Efficient Spectrum Access and Co-Existence With Receiver Nonlinearity: Frameworks and Algorithms

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Abstract—Radio frequency (RF) front-end nonlinearity significantly impairs receiver performance in non-intuitive ways. Receivers are susceptible to harmful adjacent channel interference, especially in next-generation networks with diverse radio access technologies, co-existing in space, time, and frequency. Vulnerabilities of receiver front-ends can have a severe detrimental effect on network performance and spectrum co-existence. In this paper, we propose centralized controller-based receiver-centric framework for spectrum access that accounts for receiver front-end nonlinearity, pre-selector filter bandwidth, and transmitter out-of-band emission characteristics for networks with diverse RF-layer characteristics. Furthermore, we propose computationally efficient algorithms to optimize the receiver-centric framework and examine network level performance. We demonstrate through extensive network simulations that the proposed receiver-centric framework provides substantially higher spectrum efficiency gains over receiver-agnostic spectrum access and improves co-existence in dense and diverse next-generation wireless networks. We further demonstrate through simulations that the proposed algorithms achieve close to optimal solutions for receiver-centric network optimization.

Index Terms—Receiver nonlinearity, RF front-end, co-existence, spectrum sharing, 5G, adjacent channel interference, intermodulation, network optimization.

I. INTRODUCTION

In recent times, there has been an explosive increase in the number of connected devices of quality wireless services [1]. This in turn places an enormous demand on RF spectrum. RF spectrum is an expensive and limited natural resource, and hence remains tightly regulated. Maximizing utilization of limited wireless spectrum is of immense importance. Traditionally, the RF spectrum was managed by fixed and exclusive allocations of spectrum bands to specific services. Users not allocated to a particular band were legally prohibited to transmit in those bands, irrespective of its actual spatio-temporal occupancy by the original lease holders. Consequently, this led to an extremely poor utilization of the scarce spectral resource, with large amounts of spectrum underutilized despite the mounting congestion on a small fraction of the entire RF spectrum. Several researchers have pointed out that this model of exclusive spectrum allocation is inefficient, paving way for co-existence through sharing and dynamic need based allocations for better utilization [2]–[10].

Co-existence of diverse Radio Access Technologies (RATs) through various frameworks of dynamic spectrum access and sharing have been identified as key technologies to make efficient use of the available spectrum. In order to ensure co-existence and protect the systems operating in the same spectrum band from interference, several frameworks have been proposed based on sensing, beacons, and database driven access [3]. Such frameworks can potentially allow multitudes of RATs to co-exist in the same band without causing harmful interference to each other. They also have an onerous task of managing wireless networks with diverse technologies and optimizing many parameters to maximize spectral efficiency.

In order to ease the spectral congestion and improve the overall spectrum utilization, the US FCC recently announced the adoption of a commercial spectrum sharing arrangement with the military systems in the 3550–3700 GHz band [11], [12], and the recently auctioned AWS-3 band [13]. Worldwide, many similar efforts are underway or have already been taken by several regulatory bodies in an effort to cope with the enormous demand for wireless spectrum. Thus, next generation wireless networks will see unprecedented diversity in radio technologies and RF front-ends, accessing the same band of spectrum in close spatio-temporal proximity.

However, multi-RAT co-existence makes receivers vulnerable to interference. While there has been a plenty of research in managing and mitigating co-channel interference [14]–[16], the susceptibility of receivers to adjacent channel interference has received minimal attention. Adjacent channel interference primarily arises due to limitations in RF filtering and inherent receiver non-linear imperfections in the RF chain. Receiver non-linearity introduces unwanted distortion which adversely affects the receiver performance, especially in the presence of strong adjacent channel signals. Traditionally, receivers were protected by adjacent channel interference by carefully crafted guard bands, which were customized to the respective technologies and receiver RF front-ends during band planning.
and allocation. This prevented powerful adjacent channel signals from entering the receivers. However, the framework of allocating customized and static guard bands for interference protection collapses, when exceedingly diverse radio technologies access and co-exist in the same band of spectrum.

