Joint Dynamic Resource Allocation and Waveform Adaptation for Cognitive Networks

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***Abstract*—This paper investigates the issue of dynamic resource allocation (DRA) in the context of multi-user cognitive radio networks. We present a general framework adopting generalized signal expansion functions for representation of physical-layer radio resources as well as for synthesis of transmitter and receiver waveforms, which allow us to join DRA with waveform adaptation, two procedures that are currently carried out separately. Based on the signal expansion framework, we develop noncooperative games for distributed DRA, which seek to improve the spectrum utilization on a per-user basis under both transmit power and cognitive spectral mask constraints. The proposed DRA games can handle many radio platforms such as frequency, time or code division multiplexing (FDM, TDM, CDM), and even agile platforms with combinations of different types of expansion functions. To avoid the complications of having too many active expansion functions after optimization, we also propose to combine DRA with sparsity constraints. Generally, the sparsity-constrained DRA approach improves convergence of distributed games at little performance loss, since the effective resources required by a cognitive radio are in fact sparse. Finally, to acquire the channel and interference parameters needed for DRA, we develop compressed sensing techniques that capitalize on the sparse properties of the wideband signals to reduce the number of samples used for sensing and hence the sensing time.**

***Index Terms*—Dynamic Resource Allocation, Waveform Adaptation, Game Theory, Sparsity, Compressed Sensing**

I. Introduction

IN WIRELESS cognitive networks adopting open spectrum access, radio users dynamically decide the allocation of available radio resources to improve the overall spectrum utilization efficiency, also known as dynamic resource allocation (DRA) [1], [2]. Key to this radio access paradigm are frequency-agile cognitive radios (CRs) that are aware of the radio environment and can dynamically program their parameters to efficiently utilize vacant spectrum without causing harmful interference to authorized users. Evidently, the DRA task is intertwined with channel sensing and transmitted-waveform adaptation tasks.

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In the absence of a centralized spectrum controller, DRA can be carried out in a distributed fashion using distributed games [3], [4], [5], [6]. In that case, every radio will iteratively sense the available resources and adjust its own usage of these resources accordingly. While resources in a wireless radio network can present broadly in time, frequency, space, codes and so on, most of the DRA schemes for CR networks model the radio resources in the form of power and spectrum, and hence focus on frequency band allocation and power control on the allocated bands. This is a special case of DRA commonly known as dynamic spectrum allocation (DSA), for which orthogonal frequency division multiplexing (OFDM) is generally considered as the CR platform [7], [9]. After DRA, CRs will rapidly adjust the spectral shapes of their transmitted waveforms in order to transmit on the dynamically allocated bands at permissible transmit power. There are a few waveform adaptation techniques for CRs that build on digital filter design and wireless communication techniques [10], [11], including pulse shaping and single-carrier techniques [12], [13], and multi-carrier techniques. With the exception of multi-carrier OFDM systems, the DRA and waveform adaptation tasks have been treated separately. Because it can be difficult or costly to generate a transmitted waveform that perfectly matches the allocated spectra of any flexible shape, the separate treatment may not offer desired DRA solutions for practical radios.

This paper develops a joint DRA and waveform adaptation framework for efficient spectrum utilization in multi-user CR networks. Here, physical-layer radio resources are represented by transmitter and receiver signal-expansion functions, which can be judiciously chosen to enable various agile platforms, such as frequency, time, or code division multiplexing (FDM, TDM, CDM). Besides OFDM with digital carriers as expansion functions, many mature platforms are TDM- or CDM-based and make use of different types of expansion functions such as pulses, codes, or wavelets [11]. The signal expansion framework allows us to extend the DSA approach to a more general DRA approach that handles and/or combine all kinds of expansion functions. Further, it makes it possible to combine DRA with waveform adaptation. CRs make DRA decisions on their desired spectrum occupancies, and simultaneously make adaptation on their transmitted waveform spectra to realize such DRA decisions for spectrum sharing and interference control.

Based on the representation of radio resources as transmitter and receiver functions, we will develop distributed multi-user DRA games that improve the network spectrum utilization under transmit power and cognitive spectral mask constraints.

Different from well-studied scalar or vector power control games [3], [4], [5], [9], the DRA game with waveform adaptation turns out to be a complicated matrix-valued optimization problem. To simplify implementation and analysis, we will convert the matrix-valued game into an equivalent vector-valued convex problem by use of linear precoding similar to [7], but have to deal with a nontrivial spectral mask constraint in the presence of non-orthogonal expansion functions.

In the wideband regime, the optimal number of active expansion functions can be huge, leading to a highly complex repeated game with slow convergence. To solve this problem, we will incorporate some form of sparsity constraints in the distributed games to limit the number of active signal-expansion functions and thus the number of optimization parameters. By limiting the search space of a DRA game to a small region of effective resources, sparsity-constrained repeated games exhibit improved convergence at little performance loss.

Finally, to support the proposed distributed DRA games, we will discuss the intertwined sensing task and develop efficient algorithms for channel estimation and inteference sensing using compressive sampling techniques [17], [18]. The sparseness of both the wideband channels and the interferences on certain domain is identified and then utilized for sparse signal recovery, which reduces the number of samples needed for sensing and hence the sensing time.

The rest of the paper is organized as follows. Section II presents the signal expansion framework for modeling the radio resources of various platforms. Section III formulates the design objective and constraints of a DRA problem and joins it with waveform design and adaptation. A distributed DRA game is formulated and charaterized in Section IV, and sparsity-constrained DRA games are presented in Section V. Compressed sensing techniques for acquiring the related channel and interference parameters are developed in Section VI. Simulations are carried out in Section VII to illustrate the proposed techniques, followed by a summary in Section VIII.

II. Data Model

Consider a wireless network with Q active CR users seeking radio resources, where each CR refers to a pair of one transmitter and one receiver. In this paper, the physical-layer radio resources that CRs can exploit are represented by means of a set of K bandlimited transmitter and receiver functions/filters $\{\psi_k(t)\}_{k=0}^{K-1}$ and $\{\phi_k(t)\}_{k=0}^{K-1}$, which are the same for all CRs in our design. The size K is chosen large enough on the order of the time-bandwidth product of the wideband system, in order to adequately represent available resources. Hence, each CR q, $q \in [0, Q-1]$, communicates data using the transmitter functions $\{\psi_k(t)\}_k$ and preprocesses the data at the receiver using the receiver functions $\{\phi_k(t)\}_k$. These transmitter and receiver functions can be viewed as the synthesis and analysis functions from the filter bank theory, or as frames and their dual frames from the frame theory [14]. They essentially act as signal basis functions in a signal space representation [10], [15], but are termed as signal expansion functions here because we allow K to be larger than the dimension of the signal space in order to accommodate redundant function sets. Adopting a block transmission structure, CR q transmits a $K \times 1$ coded data vector $\mathbf{u}_q = \mathbf{F}_q \mathrm{diag}(\mathbf{a}_q)\mathbf{s}_q$ in each block, where $\mathbf{s}_q$ consists of K *i.i.d.* information symbols $\{s_{q,k}\}_{k=0}^{K-1}$, $\mathbf{F}_q$ is a square linear precoding matrix, and $\mathbf{a}_q$ is a $K \times 1$ amplitude scaling vector. Without loss of generality we assume that $s_{q,k}$ has been normalized to have unit energy, namely $E(|s_{q,k}|^2) = 1$, $\forall k$ ($E(\cdot)$ denotes expectation), since any non-unit energy can be otherwise taken care of by the scaling factor $a_{q,k}$. Inter-block interference (IBI) can for instance be avoided by the use of a cyclic prefix, as we will illustrate later. Each CR q modulates the data symbol $u_{q,k}$ onto the transmitter function $\psi_k(t)$, $\forall k$, yielding the transmitted waveform $u_q(t) = \sum_k u_{q,k}\psi_k(t)$. It is worth noting that the signal expansion structure we present here for constructing the transmitted waveforms differs from that in a traditional digital filter synthesis approach for pulse shape design [10], [13], because we do not weight the transmitter expansion functions with chosen filter coefficients bur rather modulate them using data symbols based on a filter-bank structure.

The CR sends $u_q(t)$ over a dispersive channel with impulse response $g_q(t)$, and preprocesses it at the receiver using the receiver functions $\{\phi_l(t)\}_{l=0}^{K-1}$ to collect a block of K data samples $\mathbf{x}_q := [x_{q,0}, \ldots, x_{q,K-1}]^T$. Meanwhile, the receiver is inflicted with an interfering signal $v_q(t)$, which accounts for the aggregate interference from other CRs, primary users and ambient noise as well. We assume that each CR pair is synchronized, but different CRs do not have to be synchronized among one another[1]. Hence, the discrete-time data model can be described as

$$\mathbf{x}_q = \mathbf{H}_q \mathbf{u}_q + \mathbf{v}_q \tag{1}$$

where $\mathbf{H}_q$ is the $K \times K$ aggregate channel matrix with its (l,k)-th element given by $h_{q,k,l} = g_q(t) \star \psi_k(t) \star \phi_l^*(-t)|_{t=0}$ ($\star$ stands for convolution and * denotes conjugate), $\forall k, l$, and $\mathbf{v}_q$ is the $K \times 1$ filtered noise vector with $v_{q,l} = v_q(t) \star \phi_l^*(-t)|_{t=0}$, $\forall l$. Apparently, $\mathbf{H}_q$ encompasses the composite effect of not only the channel, but also the transmitter and receiver filters.

