\ \gamma_{20} \\ \vdots \\ \gamma_{n0} \\ 1 \end{bmatrix} \tag{6}$$

Using the OK interpolation technique involves: (i) determining the semivariogram function to estimate γ_{ij} values (as discussed below), (ii) using the above system of equations to predict the value at new locations.

Determining the Semivariogram Function. To use the above system of equations (Eqn. (6), we need to compute γ_{ij} values from the observation data. The simplest estimator for $\gamma(h)$ (and thus, for any γ_{ij} due to second-order stationary property) is [8]:

$$\gamma(h) = \frac{1}{2|N(h)|} \sum_{(s_i,s_j)\in N(h)} (Z(s_i) - Z(s_j))^2 \tag{7}$$

where $N(h)$ are the pairs of observations such that $h - \epsilon < |s_i - s_j| < h + \epsilon$ with ϵ being a small tolerance parameter. Now, to make the semivariogram function continuous and negative-semidefinite, a parametric semivariogram model is usually fitted to the above estimated model. We use the commonly used exponential model with two parameters C and a:

$$\gamma(h) = C\left(1 - e^{-(h/a)}\right) \tag{8}$$

Adopting OK for Pathloss Estimation: In our case of pathloss estimation, the pathloss function need not satisfy second order stationary property, and thus, the above performance guarantee of OK technique need not hold. In particular, the pathloss function $P(,)$ is not of constant mean and need not depend only on "lag." Therefore, similar to [7], to apply OK interpolation, we decompose the pathloss function as follows:

$$P(\mathbf{x},\mathbf{y})_{dB} = 10\alpha \log_{10}\left(\frac{d_0}{|\mathbf{x}-\mathbf{y}|}\right) + Z(|\mathbf{x}-\mathbf{y}|) \tag{9}$$

Herein, the function $Z(.)$ is of constant-mean and only depends on the lag or distance value. In essence, the $Z(.)$ function captures all other signal-attenuation factors (e.g., shadowing, small-scale fading) other than the distance-exponent signal attentuation. See Fig. 3. This is largely the rationale behind using OK as an interpolation scheme in our context. We thus use Eqns 6-8 to estimate $Z(.)$, Since the semivariogram is constructed offline, we consider all path-loss estimates between SSs and PUs (from the previous step) when constructing the semivariogram; this is unlike the previous IDW approach, wherein only the nearest SSs may be used.

C. SU-PUR Pathloss Estimation

Finally, we use estimated pathloss $P(P_j, S_i)$ between primary a P_j and the secondary S_i to estimate the desired pathloss between S_i and each of the primary receivers R_{jk} of P_j. To do this, we assume a log-normal pathloss model within the region created by the locations of P_j, R_{jk}, and S_i, and use the following distance-based heuristic to calculate the pathloss $P(P_j, S_i)$ between S_i and P_j.

$$\frac{P(S_i, R_{jk})}{P(P_j, S_i)} = \frac{|P_j - S_i|^\alpha}{|S_i - P_j|^\alpha}$$

$$\Rightarrow \quad P(S_i, R_{jk}) = P(P_j, S_i) \times \frac{|P_j - S_i|^\alpha}{|S_i - P_j|^\alpha}$$

Here, α is a parametric exponent. Another plausible strategy to estimate $P(S_i, R_{jk})$ could be to use a known $P(P_j, R_{jk})$ value which can be associated with each given R_{jk}; we plan to consider this in our future work.

D. Handling Multiple SUs

Multiple SU requests can be easily handled one at a time, except that in the first step of our path-estimation method, we need to also account for the fact that a SS may sense power from SU transmissions. This can be handled easily by storing information about the active SUs, and incorporating it in the step. Multiple SU requests can also be handled simultaneously, to incorporate a given fairness constraint, by solving an appropriate system of linear equations. We defer implemention and evaluation of these schemes to our future work.

IV. Evaluation

For our simulations, we use SPLAT! [1], which uses the Longley-Rice propagation model, to generate terrain-based path loss data. We consider an area of 10km $\times$ 10km with 400 PUs distributed randomly over it. Each PU has 5 PURs with 5 receivers in its vicinity. We also selected 400 random locations for SUs for spectrum allocation, one at a time. We consider an optimal spectrum power allocation scheme, wherein allocation is done as per the true path-loss values between the requesting SU and the near-by PURs. Overall, we consider four variants of our estimation algorithms depending on (i) whether PU power-splitting (PS) is done, and (ii) whether IDW or Ordinary Kriging (OK) was used for interpolation. These variants were denoted in the performance plot as (i) `IDW`: IDW without power splitting (ii) `IDW+PS`: IDW with power splitting (iii) `OK`: OK without power splitting (iv) `OK+PS`: OK with power splitting.

As mentioned above, we consider 400 SUs one at a time; once an SU allocation request is processed, it along with its 5 receivers were considered as a PU and 5 PURs for the next iteration of power allocation. A value close to zero milliwatt power allocation was regarded as a rejection of the SU request. We took average of differences between optimal power allocation and that of each of the four strategies; we took an average over the 400 requests.