Fig. 1 illustrates the results of a case study we carried out to examine the impact of receiver diversity on performance. It shows an experimental study on two widely used technologies: LTE and WiFi with setup in Table I. It demonstrates the difference in susceptibility of LTE and WiFi receivers to adjacent channel interference. A SPN-43 radar signal was swept across frequency, in the channels overlapping and adjacent to LTE and WiFi. The degradation in throughput in each case was measured. The LTE receiver achieved almost 100% of the maximum throughput as soon as the radar signal moved out of the channel, indicating a good out-of-band interference rejection capability. The WiFi receiver, on the other hand, has poor adjacent channel interference tolerance, even when the adjacent channel signal is 100 MHz apart. This is in part due to the typical inexpensive WiFi receivers, having poor selectivity and wider nonlinear operating regions.

It is imperative for next generation wireless networks with co-existence and sharing, to consider the impact of receiver front-end nonlinearity on the desired channels while performing network-wide spectrum assignments. The LightSquared (LS) controversy of 2011 is a testimony for the ill-effects of spectrum assignments agnostic to receiver sensitivities, and open ended receiver designs on spectrum efficiency and wireless performance [17]. The company after obtaining the required license to deploy terrestrial LTE repeaters in a band adjacent to the civilian GPS downlink carried out deployments worth close to $3B [17]. However, ex-post analyses and testing revealed that commercial GPS receivers would suffer severe interference, which would compromise their performance because of their poor adjacent channel tolerance limits. This problem could have been avoided had the adjacent channel co-existence analysis between commercial GPS receivers and LS transmitter regulations been carried out a priori. Such issues will be intensified when disparate systems have to co-exist dynamically, especially if channel allocations remain oblivious to receiver characteristics.

A possible approach to enable better co-existence is to impose stringent regulations on receiver performance. Receiver regulation is a very complex topic entangled in socio-economic and technological aspects [2]. Consumer electronics are reluctant to heed to minimum performance regulations because of economic reasons. High device costs take a toll on the penetration of quality wireless services. Thus, frameworks for harmonious co-existence that obviate the need for stringent regulation are needed. This has been repeatedly emphasized in the reports of several regulatory agencies and standardization bodies [9], [18]–[22]. Our preliminary study in [23] and [24] revealed that spectral assignment accounting for receiver characteristics can potentially increase spectrum efficiency over receiver-agnostic access. Further, we presented in [25] the network resource allocation for a simple two-user case and in [26] an initial study on a channel assignment technique, accounting for receiver nonlinearity. In addition to the reports of regulatory and standardization bodies, this work is motivated by our initial findings, which showed promising gains in spectrum efficiency and network performance for receiver-centric frameworks.

### Main Contributions

In this paper, we present novel frameworks on receiver-centric spectrum access that account for front-end nonlinearity, for network efficiency and spectrum co-existence. We develop frameworks for spectral access and network optimization taking into account (a) receiver RF front-end nonlinearity, (b) receiver pre-selector filter characteristics, and (c) transmitter masks out-of-band emission characteristics. Further, we propose computationally efficient algorithms optimizing the proposed framework. We demonstrate through extensive network simulations that the proposed framework of receiver-centric spectrum access and network management yields significant gains in spectral efficiency and network performance. In addition, we analyze the performance of the proposed algorithms against the optimal solution using extensive simulations. Even though receiver nonlinearity has been extensively studied, it has not been employed to design efficient spectrum access frameworks. To the best of our knowledge, this is the first attempt to develop a comprehensive network management framework inclusive of receiver nonlinearity and imperfections.