The above setup incorporates well-known multiplexing scenarios such as FDM, TDM and CDM. For example, in a baseband digital implementation, the set of transmitter and receiver functions can be chosen as

$$\psi_k(t) = \frac{1}{\sqrt{K+N}} \sum_{n=-N}^{K-1} c_{k,<n>_K} p(t - nT), \tag{2a}$$

$$\phi_l(t) = \frac{1}{\sqrt{K}} \sum_{n=0}^{K-1} c_{l,n} p(t - nT), \tag{2b}$$

where $\{c_{k,n}\}_{k,n}$ represent the digital modulation/demodulation coefficients, $<n>_K$ denotes the remainder after dividing n by K, and $p(t)$ is the normalized pulse used at the DAC and ADC. It is assumed that $p(t)$ has a time span $[0, T)$ and an essential bandwidth $[-B/2, B/2)$ ($B = 1/T$), for example, a rectangular pulse of width T. Here, the considered range is $t \in [0, (K+N)T)$, where NT is an upper bound on the length of any channel $g_q(t)$. To avoid

[1]The assumption about the asynchronous access to the channel derives from the fact that we do not separate interfering users but only deal with the composite interference.

IBI, we have assumed that the transmitter functions $\psi_k(t)$ include a cyclic prefix of length NT, and that the receive functions $\phi_k(t)$ remove this cyclic prefix. The waveforms in (2) subsume FDM, TDM and CDM as follows

$$\begin{aligned}
&\text{FDM}: && c_{k,n} = e^{j2\pi kn/K}, \quad k,n = 0,\ldots,K-1;\\
&\text{TDM}: && c_{k,n} = \sqrt{K}\delta_{k-n}, \quad k,n = 0,\ldots,K-1;\\
&\text{CDM}: && \{c_{k,n}\}_{n=0}^{K-1} \text{ is a length-}K \text{ spreading code}, \ \forall k.
\end{aligned}$$

Note that the above described FDM scheme actually corresponds to OFDM (orthogonal frequency division multiplexing), whereas the TDM scheme corresponds to SCCP (single carrier with a cyclic prefix). Passband and analog versions of FDM and TDM can be described in a similar fashion. In general, there are a number of possible choices for the transmitter and receiver functions, such as carriers, pulses, codes, wavelets, and other forms. The size K is determined by the choice of the function sets, the total network bandwidth as well as the desired precision of waveform design. Also, redundant sets of non-orthogonal functions are suggested [19], e.g., using combinations of the functions used in FDM, TDM and/or CDM, to yield over-complete representations of the available radio resources. This strategy is useful in exploring the sparsity property of CR networks for efficient DRA, which we will discuss in Section V.

III. Joint Dynamic Resource Allocation and Waveform Adaptation

DRA in a CR network concerns the spectrum utilization efficiency, measured for instance by the system capacity. From (1), DRA at the transmitter side can be carried out through the linear precoder $\mathbf{F}_q$ and the length-K amplitude scaling vector $\mathbf{a}_q$. Given the data model (1) resulted from the adopted signal expansion structure and assuming uncorrelated interferences $\{v_{q,l}\}_l$ on different receiver waveforms $\{\phi_l(t)\}_l$, the per-user capacity formula is given by

$$C(\mathbf{a}_q,\mathbf{F}_q) = \frac{1}{K}\log_2\left|\mathbf{I}_K + \text{diag}(\mathbf{a}_q)\mathbf{F}_q^H\mathbf{B}_q\mathbf{F}_q\text{diag}(\mathbf{a}_q)\right| \quad (3)$$

where $\mathbf{B}_q = \mathbf{H}_q^H\mathbf{R}_q^{-1}\mathbf{H}_q$ and $\mathbf{R}_q = E(\mathbf{v}_q\mathbf{v}_q^H)$ is the interference covariance matrix. In (3), we have omitted the impact of data detection, since there are known capacity-preserving receivers such as the minimum mean-square error (MMSE) linear receiver [15].

In our modeling of radio resources, the DRA problem is intimately related to waveform design and adaptation. The design parameters $\{(\mathbf{a}_q,\mathbf{F}_q)\}_q$ not only affect the DRA efficiency via (3), but also determine the spectral shapes of the transmitted waveforms. Specifically for CR q, the power spectral density (PSD) of the transmitted signal $u_q(t)$ with respect to the frequency f is given by

$$S_q(f;\mathbf{a}_q,\mathbf{F}_q) = \textstyle\sum_{k=0}^{K-1} a_{q,k}^2 \left|\sum_{i=0}^{K-1}[\mathbf{F}_q]_{i,k}\ \psi_i(f)\right|^2. \quad (4)$$

In CR applications, the spectral shapes of transmitted waveforms need to comply with some design and regulatory requirements. For example, the average transmit power P_q of CR q has to be confined below an upper limit $P_{q,\max}$, $\forall q$, which can be expressed as

$$\begin{aligned}
P_q(\mathbf{a}_q,\mathbf{F}_q) &= \int S_q(f;\mathbf{a}_q,\mathbf{F}_q)df\\
&= \text{tr}\big(\text{diag}(\mathbf{a}_q)\mathbf{F}_q^H\mathbf{S}_\psi\mathbf{F}_q\text{diag}(\mathbf{a}_q)\big) \le P_{q,\max} \quad (5)
\end{aligned}$$

where $\mathbf{S}_\psi$ is the $K\times K$ pulse-shaping autocorrelation matrix with $[\mathbf{S}_\psi]_{k,l} = \int\psi_k^*(f)\psi_l(f)df$, and $\text{tr}(\cdot)$ denotes trace.

We further impose a cognitive spectral mask $S_c(f)$ that accounts for both policy-based long-term regulatory spectral masks and cognition-based dynamic frequency notch masks for interference control. Once an active primary user is detected, a frequency notch on the licensed spectrum band(s) would be imposed on the spectral masks of CRs in order to protect the primary user. Intersection of these masks yields a composite cognitive mask $S_c(f)$, resulting in the following spectral mask constraint for any CR q:

$$S_q(f;\mathbf{a}_q,\mathbf{F}_q) \le S_c(f), \quad \forall f. \quad (6)$$

From a global network perspective, the objective of DRA is to determine the collective actions $\{(\mathbf{a}_q,\mathbf{F}_q)\}_{q=0}^{Q-1}$ that maximize the sum-rate of all users, that is,

$$\begin{aligned}
&\max_{\{\mathbf{a}_q\succeq\mathbf{0}\}_q,\{\mathbf{F}_q\}_q} && \sum_{q=0}^{Q-1} C(\mathbf{a}_q,\mathbf{F}_q), \quad (7)\\
&\text{s.t.} && (5),(6), \quad q = 0,1,\ldots,Q-1,
\end{aligned}$$

where $\succeq$ denotes element-by-element $\ge$ operation. In our DRA optimization, the transmitter and receiver functions $\{\psi_k(t)\}_k$ and $\{\phi_l(t)\}_l$ are pre-defined for DSP implementation simplicity. Nevertheless, the spectral shapes $S_q(f;\mathbf{a}_q,\mathbf{F}_q)$ of the transmitted waveforms can adapt to the radio resources via adjusting $(\mathbf{a}_q,\mathbf{F}_q)$. As we dynamically sense the channel parameters $\{\mathbf{H}_q,\mathbf{R}_q\}$ used in (3) and accordingly optimize the adaptation parameters $(\mathbf{a}_q,\mathbf{F}_q)$ via (7), a joint DRA and waveform adaptation approach arises.

However, the formulation in (7) leads to a centralized non-convex optimization problem, which is NP-hard with complexity scaling exponentially in the number of users [4]. Furthermore, it requires knowledge of all the available resource information $\{\mathbf{H}_q,\mathbf{R}_q\}_q$, which can be infeasible to obtain even for a central spectrum controller such as a base station. For any-to-any connections, it is more appropriate to perform decentralized DRA, for which the game-theoretic approach is well motivated due to its distributed nature.

IV. Multi-user DRA Game

This section develops a distributed DRA game that adopts individual (per-user) objective functions and constraints for optimizing the design parameters $\{(\mathbf{a}_q,\mathbf{F}_q)\}_q$. Formulation, implementation and characterization of the DRA game are presented in this section, while acquisition of the related channel and interference parameters $\mathbf{H}_q$ and $\mathbf{R}_q$, and hence $\mathbf{B}_q$ in (3), will be presented in Section VI.

A. Distributed Game Formulation and Implementation

In a DRA game, CRs are game players, each of which seeks to maximize a capacity-related utility function by taking allocation actions on $(\mathbf{a}_q, \mathbf{F}_q)$ from its own set of permissible strategies. In contrast to the centralized DRA formulation in (7), a standard noncooperative game can be formulated by decoupling the objective function and constraints for each CR user [16], as follows:

$$\max_{\mathbf{a}_q \succeq \mathbf{0}, \mathbf{F}_q} \quad C(\mathbf{a}_q, \mathbf{F}_q), \quad \text{s.t.} \;\; (5), (6). \tag{8}$$

On a per-user basis, (8) results in the optimal decentralized DRA solutions $(\mathbf{a}_q^\star, \mathbf{F}_q^\star)$, without knowledge of other users' allocation $\{(\mathbf{a}_r, \mathbf{F}_r)\}_{r \neq q}$. Nevertheless, the interference $\mathbf{R}_q$ needs to be sensed while other users are transmitting using their allocation actions $\{(\mathbf{a}_r, \mathbf{F}_r)\}_{r \neq q}$. The intricacy among sensing, transmission and distributed DRA suggests a repeated game approach, wherein players change their strategies one at a time according to (8), as a reaction to changes in the strategies of the other players. Players repeatedly change their strategies in a sequential, simultaneous or asynchronous fashion [7], [16], until reaching steady-state DRA decisions, if existent. Particularly, a repeated game with asynchronous moves is most suited for distributed DRA, where not all players may revise their actions in every round, and the convergence can be treated as a sequential repeated game as long as players take actions in an almost cyclic pattern.

Let the CRs initialize their transmissions with no precoding and equal power loading, i.e., $\mathbf{F}_q = \mathbf{I}_K$ and $\mathbf{a}_q = \mathbf{1}$. The ensuing iteration steps in a repeated DRA game can be summarized as below.