Besides synthetic data based on SPLAT!, we also considered a case of 2 USRP transmitters and RTL-SDR receivers in the frequency band of 915 MHz in an open field with an area of about 500m $\times$ 500m. Using the USRP and RTL-SDR set-up, we generate a trace-driven dataset to generate required path losses for specific sensor density. We consider the

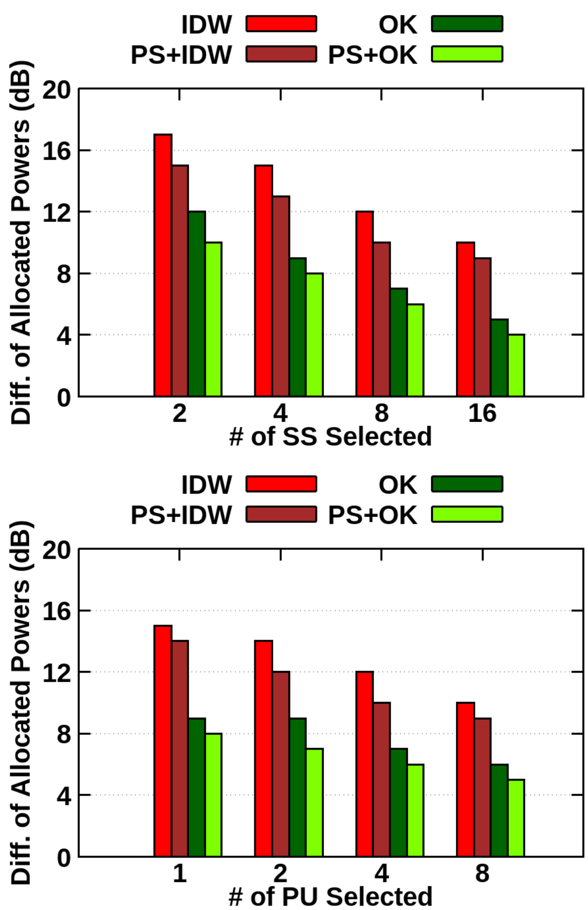

Fig. 4. Difference with optimal power allocated, for varying # of nearest (a) SS nodes, or (b) PU nodes, selected, for SPLAT! based path-loss data.

difference between optimal power allocation and our schemes, for varying number of SS, PU selected, and varying SS density for both the synthetic and real dataset. We used the following values as default when changing other parameters: (i) # of nearest SS selected = 8, (ii) # of nearest PU Selected = 4, (iii) # of SS deployed per 100m $\times$ 100m grid = 10.

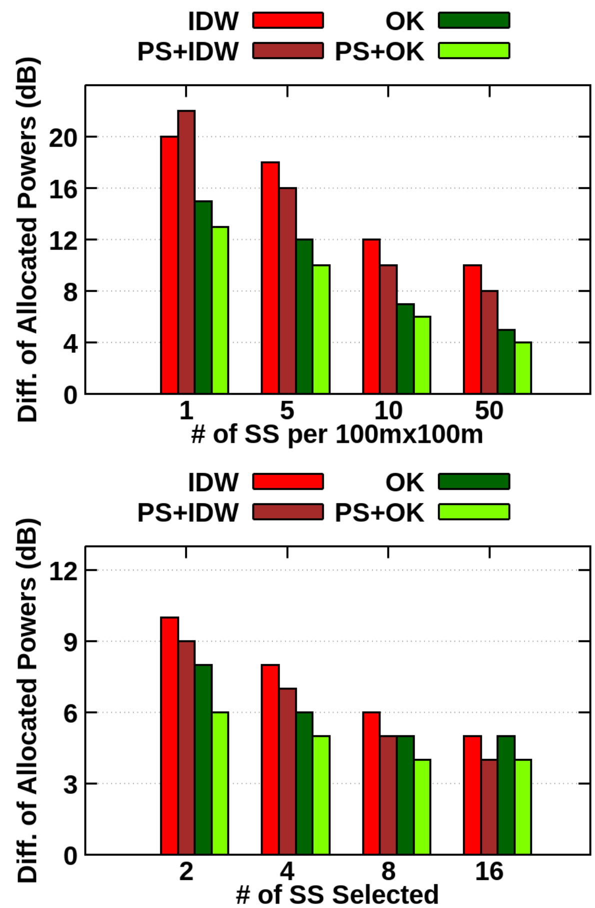

Fig. 5. Difference with optimal power allocated, for varying (a) SS density, and (b) # of nearest SS nodes selected, for the trace-driven dataset from deployment of 2 TXs (915MHz) in an open field.

We see in Figures 4 and 5 that `OK+PS` strategy outperforms all other strategies in all cases. In particular the order the difference with optimal strategy is: `OK+PS` $<$ `OK` $<$ `IDW+PS` $<$ `IDW`. We observe a 3-5dB gap between `PS+OK` and the optimal strategy; this is essentially the aggregate estimation error of our overall path loss estimation scheme.

V. Conclusion

In this work, we have explored a novel strategy for allocation of spectrum power based on path loss estimation from real-time sensing reports. To the best of our knowledge, ours is the first work in this regard. However, there is much scope for improvement in our work—especially with regards to estimation error. Can there be *specialized* path estimation and interpolation techniques in the context of spectrum allocation? For instance, we could divide the path loss estimation into two parts: offline and online, wherein the offline part estimates parameters that do not depend much on real-time channel state, while the online part depends on real-time sensing report. We plan to investigate such strategies in our future works.

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