This paper is organized as follows: Section II describes the pre-requisites on receiver front-end nonlinearity required for the ensuing discussion in the paper. Section III develops a
receiver-centric network optimization framework for the case of single or co-located transmitter with multiple receivers with diverse characteristics, Section IV develops a receiver-centric network optimization framework for the generalized case of multiple transmit-receive links with diverse radio technologies, Section V presents a framework to incorporate the transmitter out-of-band emissions in receiver-centric network optimization, Section VI presents the results of network simulations, and Section VII concludes the paper.

II. PRELIMINARIES

A. Receiver Nonlinearity and the IIP3 Point

We consider a memoryless polynomial receiver front-end model with input-output relation described by [27]–[29],

$$V_{out}(t) = \sum_{k=0}^{K} \alpha_k V_{in}^k(t).$$  (1)

When subjected to a two-tone input of the form, $V_{in}(t) = A_1 \cos(\omega_1 t) + A_2 \cos(\omega_2 t)$, the several terms that feature in the output, $V_{out}(t)$ are: (1) One of the DC terms is given by the $\alpha_0$ (2) The first-order term produces outputs at $\omega_1$ and $\omega_2$. (3) The second order term produces outputs at DC, $\omega_1 - \omega_2$ and $\omega_1 + \omega_2$. (4) The third order term produces outputs at DC, the fundamental frequencies ($\omega_1$ and $\omega_2$), third order harmonics ($3\omega_1$ and $3\omega_2$), and certain new frequencies at $2\omega_1 + \omega_2, \omega_1 + 2\omega_2, 2\omega_1 - \omega_2$ and $2\omega_2 - \omega_1$. In this, we observe that $2\omega_1 - \omega_2$ and $2\omega_2 - \omega_1$ fall in the region of operation of the device, while others can be further filtered out. (5) The fourth order term generates outputs at DC, $2\omega_1, 2\omega_2, 4\omega_1, 4\omega_2, \omega_1 \pm \omega_2, 2\omega_1 \pm 2\omega_2, 3\omega_1 \pm \omega_2$ and $3\omega_2 \pm \omega_1$ and so on.

In general, we can easily deduce that the two-tone input generates distortions at various frequencies surrounding the harmonics of both the input signals. At a given harmonic, the frequencies produced are spaced at $\Delta \omega = |\omega_1 - \omega_2|$. We can thus generalize the spurious frequencies to be present at $\omega_{out} = |\pm p\omega_1 \pm q\omega_2|$, where $p$ and $q$ assume positive integer values. Upon expanding the terms, we also find that the power of the intermodulation signals decreases as the polynomial order increases.

The third order term contributes significantly larger to the in-band intermodulation distortion products than higher order harmonics. Thus, a third order approximation gives a good estimate of the nonlinearity for receivers. To quantify the extent of nonlinearity, standard procedure is to extend the third order and the fundamental curves, on the transfer characteristics plot of powers on the decibel scale, so that they intersect. The point of intersection is known as Third Order Intercept point or IIP3 = $\sqrt{\frac{A_1^2 A_2^2}{4}}$ [27] (or Intermodulation Intercept Point), an example of which is shown in Fig. 2. IIP3 is one of the important parameters specified by the vendors of RF chip manufacturers to convey the receiver nonlinearity.

Nonlinear distortion adversely affects the receiver performance, especially when the interacting signals operate in the nonlinear region of the receiver. Consider three band limited signals in adjacent channels, centered around frequencies $\omega_0$, $\omega_1$, and $\omega_2$ such that $|\omega_0 - \omega_1| = |\omega_1 - \omega_2|$. Suppose that they enter the pre-selector filter of a receiver whose desired signal is centered around $\omega_0$, as shown in Fig. 4. The third order distortion results in a double convolution of the signals in frequency domain and produces an intermodulation interference product centered directly around the desired signal, $\omega_0 = 2\omega_1 - \omega_2$. Fig. 3 illustrates this distortion that adjacent channel signals can cause for a desired signal.