—

S1) At the present round of the DRA game, choose the order for CRs to take actions, in a sequential, simultaneous, or asynchronous fashion;

S2) For CR q that is in its order to take action, it
   - a) senses the channel and interference parameters $\mathbf{H}_q$ and $\mathbf{R}_q$, using possibly the compressed sensing techniques developed in Section VI;
   - b) finds the current best response strategy $(\mathbf{a}_q^\star, \mathbf{F}_q^\star)$ that optimizes (8), which we will elaborate in Section IV-B;
   - c) adapts its transmission by implementing $(\mathbf{a}_q^\star, \mathbf{F}_q^\star)$ on the signal expansion functions;

S3) iterate to the next round, until convergence.

—

This game procedure joins the two tasks of DRA optimization (in S2(b)) and online waveform adaptation (in S2(c)), thanks to the enabling signal expansion framework we adopt. By doing so, it is feasible for CRs to perform dynamic sensing of the *aggregate interference* (in S2(a)). In contrast, existing work separately treats DRA and waveform adaptation: the DRA literature focuses on direct optimization of the power spectrum $S_q(f)$ based on proper spectrum efficiency criteria [3], [4], [5], while the waveform design literature investigates analog or digital pulse shaping techniques to comply with the allocated power spectrum $S_q(f)$ [10], [12], [13]. The separate approach to DRA and waveform design has several limitations:

- When waveform adaptation is based on finalized DRA decisions and thus completely decoupled from the DRA process, sensing the aggregate interference is impossible prior to transmission. One way to solve this problem is to formulate centralized DRA, but this will cause a large communication overhead from the CRs to the spectrum controller.
- In the absence of waveform shaping and adaptation, distributed DRA is still possible. However, this mandates each DRA decision be made from the knowledge of the *all the received interfering channels*, in combination with either a one-shot game or a repeated game. One-shot games do not require knowledge of other users' DRA decisions, but exhibit a considerable performance gap from the socially optimal sum-capacity in (7). Repeated games, on the other hand, require users to broadcast their DRA decisions during iterations, resulting in a heavy communications overhead over a dedicated control channel.
- It can be difficult or costly to generate a transmitted waveform that perfectly matches the allocated $S_q(f)$ of any flexible shape [13]. Without respecting the implementation limitations of waveform design, the DRA decisions made on $S_q(f)$ are no longer optimal when implemented in practical radios.

Our DRA approach overcomes the above limitations. It offers a truly distributed framework in which the allocation vectors are optimized under a practical transmitter implementation structure. Besides, the need for sensing all the interfering channels in the separate approach is circumvented, but rather only aggregate channels need to be acquired in our joint approach. For some special transmission types, such as OFDM, the allocated $S_q(f)$ can be implemented exactly by power loading on subcarriers, thus joining DRA with spectrum shaping [7], [9]. Dynamic power loading for OFDM can be treated as a special case of our signal expansion framework using complex exponentials as expansion functions. However, many platforms are TDM- or CDM-based and make use of different types of expansion functions. Thus, our DRA approach is more general in treating diverse radio platforms. Furthermore, we will develop in Section V a sparsity-constrained DRA formulation to alleviate the slow convergence and high communication overhead that existing iterative OFDM power loading games may encounter over wideband channels.

B. Best Response in the DRA Game

This subsection solves for the best response $(\mathbf{a}_q^\star, \mathbf{F}_q^\star)$ to the per-user optimization problem in (8). From (3) and (5), it is obvious that the DRA game formulation in (8) is a matrix-valued problem with respect to actions $(\mathbf{a}_q, \mathbf{F}_q)$, which is much more involved than a game with scalar or vector actions [7]. Particularly when the pulse-shaping autocorrelation matrix $\mathbf{S}_\psi$ in (5) is non-diagonal due to non-orthogonal transmitter functions, simultaneous optimization of the action pair $(\mathbf{a}_q, \mathbf{F}_q)$ is nontrivial.

To deal with a general-form $\mathbf{S}_\psi$ in (5), we define $\bar{\mathbf{F}}_q = \mathbf{\Lambda}_s^{1/2}\mathbf{U}_s^H\mathbf{F}_q$, where $\mathbf{U}_s$ and $\mathbf{\Lambda}_s$ are the eigenvector and eigenvalue matrices of $\mathbf{S}_\psi$ respectively. Rewriting the power constraint as $\mathrm{tr}(\mathrm{diag}(\mathbf{a}_q)\bar{\mathbf{F}}_q^H\bar{\mathbf{F}}_q\mathrm{diag}(\mathbf{a}_q)) \leq P_{q,\max}$, and using the Hadamard inequality, we deduce that the determinant in (3) is maximized when $\bar{\mathbf{F}}_q$ diagonalizes $\bar{\mathbf{B}}_q = \mathbf{\Lambda}_s^{-1/2}\mathbf{U}_s^H\mathbf{B}_q\mathbf{U}_s\mathbf{\Lambda}_s^{-1/2}$. Let $\mathbf{U}_q$ and $\mathbf{\Lambda}_q$ denote the eigenvector and eigenvalue matrices of $\bar{\mathbf{B}}_q$, respectively. This suggests setting $\bar{\mathbf{F}}_q = \mathbf{U}_q$ and $\mathbf{F}_q = \mathbf{U}_s\mathbf{\Lambda}_s^{-1/2}\mathbf{U}_q$, which yields

$$C(\mathbf{a}_q) = \max_{\mathbf{F}_q} C(\mathbf{a}_q, \mathbf{F}_q) = \frac{1}{K}\log_2\left|\mathbf{I}_K + \mathbf{\Lambda}_q\mathrm{diag}(\mathbf{a}_q)^2\right| = \frac{1}{K}\sum_{k=0}^{K-1}\log_2(1 + a_{q,k}^2\lambda_{q,k}), \tag{9}$$

where $\lambda_{q,k} = [\mathbf{\Lambda}_q]_{k,k}$, $\forall k$.

Let us define a $K \times 1$ power loading vector $\mathbf{p}_q$ whose k-th element is $p_{q,k} = a_{q,k}^2$. Since $\mathbf{F}_q^H\mathbf{S}_\psi\mathbf{F}_q = \bar{\mathbf{F}}_q^H\bar{\mathbf{F}}_q = \mathbf{I}$, the power constraint in (5) is simplified to

$$\mathbf{1}^T\mathbf{p}_q \leq P_{q,\max}. \tag{10}$$

Meanwhile, the transmitted PSD in (4) can be rewritten as $S_q(f;\mathbf{p}_q) = \mathbf{z}_q^T(f)\mathbf{p}_q$, where $[\mathbf{z}_q(f)]_k = \left|\sum_{i=0}^{K-1}[\mathbf{F}_q]_{i,k}\psi_i(f)\right|^2$, $\forall k$. To render the number of spectral mask constraints finite, we sample $S_q(f;\mathbf{p}_q)$ uniformly in frequency at N points $F_N := \{f_1,\ldots,f_N\}$, $N \geq K$, and replace the spectral mask constraint in (6) by

$$\mathbf{Z}_{q,N}\mathbf{p}_q \leq \mathbf{S}_{c,N}, \tag{11}$$

where $\mathbf{Z}_{q,N} = [\mathbf{z}_q(f_1),\ldots,\mathbf{z}_q(f_N)]^T$ is of size $N \times K$, and $\mathbf{S}_{c,N} = [S_c(f_1),\ldots,S_c(f_N)]^T$ is the $N \times 1$ sampled vector of the cognitive spectral mask $S_c(f)$. Multiplying the pseudo-inverse $\mathbf{Z}_{q,N}^\dagger$ of $\mathbf{Z}_{q,N}$ on both sides of (11), it is straightforward that $\mathbf{p}_q$ shall be upper bounded by $\mathbf{p}_{q,\max} = \mathbf{Z}_{q,N}^\dagger\mathbf{S}_{c,N}$.

With (9), (10) and (11), the matrix-valued DRA optimization problem in (8) with respect to $(\mathbf{a}_q, \mathbf{F}_q)$ can be reformulated into a vector-valued problem with respect to $\mathbf{p}_q$ as follows:

$$\max_{\mathbf{p}_q \succeq \mathbf{0}} \quad C(\mathbf{p}_q) = \frac{1}{K}\sum_{k=0}^{K-1}\log_2(1 + p_{q,k}\lambda_{q,k}) \tag{12a}$$

$$\text{s.t.} \quad \mathbf{1}^T\mathbf{p}_q \leq P_{q,\max}; \tag{12b}$$

$$\mathbf{p}_q \leq \mathbf{p}_{q,\max}. \tag{12c}$$

This re-formulation does not incur performance loss compared with the original problem (8). The best response $(\mathbf{a}_q^\star, \mathbf{F}_q^\star)$ to (12) is the well-known water-filling scheme [3], [7], [9], that is,

$$\mathbf{F}_q^\star = \mathbf{U}_s\mathbf{\Lambda}_s^{-1/2}\mathbf{U}_q, \qquad \mathbf{p}_q^\star : p_{q,k}^\star = \left[\mu_q - \lambda_{q,k}^{-1}\right]_0^{p_{q,\max}(k)}, \forall k. \tag{13}$$

where $[x]_a^b$ indicates the Euclidean projection of x onto $[a,b]$ such that $x = x, a$ and b for $x \in [a,b]$, $x < a$ and $x > b$ respectively, and the water level μ_q is chosen to satisfy $\sum_{k=0}^{K-1} p_{q,k} = P_{q,\max}$ as in (12b) [7]. The closed-form solution in (13) to the per-user best response facilitates the implementation of the DRA game in Step S2(b).

C. Game Characterization

When playing a repeated game, it is essential to understand whether an equilibrium point can be reached [6]. This subsection characterizes the properties of steady state Nash Equilibriums (NEs) of the proposed DRA game. Relevant issues include the existence, optimality, uniqueness of NEs, and whether a game implementation converges to the NEs.