B. characterization of intermodulation distortion

1) Two-tone intermodulation products: We now define three sets related to two-tone intermodulation products and point the reader to [31] and [32] for detailed analysis. Let $A$ denote the $N \times 1$ vector of discretized input spectrum, where $N$ denotes the number of input signals at the pre-selector filter. Two signals at frequency bins $j$ and $k$ respectively, $j, k \in \{1, N\}$ produce third order intermodulation products at a frequency bin $n \in \{1, N\}$; $n \neq j, n \neq k$, if the condition, $|j - k| = \min\{|n - j|, |n - k|\}$ is satisfied [30]–[32]. We denote $\Psi_{n,N}$ to be the set of all ordered pairs $(j,k)$; $\forall j, k \in \{1, N\}; \forall j, k \neq n$ of adjacent channel frequency bins that produce intermodulation products at a given frequency bin $n \in \{1, N\}$ where [30]–[32],

$$\Psi_{n,N} = \left\{ \left( n - 2 \left\lfloor \frac{n - 1}{2} \right\rfloor, n - \left\lfloor \frac{n - 1}{2} \right\rfloor \right), \ldots, \right. \left. \left( n - 2, n - 1 \right), \left( n + 1, n + 2 \right), \ldots, \left( n + \left\lfloor \frac{N - n}{2} \right\rfloor, n + 2 \left\lfloor \frac{N - n}{2} \right\rfloor \right) \right\},$$  (2)

where $\lfloor \cdot \rfloor$ is the floor function. The amplitude of the intermodulation distortion is given by $A_j^2 A_k$. We define $\Phi_{n,N}$ as the
III. FRAMEWORK FOR SINGLE TRANSMITTER, MULTIPLE RECEIVERS

In this section, we consider a network with \( N \) receivers wirelessly connected to a single transmitter or gateway, over \( N \) discrete adjacent channels. The \( N \) receivers have disparate technologies and hence, have diverse RF front-end characteristics. We assume the receivers are distributed in a geographical area within the range of the transmitter as shown in Fig. 4. Consider the downlink channel allocation problem.

We further assume that the transmitter is using an omnidirectional antenna, simultaneously transmitting on \( N \) channels, each with a bandwidth \( W \). Each of those \( N \) downlink channels has a center frequency of \( f_\ell, \ell \in [1, N] \). Let each receiver be indexed by \( n \in [1, N] \). Each receiver’s front-end nonlinearity is described by the third order co-efficient \( \alpha_3, \) which is a function of the intermodulation intercept point, IIP3. Further, each receiver is allotted a unique channel.

An example use case of this is the IoT networks of the next generation wireless systems, with a transmitter gateway delivering disparate downlink information for nodes of the network that are serving different interests. Typically, each node comprises an inexpensive receiver with a potentially different technology (WiFi, Bluetooth, Zigbee, etc.) and an RF front-end. This can be conceptualized for indoor networks such as smart homes, or outdoor networks, where for example, the transmitter gateway can be based on a UAV based platform. Note that the framework presented here is generic and not technology specific. Thus, it can be adopted for any scenario in which multiple receivers are being served by a single transmitter on different channels.

A. Adjacent Channel Interference Formulation

In this section, we discuss the formulation for evaluating the adjacent channel interference. We initially assume that the pre-selector filter of each receiver in the network spans the entire band of operation, and later discuss the development to relax this assumption. Thus, each receiver receives \( N \) signals, of which one of them is the desired signal, and others are adjacent channel signals. The received power on each channel for receiver \( n \) is denoted as \( P_{R_n} = P_T d_{n,T}^{-\mu}, \) where \( P_T \) is the transmitted power per channel, \( d_{n,T} \) is the distance of the receiver \( n \) from the transmitter, and \( \mu \) is the path loss exponent. For simplicity, we do not assume any frequency selective fading and hence, the received power is same across all frequencies for a given receiver. The noise power in the bandwidth \( W \) is denoted by \( \eta. \)

We now define an indicator function,

\[
x_{n\ell} = \mathbb{1}(\text{Channel } \ell \text{ is allocated to receiver } n, \text{ denoted as } \ell \rightarrow n).
\]

Number of Intermodulation Products: The number of intermodulation products, \( \nu_{n,N} \) at a given frequency bin \( n \) can be calculated as,

\[
\nu_{n,N} = |\Psi_{n,N}| + |\Upsilon_{n,N}|
\]

where \( |\bullet| \) denotes cardinality of the set. From (2) and (3) we have,

\[
|\Psi_{n,N}| = \left\lfloor \frac{n-1}{2} \right\rfloor + \left\lfloor \frac{N-n}{2} \right\rfloor.
\]
An approximate formulation for cardinality of the set $\Upsilon_{n,N}$ is deduced from several empirical experiments [35], [36],
\[
|\Upsilon_{n,N}| \approx \frac{(N-1)^2}{4} + \frac{(N-n)(n-1)}{2} - \frac{N}{4}.
\] (9)
For a given channel $\ell$, the number of intermodulation products produced due to nonlinearity for the receiver $n$ is given by,
\[
\kappa_{n,\ell} = |\Psi_{\ell,N}| + |\Upsilon_{\ell,N}|, \tag{10}
\]
where $|\bullet|$ represents the cardinality of the set.

The adjacent channel interference due to intermodulation distortion faced by receiver $n$ is given by,
\[
P_{ACI_n} = \alpha_3 P_R^n \sum_{\ell=1}^{N} x_{n\ell} \kappa_{n,\ell}, \tag{11}
\]
where $\alpha_3$ is the co-efficient of the third order nonlinearity, which can be obtained from \text{IIP}_3. As evident from (11), each receiver faces a different interference depending its nonlinear function and propose a computationally efficient algorithm for channel assignment. We have,
\[
R_n = W \log_2 \left( 1 + \frac{P_R^n}{\alpha_3 P_R^n \sum_{\ell=1}^{N} x_{n\ell} \kappa_{n,\ell}} + \eta \right), \tag{12}
\]
\[
R = W \sum_{n=1}^{N} \log_2 \left( 1 + \frac{P_R^n}{\alpha_3 P_R^n \sum_{\ell=1}^{N} x_{n\ell} \kappa_{n,\ell}} + \eta \right). \tag{13}
\]
The sum rate maximization framework can now be formulated as,
\[
J_1 = \max_{x_{n\ell}} W \sum_{n=1}^{N} \log_2 \left( 1 + \frac{P_R^n}{\alpha_3 P_R^n \sum_{\ell=1}^{N} x_{n\ell} \kappa_{n,\ell}} + \eta \right) \tag{14}
\]
\[
\text{s.t.} \sum_{\ell} x_{n\ell} = 1; \sum_{n} x_{n\ell} = 1. \tag{15}
\]

This formulation is nonlinear and non-convex in the channel assignment variables and it is hard to obtain computationally efficient algorithms. Henceforth, this objective function is referred as the ‘original problem 1’. We now approximate the original problem 1 and reduce the complexity of the objective function. Further, we utilize the approximated objective function and propose a computationally efficient algorithm for channel assignment. We have,
\[
R = W \sum_{n=1}^{N} \log_2 \left( \alpha_3 P_R^n \sum_{\ell=1}^{N} x_{n\ell} \kappa_{n,\ell} + \eta + P_R^n \right)
\]
\[
- W \sum_{n=1}^{N} \log_2 \left( \alpha_3 P_R^n \sum_{\ell=1}^{N} x_{n\ell} \kappa_{n,\ell} + \eta \right), \tag{16}
\]
Lower-bounding the sum rate in (16), we get,
\[
R \geq W \sum_{n=1}^{N} \log_2 \left( \eta + P_R^n \right)
\]
\[
- W \sum_{n=1}^{N} \log_2 \left( \alpha_3 P_R^n \sum_{\ell=1}^{N} x_{n\ell} \kappa_{n,\ell} + \eta \right). \tag{17}
\]
Using Jenson’s inequality, we have
\[
\sum_{n=1}^{N} \log_2 \left( \alpha_3 P_R^n \sum_{\ell=1}^{N} x_{n\ell} \kappa_{n,\ell} + \eta \right)
\]
\[
\leq \log_2 \left( \sum_{n=1}^{N} \alpha_3 P_R^n \sum_{\ell=1}^{N} x_{n\ell} \kappa_{n,\ell} + N \eta \right), \tag{18}
\]
\[
= \log_2 \left( \sum_{n=1}^{N} \sum_{\ell=1}^{N} \alpha_3 P_R^n x_{n\ell} \kappa_{n,\ell} + N \eta \right). \tag{19}
\]
Using (18) in (17) we have,
\[
R \geq W \sum_{n=1}^{N} \log_2 \left( \eta + P_R^n \right)
\]
\[
- W \log_2 \left( \sum_{n=1}^{N} \sum_{\ell=1}^{N} \alpha_3 P_R^n x_{n\ell} \kappa_{n,\ell} + N \eta \right). \tag{20}
\]