In Section IV-B, we have shown that the matrix-valued problem in (8) with respect to $(\mathbf{a}_q, \mathbf{F}_q)$ can be transformed into a vector-valued problem in (12a) with respect to the power allocation vector $\mathbf{p}_q$; in addition, the transformed power constraint (12b) entails a diagonalized channel structure. Hence, it can be shown that the noncooperative game in (12a) is a convex problem, because the utility is continuously quasi-concave in $\mathbf{p}_q$, and the action space defined by the power and mask constraints is a non-empty compact convex set. As such, the Glicksberg-Fan fixed point theorem ensures the *existence* of NEs by pure strategies [16].

Note that (12a) resembles a standard OFDM-based game based on orthogonal carriers. For synchronous OFDM systems that appear in DSL applications, sufficient conditions for uniqueness have been delineated under the power and mask constraints [7], [9]. For the mask-constrained asynchronous case that we consider here, the *uniqueness* of the NE is still an open problem [8].

Finally, we remark that a noncooperative game has been proposed in [7] using linear precoding strategies under both power and spectral mask constraints. For analysis purposes, the schemes therein use an IFFT matrix to diagonalize all the intended and interfering channel matrices that are Toeplitz. This implies block-by-block synchronization among users, whereas this paper obviates this assumption. In [15], a filterbank structure is proposed for centralized transceiver optimization, whereas our expansion functions are not confined to be mutually orthogonal. In both [7] and [15], the channel matrices have to be linear transformations of a Toeplitz matrix and the properties of Toeplitz matrices are capitalized, which is not necessary in our case. The capability in subsuming various types of expansion functions offers added flexibility in reshaping the dispersive channels. Even though these expansion functions are fixed in this paper for simplicity, we do allow for redundant non-orthogonal functions to explore the sparsity property in CR networks, as discussed next.

V. Sparsity-Constrained DRA Games

CRs often search for resource opportunities over a very wide spectrum range. In order to represent the optimal transmitted PSD over a very wide band, the required number of expansion functions can generally be very large. In this case, it is costly to compute, communicate, and implement the allocation vector $\mathbf{a}_q$ of size K. On the other hand, the effective resources needed for a CR to transmit reliably are in fact sparse compared with the total available resources in the wideband network. This observation suggests that (near-)optimal DRA may be carried out over a few selected expansion functions, instead of over the entire function set. It boils down to imposing zero entries in the allocation vector $\mathbf{a}_q$ and performing DRA over the remaining nonzero entries only. With a small number of allocation elements to be optimized, the resulting repeated games may benefit from reduced computational complexity and improved convergence rates. Due to the dynamic nature of channel resources, however, the locations of those effective nonzero entries cannot be preset and shall be optimized during waveform adaptation. This section presents such a sparsity-constrained formulation for DRA in the wideband regime.

Suppose that each CR transmits data over M expansion functions, $M < K$. Functions are selected via a selection matrix $\mathbf{J}_q = \mathrm{diag}(\mathbf{j}_q)$, where $\mathbf{j}_q \in \{0,1\}^K$ indicates whether $\psi_{q,k}(t)$ is selected ('1') or not ('0'). Removing those all-zero columns in $\mathbf{J}_q$, we get $\tilde{\mathbf{J}}_q$ of size $K\times M$. DRA are performed on the M selected functions, via an $M\times 1$ loading vector $\tilde{\mathbf{a}}_q = \tilde{\mathbf{J}}_q^H \mathbf{a}_q$ and an $M\times M$ precoder $\tilde{\mathbf{F}}_q = \tilde{\mathbf{J}}_q^H \mathbf{F}_q \tilde{\mathbf{J}}_q$. The aggregated channel effect is captured in $\tilde{\mathbf{B}}_q = \tilde{\mathbf{J}}_q^H \mathbf{B}_q \tilde{\mathbf{J}}_q$, and the capacity formula in (3) is modified to

$$C(\mathbf{a}_q,\mathbf{F}_q,\mathbf{J}_q)=\frac{1}{M}\log_2\left|\mathbf{I}_M+\mathrm{diag}(\tilde{\mathbf{a}}_q)\tilde{\mathbf{F}}_q^H\tilde{\mathbf{B}}_q\tilde{\mathbf{F}}_q\mathrm{diag}(\tilde{\mathbf{a}}_q)\right|. \tag{14}$$

Replacing the utility function in (12a) by (14), we reach a DRA game with dynamic function selection. We note now that selecting M functions is equivalent to setting $(K-M)$ elements of the allocation vector $\mathbf{a}_q$ to be zeros, that is, $||\mathbf{a}_q||_0 = M$. Hence, when $M \ll K$, $\mathbf{a}_q$ becomes a sparse vector, which can be treated under the framework of sparse signal recovery [18].

In the absence of linear precoding, function selection boils down to limiting a general-form sparsity measure of $\mathbf{a}_q$, that is its l-norm $||\mathbf{a}_q||_l$, where $0 \le l < 2$, by an upper bound $L_{q,\max}^{(l)}$. Adding this sparsity constraint to (12), we merge DRA with function selection to formulate a sparsity-constrained DRA problem as follows

$$\begin{aligned} \max_{\mathbf{a}_q\succeq\mathbf{0}} \quad & C(\mathbf{a}_q,\mathbf{F}_q=\mathbf{I}_K) \\ \text{s.t.} \quad & (5),(6); \\ & ||\mathbf{a}_q||_l \le L_{q,\max}^{(l)}. \end{aligned} \tag{15}$$

When $l=0$, the parameter $L_{q,\max}^{(0)}$ directly reflects the number of functions selected, but (15) is nonconvex and difficult to solve. When $l\in[1,2)$, (15) is a convex problem that permits well-behaved numerical algorithms. However, the parameter $L_{q,\max}^{(l)}$ is more difficult to choose in order to produce exact sparsity. Some cross-validation techniques can be tailored to this problem to aid the selection of $L_{q,\max}^{(l)}$. Following the arguments in Section IV-C, this sparsity-constrained DRA game reaches steady-state Nash equilibria when $1\le l<2$.

When linear precoding is present ($\mathbf{F}_q \neq \mathbf{I}_K$), we note from (9) that the linear precoder $\bar{\mathbf{F}}_q$ serves to diagonalize the channel $\bar{\mathbf{B}}_q$, while the ensuing power loading in (12) is determined by the channel eigenvalues $\mathbf{\Lambda}_q$. This observation suggests to perform function selection by finding a primary minor channel matrix $\tilde{\mathbf{B}}_q$ with the best eigenvalue quality measured by $|\mathbf{I}_M+\tilde{\mathbf{B}}_q|=|\mathbf{I}_K+\mathbf{J}_q^H\bar{\mathbf{B}}_q\mathbf{J}_q|$, i.e.,

$$\begin{aligned} \max_{\mathbf{j}_q\succeq\mathbf{0}} \quad & \log_2\left|\mathbf{I}_K+\mathbf{J}_q^H\bar{\mathbf{B}}_q\mathbf{J}_q\right| && (16a)\\ \text{s.t.} \quad & ||\mathbf{j}_q||_l \le L_{q,\max}^{(l)}; && (16b)\\ & \mathbf{e}_k^T\mathbf{J}_q\mathbf{e}_k = j_{q,k}, \quad k=0,\ldots,K-1; && (16c)\\ & \mathbf{e}_k^T\mathbf{J}_q\mathbf{e}_l = 0, \qquad \forall k\neq l. && (16d) \end{aligned}$$

In (16), (16c)-(16d) are used together to express the relationship $\mathbf{J}_q = \mathrm{diag}(\mathbf{j}_q)$ as the intersection of a set of convex functions in $\mathbf{j}_q$ and $\mathbf{J}_q$, $\mathbf{e}_k$ denotes the k-th column of the identity matrix $\mathbf{I}_K$, $\forall k$. Relaxing l to be $l=1$, (16) becomes a convex problem that obviates undesired combinatorial search. Afterwards, DRA is carried out on the M functions using (14), in which the linear precoder $\tilde{\mathbf{F}}_q$ can diagonalize the channel to simplify the problem to a water-filling scheme.

Additionally, considering that the design vector $\mathbf{j}_q$ is binary valued, the function selection problem can be relaxed and formulated as

$$\begin{aligned} \max_{\mathbf{j}_q} \quad & \log_2\left|\mathbf{I}_K+\mathbf{J}_q^H\bar{\mathbf{B}}_q\mathbf{J}_q\right| \\ & + \mu\textstyle\sum_{k=1}^K\left(\log(j_{q,k})+\log(1-j_{q,k})\right) && (17a)\\ \text{s.t.} \quad & \mathbf{1}^T\mathbf{j}_q = L_{q,\max}^{(0)}; && (17b)\\ & \mathbf{e}_k^T\mathbf{J}_q\mathbf{e}_k = j_{q,k}, \quad k=0,\ldots,K-1; && (17c)\\ & \mathbf{e}_k^T\mathbf{J}_q\mathbf{e}_l = 0, \qquad \forall k\neq l. && (17d) \end{aligned}$$

Here, the variables $j_{q,k}$ are relaxed to be real-valued, and the sparsity constraint in (16b) is replaced by a penalty term in the objective function along with a linear constraint (17b), as suggested in [22]. The penalty term implicitly confines $j_{q,k}$ to be within $[0,1]$, $\forall k$, and μ is a positive parameter that controls the quality of approximation. Meanwhile, the number of selected functions can be explicitly set by choosing $L_{q,\max}^{(0)}$. As explained in [22], the objective function is concave and smooth, so the problem (17) can be efficiently solved by the Newton's method.

As a final remark, it is interesting to observe that our DRA problem based on the signal expansion framework resembles the multiuser MIMO problems. Expansion functions play the roles of transmitter and receiver antennas, corroborated by the capacity formula (3) that applies to both problems. Hence, the literature on multiuser MIMO can benefit our work and from our work as well. For example, [25] suggests the use of antenna selection techniques for MIMO systems to solve the sparsity-constrained DRA games. Nevertheless, our design focus is to perform efficient resource allocation rather than harvesting antenna diversity and multiplexing gains. As such, we may use a large number of expansion functions to induce redundancy in resource representation, followed by dynamic function selection to allocate resources efficiently at reduced implementation costs. In this sense, our theme departs from that of multiuser MIMO problems. Besides, channel estimation is an easier task in our problem, allowing possibly compressed sensing at reduced sampling rates.

VI. Compressed Sensing for DRA

This section develops channel estimation and interference sensing methods for acquiring the knowledge of $\mathbf{H}_q$ and $\mathbf{R}_q$ as required by the sensing step S2(a) in Section IV-A. This sensing task takes place during the training phase by sending out training symbols $\mathbf{s}_q$ and hence known data symbols $\mathbf{u}_q = \mathbf{F}_q\mathbf{s}_q$, which yield the received samples $\mathbf{x}_q = \mathbf{H}_q\mathbf{u}_q + \mathbf{v}_q$. We will first estimate the channel matrix $\mathbf{H}_q$ by treating $\mathbf{v}_q$ as an unknown nuisance noise, and then cancel the estimated $\mathbf{H}_q\mathbf{u}_q$ from $\mathbf{x}_q$ in order to sense the inference $\mathbf{v}_q$ and estimate its covariance matrix $\mathbf{R}_q$ as the sample average. For both channel estimation and interference sensing, we will develop compressive sampling techniques for efficient estimation using a small number of samples only.

A. Channel Estimation

Our channel estimation algorithm is based on modeling the channel impulse response $g_q(t)$ as a tapped delay line:

$$g_q(t) = \sum_{n=0}^{N-1} g_{q,n}\delta(t - nT),$$

where N is the number of taps and T is the tap spacing corresponding to the essential bandwidth B as $T = 1/B$. This tapped delay line model serves as a mathematical description of the interested wideband channel, and it has been shown to be a valid model even for ultra wideband scenarios [24]. Under the above assumption, the channel coefficients $\{h_{q,k,l}\}_{k,l}$ can be written as

$$h_{q,k,l} = \sum_{n=0}^{N-1} g_{q,n}\ \psi_k(t - nT) \star \phi_l^*(-t)|_{t=0} = \sum_{n=0}^{N-1} g_{q,n} r_{n,k,l}^{(\psi\phi)}. \tag{18}$$

where $r_{n,k,l}^{(\psi\phi)} = \psi_k(t - nT) \star \phi_l^*(-t)|_{t=0}$. Evidently, there is a linear relationship between the composite channel coefficients $\{h_{q,k,l}\}_{k,l}$ and the channel taps $\{g_{q,n}\}_n$, and the latter set of size N is generally much smaller than the first set of size K^2, with $N \le K \le K^2$. Furthermore, the channel taps are often sparse for a wideband channel. This observation suggests us to directly estimate the channel vector $\mathbf{g}_q = [g_{q,0}, \ldots, g_{q,N-1}]^T$ and then compute $\{h_{q,k,l}\}_{k,l}$ via (18).

The minimum number of training symbols we require to estimate $\mathbf{g}_q$ is N. Thus, we will only make use of a small number $\bar{M}$, with $N \le \bar{M} \ll K$, of transmitter and receiver functions during the training phase, thereby reducing the complexity. Suppose that during the training phase, we only use the transmitter and receiver functions with indices from the set $\bar{\mathcal{K}} = \{\bar{k}_0, \ldots, \bar{k}_{\bar{M}-1}\}$, where we assume that $\bar{k}_0 < \bar{k}_1 < \cdots < \bar{k}_{\bar{M}-1}$. Then, we obtain

$$\begin{aligned} x_{q,l} &= \sum_{k\in\bar{\mathcal{K}}} u_{q,k} h_{q,k,l} + v_{q,l} = \sum_{k\in\bar{\mathcal{K}}} u_{q,k} \sum_{n=0}^{N-1} g_{q,n} r_{n,k,l}^{(\psi\phi)} + v_{q,l} \\ &= \bar{\mathbf{u}}_q^T \bar{\mathbf{A}}_l \mathbf{g}_q + v_{q,l}, \end{aligned}$$

where $\bar{\mathbf{u}}_q = [u_{q,\bar{k}_0}, \ldots, u_{q,\bar{k}_{\bar{M}-1}}]^T$, $\bar{\mathbf{A}}_l$ is an $\bar{M} \times N$ matrix with its (m,n)-th element given by $[\bar{\mathbf{A}}_l]_{m,n} = r_{n,\bar{k}_m,l}^{(\psi\phi)}$, and $\mathbf{g}_q = [g_{q,0}, \ldots, g_{q,N-1}]^T$. Stacking the $\bar{M}$ outputs $\{x_{q,\bar{k}_m}\}_{m=0}^{\bar{M}-1}$ into the vector $\bar{\mathbf{x}}_q = [x_{q,\bar{k}_0}, \ldots, x_{q,\bar{k}_{\bar{M}-1}}]^T$, we finally obtain

$$\bar{\mathbf{x}}_q = (\mathbf{I}_{\bar{M}} \otimes \bar{\mathbf{u}}_q^T)\bar{\mathbf{A}}\mathbf{g}_q + \bar{\mathbf{v}}_q, \tag{19}$$

where $\bar{\mathbf{v}}_q = [v_{q,\bar{k}_0}, \ldots, v_{q,\bar{k}_{\bar{M}-1}}]^T$ and $\bar{\mathbf{A}} = [\bar{\mathbf{A}}_0^T, \ldots, \bar{\mathbf{A}}_{\bar{M}-1}^T]^T$. Since the interference vector $\bar{\mathbf{v}}_q$ is unknown at this point (as well as its statistics), we simply stick to a least-squares (LS) algorithm to solve for $\mathbf{g}_q$ from (19), yielding:

$$\hat{\mathbf{g}}_q = [(\mathbf{I}_{\bar{M}} \otimes \bar{\mathbf{u}}_q^T)\bar{\mathbf{A}}]^\dagger \bar{\mathbf{x}}_q.$$

For wideband channels that are typically considered as having sparse multipath echos, the channel vector $\mathbf{g}_q$ is sparse with a small number of nonzero amplitudes at unknown delays. The sparsity feature can be incorporated as prior knowledge to enhance the estimation accuracy, via the following ℓ_1-regularized LS formulation:

$$\hat{\mathbf{g}}_q = \arg\min_{\mathbf{g}_q} \left\{ \|\mathbf{g}_q\|_1 + \lambda \left\|\bar{\mathbf{x}}_q - (\mathbf{I}_{\bar{M}} \otimes \bar{\mathbf{u}}_q^T)\bar{\mathbf{A}}\mathbf{g}_q\right\|_2^2 \right\} \tag{20}$$

where the ℓ_1-norm term imposes sparsity on the recovered channel vector, and the positive weight λ balances the bias-variance tradeoff in the channel estimate [21].

For OFDM, the channel estimation problem greatly simplifies, because $r_{n,k,l}^{(\psi\phi)} = 0$, $\forall k \ne l$, in this special case. As a result, when $\bar{M} \ge N$, the LS solution is reduced to

$$\hat{\mathbf{g}}_q = \bar{\bar{\mathbf{A}}}^\dagger \mathrm{diag}(\bar{\mathbf{u}}_q)^{-1}\bar{\mathbf{x}}_q,$$

where $\bar{\bar{\mathbf{A}}}$ is an $\bar{M} \times N$ matrix with its (m,n)-th element given by $[\bar{\bar{\mathbf{A}}}]_{m,n} = r_{n,\bar{k}_m,\bar{k}_m}^{(\psi\phi)}$. Note that under a zero-mean white Gaussian interference assumption, the ML-optimal training consists of using $\bar{M}$ equi-powered and equi-spaced training symbols [23].

Estimates of the channel coefficients $\{h_{q,k,l}\}_{k,l}$ can finally be obtained according to (18).

B. Interference Sensing

Having estimated $\mathbf{H}_q$, it is possible to estimate the filtered interference sample vector $\mathbf{v}_q$ simply as $\hat{\mathbf{v}}_q = \mathbf{x}_q - \hat{\mathbf{H}}_q\mathbf{u}_q$. Subsequently, the interference covariance matrix $\mathbf{R}_q$ can be computed from the sample average. Although conceptually simple, this approach to interference sensing makes use of all K receiver functions to collect at least K samples per block in order to form $\mathbf{x}_q$. To reduce hardware-related implementation costs, we develop a compressive sampling mechanism for sensing $\mathbf{v}_q$ using a small number of samples.

Consider the signal space spanned by the receiver functions $\{\phi_k(t)\}_{k=0}^{K-1}$. To assess the filtered outputs $\{v_{q,l}\}_l$, it suffices to ignore irrelevant noise outside the signal space and represent $v_q(t)$ by the following expansion model:

$$v_q(t) = \sum_{k=0}^{K-1} \alpha_{q,k}\phi_k(t) \tag{21}$$

where $\boldsymbol{\alpha}_q = [\alpha_{q,0}, \ldots, \alpha_{q,K-1}]^T$ is the vector representation of $v_q(t)$ on the space spanned by $\{\phi_k(t)\}_{k=0}^{K-1}$. Accordingly, the filtered interference sample $v_{q,l}$ can be written as

$$v_{q,l} = \sum_{k=0}^{K-1} \alpha_{q,k}\ \phi_k(t) \star \phi_l^*(-t)|_{t=0} = \sum_{k=0}^{K-1} \alpha_k r_{l,k}^{(\phi\phi)}, \quad l = 0, \ldots, K-1, \tag{22}$$

or in a matrix form,

$$\mathbf{v}_q = \mathbf{R}_{\phi\phi}\boldsymbol{\alpha}_q \tag{23}$$

where $\mathbf{R}_{\phi\phi}$ is a $K \times K$ known matrix with its (l,k)-th element given by $[\mathbf{R}_{\phi\phi}]_{l,k} = r_{l,k}^{(\phi\phi)}$. The sensing task of estimating $\mathbf{v}_q$ is now equivalent to estimating $\boldsymbol{\alpha}_q$.

Our interference sensing strategy hinges on the observation that $v_q(t)$ is sparse in the signal space spanned by $\{\phi_k(t)\}_k$, that is, its vector representation $\boldsymbol{\alpha}_q$ in (21) is a sparse vector with only a small number of nonzero elements, whose locations are clearly unknown. The sparse nature of $\boldsymbol{\alpha}_q$ results from both the CR context of interest and the sparsity-constrained DRA problem that we have formalized in (16). First, the set of expansion functions $\{\phi_k(t)\}_k$ we adopt at the receiver can be a redundant non-orthogonal set or a combination of sets of orthogonal functions tailored for communication signals, e.g., a combination of the functions used in FDM and TDM; accordingly, it provides an over-complete representation of the signal space. Second, as elaborated in Section V, we impose sparsity constraints to limit the number of transmitter functions employed, which results in sparse resource occupancy by CR users after DRA optimization. As a result, there is only a small number of nonzero elements in $\boldsymbol{\alpha}_q$, measured by its l_0-norm $K_0 = ||\boldsymbol{\alpha}_q||_0$. The upper bound of K_0 is known empirically, but the locations of nonzero elements in $\boldsymbol{\alpha}_q$ are unknown. Further, the sparsity of $\boldsymbol{\alpha}_q$ can be induced or made stronger by using a sparsifying basis $\mathbf{T}_q$ for $\boldsymbol{\alpha}_q$, such that $\tilde{\boldsymbol{\alpha}}_q = \mathbf{T}_q^{-1}\boldsymbol{\alpha}_q$ has a low sparsity order. With the use of $\mathbf{T}_q$, $\mathbf{v}_q = (\mathbf{R}_{\phi\phi}\mathbf{T}_q)\tilde{\boldsymbol{\alpha}}_q$ has a sparse representation $\tilde{\boldsymbol{\alpha}}_q$ on the transformed receiver waveforms $\mathbf{R}_{\phi\phi}\mathbf{T}_q$. We focus on recovering $\boldsymbol{\alpha}_q$, while $\tilde{\boldsymbol{\alpha}}_q$ can be recovered similarly when stronger sparsity is desired and $\mathbf{T}_q$ is properly chosen.

Due to its sparseness, $\boldsymbol{\alpha}_q$ can be possibly recovered from a small number of M linear representations, $K_0 < M \leq K$, according to recent results in compressive sampling [17], [18]. To implement a compressive sampler, we employ an auxiliary wideband filter $\zeta(t)$ of essential bandwidth $B = 1/T$ at the receiver end, in parallel to those receiver functions. The filter output $x_q(t) \star \zeta^*(-t)$ is sampled at M time instances $\{t_m\}_{m=0}^{M-1}$, $M < K$, taken within each block after skipping the cyclic prefix length NT. For each sample $y_{q,m} = x_q(t) \star \zeta^*(-t)|_{t=t_m}$, the signal part $\sum_k u_{q,k}\psi_k(t) \star g_q(t) \star \zeta^*(-t)|_{t=t_m}$ can be cancelled out after channel estimation of $\mathbf{g}_q$, yielding the filtered interference sample $\zeta_{q,m} = v_q(t) \star \zeta^*(-t)|_{t=t_m}$, $\forall m$, as follows:

$$\zeta_{q,m} = y_{q,m} - \sum_k u_{q,k} \sum_{n=0}^{N-1} \hat{g}_{q,n}[\psi_k(t-nT) \star \zeta^*(-t)|_{t=t_m}]. \tag{24}$$

Compressive sampling theory has alluded to several effective means for generating $\{\zeta_{q,m}\}_{m=0}^{M-1}$ as random measurements, in order to ensure recovery of the sparse unknowns with high probability from an under-determined linear measurement system [17], [18], [20]. For example, when the sampling filter $\zeta(t)$ takes a general shape such as a rectangular pulse of length T, the sampling instances $\{t_m\}$ shall be random and spaced at least a time span T apart. Alternatively, when $\zeta(t)$ is properly designed with inherent randomness, such as the analog-to-information (AIC) converter [20], a reduced-rate uniform sampler can be employed with $t_m = m(K/M)T$, $m = 0, 1, \ldots, M-1$.

With (21), $\zeta_{q,m}$ can be expressed as

$$\zeta_{q,m} = \sum_{k=0}^{K-1} \alpha_{q,k}\ \phi_k(t) \star \zeta^*(-t)|_{t=t_m} = \sum_{k=0}^{K-1} \alpha_{q,k} r_{m,k}^{(\phi\zeta)}, \tag{25}$$

or in a matrix form,

$$\boldsymbol{\zeta}_q = \mathbf{R}_{\phi\zeta}\boldsymbol{\alpha}_q \tag{26}$$

where $\boldsymbol{\zeta}_q = [\zeta_{q,0}, \ldots, \zeta_{q,M-1}]^T$ is an $M \times 1$ linear measurement vector and $\mathbf{R}_{\phi\zeta}$ is an $M \times K$ known random measurement matrix with its (m,k)-th element given by $[\mathbf{R}_{\phi\zeta}]_{m,k} = r_{m,k}^{(\phi\zeta)} = \phi_k(t) \star \zeta^*(-t)|_{t=t_m}$. Accordingly, the sparse signal $\boldsymbol{\alpha}_q$ can be recovered from the compressive measurements $\boldsymbol{\zeta}_q$ using an ℓ_1-norm regularized least squares formulation [21], as follows:

$$\hat{\boldsymbol{\alpha}}_q = \arg\min_{\boldsymbol{\alpha}_q} ||\boldsymbol{\alpha}_q||_1 + \lambda||\boldsymbol{\zeta}_q - \mathbf{R}_{\phi\zeta}\boldsymbol{\alpha}_q||_2^2. \tag{27}$$

Here, the first ℓ_1-norm term imposes sparsity on the recovered signal, the second least-squares term accounts for the measurement equation (26), and the weight λ reflects the tradeoff between bias and variance of the signal estimate [21]. Computationally feasible algorithms exist to accurately approximate the solution of (27), such that the Lasso algorithm [21] and greedy algorithms.

Subsequently, the interested $\mathbf{v}_q$ can be estimated as $\hat{\mathbf{v}}_q = \mathbf{R}_{\phi\phi}\hat{\boldsymbol{\alpha}}_q$. Sensing the interference on a number of blocks, we will be able to construct an estimate of the interference covariance matrix $\mathbf{R}_q = E(\mathbf{v}_q\mathbf{v}_q^H)$ by its sample average.

VII. Simulations

Consider a Q-user peer-to-peer CR network. Each user corresponds to one pair of unicast transmitter and receiver, giving rise to Q^2 channel links: Q of them are desired links while the others are interference links. We suppose that each link experiences frequency-selective fading modeled by an N_t-tap tapped delay line, where each tap coefficient is complex Gaussian with zero-mean and unit variance. For each link, we generate these random tap coefficients and then use (18) to generate the channel matrices $\{\mathbf{H}_q\}_q$. The link power gain is denoted by a scalar $\rho_{rq} > 0$, $\forall r, q \in [1, Q]$, which captures both the path loss and the fading power. The noise variance is assumed to be 1 in all cases. Subsequently, the interference covariance matrix $\mathbf{R}_q$ is given by the covariance of the aggregated interference (from all the $Q-1$ received interference channels) plus noise. Note that the interference from primary users reflects in $\mathbf{R}_q$ as well, which can be acquired via sensing. Hence, as long as the sensing results are accurate, the impact of primary users can be treated in the same way as that of other secondary users. We simulate $\mathbf{R}_q$ using interfering CR users without loss of generality, and test the impact of sensing errors on the DRA efficiency. Focusing on the sparsity issue in DRA, we drop the mask constraint (6) and correspondingly (12c) in all examples.

A. Distributed DRA and Waveform Adaptation

To demonstrate the flexibility of our joint approach to DRA and waveform adaptation, we first consider the distributed DRA formulation in (12) in the absence of sparsity constraints. The channel and interference information $\{\mathbf{H}_q, \mathbf{R}_q\}$ is assumed known, while the impact of estimation errors will be investigated later. Figure 1 shows the transmitted power spectra of the resulting multicarrier (MC) power allocation for 3 users operating in different scenarios described by following parameters: (a) $P_2 = P_3 = 10$, $P_1 = 5$, $\rho_{rq} = 5$, $\forall r \neq q$, and $N_t = 8$; (b) $P_q = 20$, $\forall q$, $\rho_{rq} = 0.2$, and $N_t = 4$. In both cases, we assume $\rho_{qq}=1$ w.l.o.g., and $K=32$ digital carriers as the transmitter and receiver functions. In (a), all users experience strong interference, and the DRA game results in an FDM-type solution where the power spectra of different users are non-overlapping in frequency. In contrast, users in (b) have high transmit power and low interference, and the optimal DRA suggests frequency reuse via spread spectrum (SS) transmission. Users overlap in frequency to occupy nearly the entire bandwidth, and adapt mainly to their own channels. Such results confirm the theoretical prediction in [7], and demonstrate the flexibility of our signal expansion framework in instantiating various optimal multiple access schemes under available resources.

For scenario (b), we also select a different set of expansion functions whose frequency responses are piecewise flat at levels $\{0,1\}$ that match to length-K Hadamard codes (HC). The optimal allocation using Hadamard codes has low exact sparsity of $||\mathbf{p}_q^{(\mathrm{HC})}||_0 = 11, 10, 8$ for various q's, whereas the multi-carrier design is less sparse with $||\mathbf{p}_q^{(\mathrm{MC})}||_0 = 18, 25, 28$. Both sets of expansion functions result in the same transmitted spectra and user capacity (hence, we do not include the curves which overlap with those for (b)). Low sparsity means low hardware cost, and may even reduce computational load and improve the convergence of iterative games.

B. Capacity under Sparsity Constraints

To shed light on the inherent sparsity of the DRA problem in the CR context, we compare three DRA techniques: *i*) DRA via (12) without sparsity constraints; *ii*) DRA via (12) performed over a fixed subset of $L_{q,\max}^{(0)}=K'$ subcarriers out of the K transmitter and receiver functions, with $K' \leq K$; and, *iii*) DRA via (15) under sparsity constraints on the l-norm, for $l=0.2$ and $l=1$. Both *ii*) and *iii*) aim at limiting the l_0-norm of the DRA solutions in order to reduce the implementation complexity.

First, we consider a 4-user system with the following parameters: $P_q=20$, $\rho_{qq}=1$, $\forall q$, and $\rho_{rq}=5$ for $\forall r \neq q$. All the channels are randomly generated as we specified before, using $N_t=5$ taps. FDM subcarriers are used as the transmitter and receiver functions, with $K=32$ subcarriers. Fig. 2(a) depicts the sum capacity of all users versus the sparsity parameter $L_{q,\max}^{(l)}$, averaged over 100 sets of channel realizations by Monte Carlo simulations. For any power-constrained $\mathbf{p}_q$, its l-norm is upper bounded by K for $l=0$ and by $\sqrt{P_q K^{(2/l)-1}}$ for $l>0$. The K-point grid on the x-axis is equally spaced from 1 to K for K' in *ii*), and from 1 to $\sqrt{P_q K^{(2/l)-1}}$ for $L_{q,\max}^{(l)}$ in *iii*).

When the sparsity constraints in *ii*) and *iii*) are loose, all DRA designs converge to the same $C(\mathbf{p}_q^\star)$ of the sparsity-unconstrained design *i*), indicated by the rightmost region in Fig. 2(a). In design *ii*), as K' decreases, the sparsity constraints becomes tighter, and the resulting capacity exhibits a noticeable gap from that of *i*). In essence, *ii*) can be regarded as a naive way to constrain the l_0-norm sparsity, by pre-defining the possible locations of nonzero elements in $\mathbf{p}_q$ regardless of the channel dynamics. In contrast, the sparsity-constrained DRA designs in *iii*) result in average capacities close to that

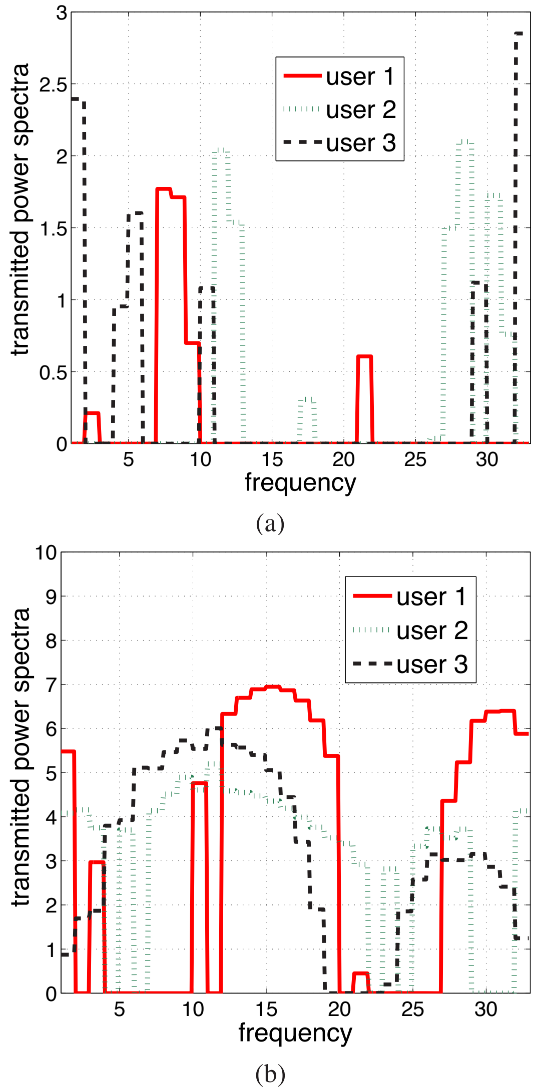
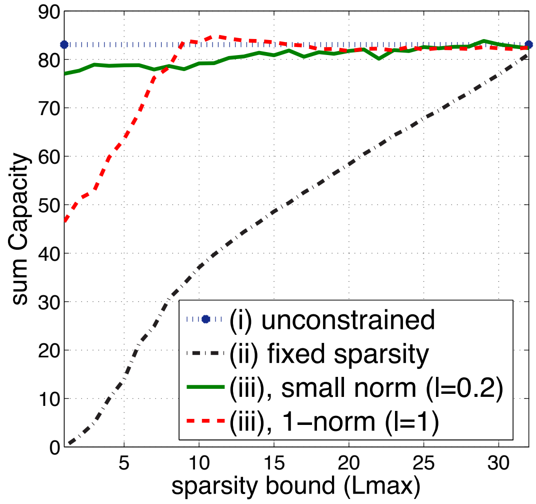


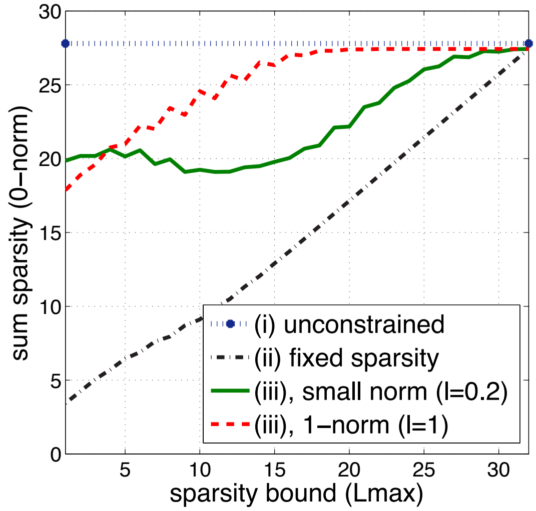
Fig. 1. Optimal transmitted power profiles of two users: (a) strong interference case, (b) weak interference case.

in *i*), because *iii*) optimally selects active expansion functions where the effective resources lie dynamically.

In terms of the sparsity metric, the l_0-norm constraint directly controls the exact sparsity and thus complexity, but incurs combinatorial computational load. When l is close to 0, e.g., $l=0.2$, the optimal solution closely approximates a sparse representation. However, $l<1$ results in a nonlinear concave constraint. Solving for the global optimum can be computationally intractable, while suboptimal local minima give rise to convergence errors. For $l \geq 1$, the sparsity constraint becomes convex, thus circumventing convergence errors. However, as l increases, the resulting allocation tends to be less sparse. The global optimum does not necessarily coincide with the sparsest solutions, resulting in structural errors. Further, when l gets close to 2, a small value of $L_{q,\max}^{(l)}$ may limit the transmit power, which in turn degrades the attainable capacity. These assessments are corroborated in Fig. 2(b), which depicts the average complexity and hardware costs measured by the sum of the l_0-norm of the optimized allocation vectors of all users. When the norm order l and



(a)



(b)

Fig. 2. Sparsity-constrained DRA: (a) average sum capacity measured in bits/second/Hertz, (b) average sum complexity measured by l_0-norm.

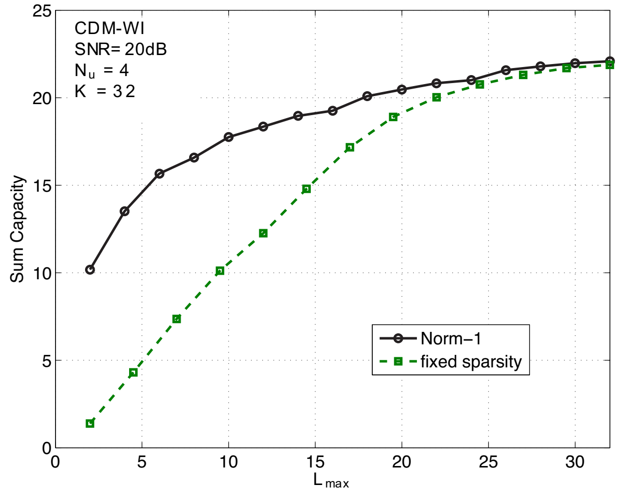


Fig. 3. Average sum capacity measured in bits/second/Hertz for the sparsity-constrained DRA with $N_u = 4$ users for CDM in weak interference.

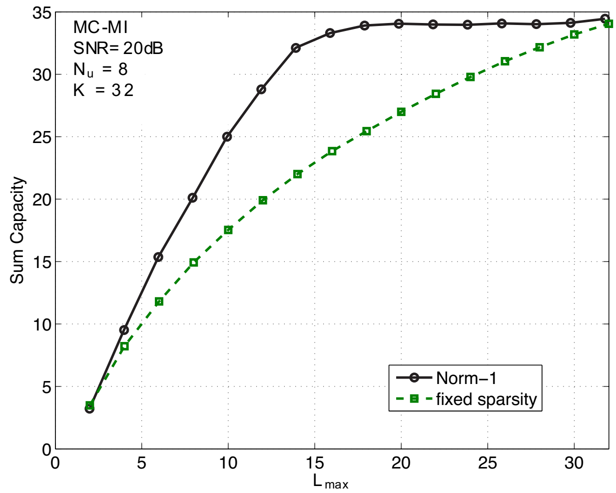


Fig. 4. Average sum capacity measured in bits/second/Hertz for the sparsity-constrained DRA with $N_u = 8$ users for FDM in medium interference.

the sparsity upper bound $L_{q,\max}^{(l)}$ are properly chosen, e.g. $l = 0.2$ and $L_{q,\max}^{(l)} \in [10, 15]$ in this simulation case, the sparsity-constrained DRA reaches high capacity performance comparable to that of the unconstrained case, with noticeable saving in complexity.

Next, we test and compare the sparsity-constrained DRA performance using different transmitter and receiver functions and adopting the function selection scheme defined in (16). We consider a CR system with $N_u = 4$ or $N_u = 8$ users with equal power levels $P_q = 20$ and link power gains $\rho_{qq} = 1$, with $1 \leq q \leq N_u$. Three sets of systems parameters are tested: *i*) in the weak interference case, we set $\rho_{rq} = 0.1$ for $\forall r \neq q$, and use $K = 32$ Hadamard codes as transmitter and receiver spreading codes; *ii*) in the medium interference case, we set $\rho_{rq} = 1$ for $\forall r \neq q$, and use $K = 32$ FDM subcarriers as transmitter and receiver functions; *iii*) in the strong interference case, we set $\rho_{rq} = 5$ for $\forall r \neq q$, and use $K = 32$ FDM subcarriers as transmitter and receiver functions. In the above cases, all the channels are randomly generated as we specified before, using $N_t = 5$ taps. The sparsity norm order is set to $l = 1$ for computational easiness. Fig. 3 depicts the sum-capacity averaged over the active users for the CDM system in *i*). It can be observed that the sparsity-constrained DRA optimization induced by the l-norm outperforms that with fixed sparsity, and converges to the same sum-capacity level when the constraint becomes loose, i.e., $L_{q,\max}^{(l)}$ is large. In Figs. 4-5, we increase the number of users to $N_u = 8$, and focus on the FDM system in *ii*) and *iii*), respectively. Interestingly, the same superiority of the sparsity-constrained DRA exhibits, and the sum-capacity level reaches asymptotically to a higher level than that in Figure 3 due to the increased number of active users. Further, for both the FDM and CDM systems the sparsity-constrained solution offers a considerable gain in the sparsity order measured as the sum of the 0-norm of the optimized coefficients (results not shown due to space limitation).

C. Performance and Impact of Interference Sensing

To testify the effectiveness of the compressed interference sensing technique in Section VI-B, we now revisit scenario

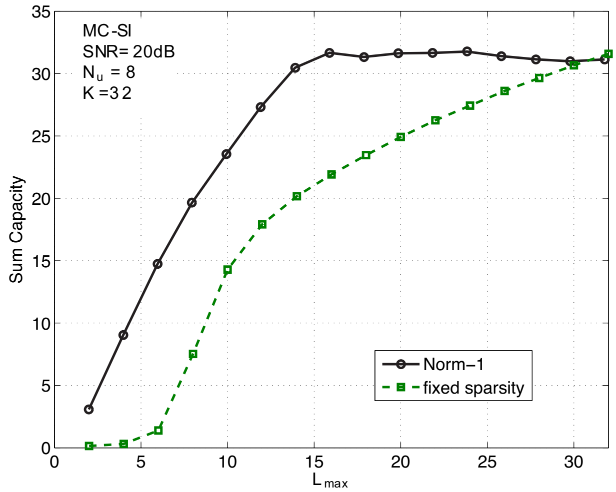


Fig. 5. Average sum capacity measured in bits/second/Hertz for the sparsity-constrained DRA with $N_u = 8$ users for FDM in strong interference.

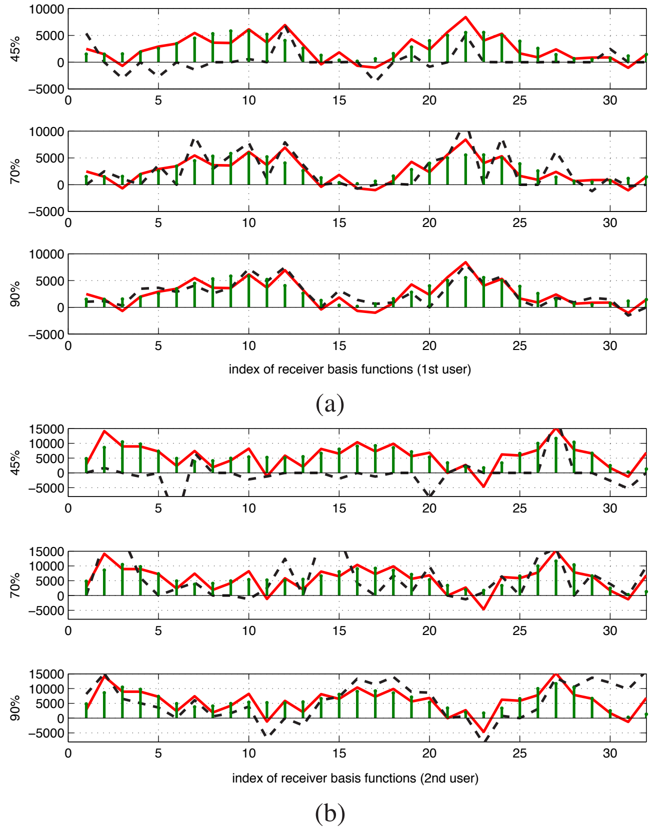


Fig. 6. Estimated interference values $\{v_{q,l}\}_{q=1,2,3}$ versus index l, for (a) 1st user ($q = 1$), and (b) 2nd user ($q = 2$). In each subplot, dotted vertical lines indicate the interference profile in the noise free case, the dashed line is its noisy realization, and the solid line is the estimated interference by compressed sensing. The results of user 3 are omitted to save space. The case of full-rate sampling, i.e., $M/K = 100\%$, results in perfect recovery ans is not shown.

(a) in Figure 1 and focus on OFDM-based DRA. We assume perfect channel knowledge, since accurate OFDM channel estimation has been demonstrated in the literature for non-cognitive wireless systems. The auxiliary wideband filter $\zeta(t)$ is chosen to be a rectangular pulse of time-span T. Figure 6 depicts the recovered interference vector $\mathbf{v}_q$ within one data block, for various compression ratios $M/K = 45\%, 70\%, 90\%$ and 100%. When the compression ratio is chosen moderately, the compressed sensing scheme is able to reliably recover the instantaneous interference profile, without having to collecting a minimum of K samples per block or activating all K receiver functions.

Figure 7 evaluates the impact of sensing errors on the capacity performance of DRA. During DRA, the allocation vectors $\{\mathbf{p}_q\}_q$ are decided based on imperfect interference values $\{\hat{\mathbf{v}}_q\}_q$ which deviate from the true values $\{\mathbf{v}_q\}_q$ element by element by a standard deviation σ_v. We compare the attained sum capacity versus SNR for DRA under scenario (a), for the cases of no sensing errors ($\sigma_v = 0$) and moderately large sensing errors ($\sigma_v = 0.1$). Both the sparsity-unconstrained DRA scheme in (12) and the sparsity-constrained DRA scheme in (15) are evaluated. It can be observed from Figure 7 that the capacity performance is quite robust to interference estimation errors. This is because each allocation vector is determined by relative values of the signal to interference and noise ratio on the K receiver functions. Hence, the deviations of the relative values $\{\hat{v}_{q,k}/\hat{v}_{q,l}\}_{k\neq l}$ from $\{v_{q,k}/v_{q,l}\}_{k\neq l}$ degrade the capacity more than the deviations of the actual values $\{\hat{v}_{q,k}\}_k$ from $\{v_{q,k}\}_k$. As SNR increases, σ_v has less noticeable impact on the relative values $\{\hat{v}_{q,k}/\hat{v}_{q,l}\}_{k\neq l}$, compared to its impact on $\{\hat{v}_{q,k}\}_k$. The performance robustness of DRA to sensing errors allows us to alleviate the complexity burden of sensing by using a small compression ratio M/K.

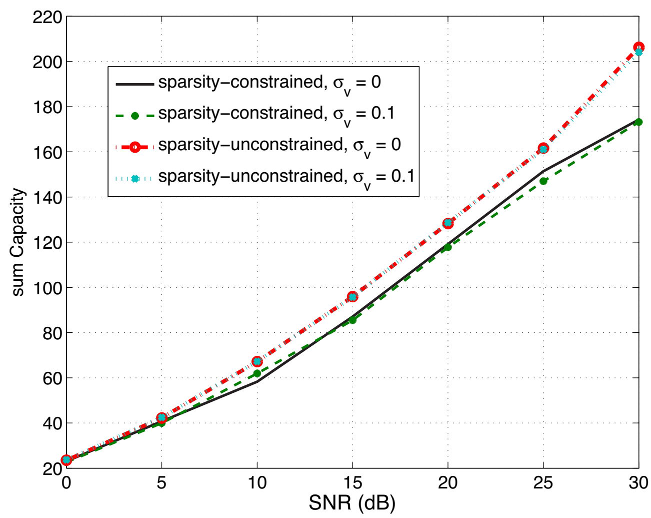


Fig. 7. Average sum capacity measured in bits/second/Hertz subject to sensing errors.

VIII. Summary

This paper has presented a general framework for joint DRA and waveform adaptation based on the signal expansion approach. Generalized transmitter and receiver signal-expansion functions are employed to formulate CR-oriented DRA design objectives and cognitive spectral mask constraints. This approach offers a truly distributed DRA optimization framework with waveform adaptation capability under a practical transceiver implementation structure. This signal expansion structure is also amenable to carrying out additional flexible designs such as quantized feedback and low-resolution DSP implementations, which we will explore in future work.

Sparsity properties are explored in this paper for channel estimation, interference sensing and DRA optimization. In all cases, the inherent sparsity in various elements of a CR network allows us to considerably reduce the computation and implementation complexities, at little performance cost. For DRA optimization, the use of redundant signal-expansion functions, together with properly imposed sparsity constraints, can attain high capacity performance at reduced complexity and improved convergence speed, and naturally lead to optimized adaptation to diverse channel environments.

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