We intend to carry out channel assignments such that the sum rate, $R$, is maximized. In order to maximize $R$, from (19) it is clear that $W \log_2 \left( \sum_{n=1}^{N} \sum_{\ell=1}^{N} \alpha_3 P_R^n x_{n\ell} \kappa_{n,\ell} + N \eta \right)$ needs to be minimized, since the first term on R.H.S of (19) is a constant. Since $\log_2 (\bullet)$ is a monotonically increasing concave function, minimizing the total Adjacent Channel Interference, $P_{ACI} = \sum_{n=1}^{N} \sum_{\ell=1}^{N} \alpha_3 P_R^n x_{n\ell} \kappa_{n,\ell}$ will minimize the function, since $N \eta$ is a constant.

C. Problem Formulation

Let $\kappa_{n,\ell}$ denote the number of adjacent channel interfering signals encountered by receiver $n \in [1,N]$ when placed (assigned) in channel $\ell \in [1,N]$. We now define a matrix $K$ whose $\ell^{\text{th}}$ row represents the number of adjacent channel signals entering each of the $N$ receivers when placed in the $\ell^{\text{th}}$ channel, (20) as shown at the bottom of the next page.

Let $X = [x_{n\ell} : n, \ell = 1, \ldots, N]$ denote a binary-integer channel assignment matrix with rows representing receivers and columns representing channels.

The number of interfering signals for any receiver depends on the channel assigned and the pre-selector bandwidth. Thus the adjacent channel interference for the $n^{\text{th}}$ receiver is given by the $n^{\text{th}}$ element of $\text{diag}(XK)$. The total adjacent channel interference is given by,
\[
P_{ACI} = \text{tr}(XK) \tag{21}
\]
where $\text{tr}(\bullet)$ represents the trace of the matrix. Our goal now is to minimize the network wide adjacent channel interference given by (21). Thus, the modified optimization problem can be formulated as,
\[
J_2 = \min_{X} \text{tr}(XK) \tag{22}
\]
\[
\text{s.t.} \sum_{n} x_{n\ell} = 1; \sum_{\ell} x_{n\ell} = 1; \forall n, \ell \in \{0,1\}. \tag{23}
\]
D. Algorithms for Channel Assignment

1) The Munkres Assignment Algorithm: The solution is to pick \( N \) elements of matrix \( K \) whose sum is the least, with the constraint that each of those elements is from a unique row and column. This binary-integer assignment problem has an optimal solution in the Hungarian algorithm [37], [38] and is solved with computational complexity \( O(N^3) \) using the Munkres assignment method [39]. The algorithm is adopted to solve our problem and is presented in Algorithm 1 Let \( k^r_\ell \) represent the \( \ell \)th row vector and \( k^n_c \) represent the \( n \)th column vector of the matrix \( K \). This algorithm finds the optimal assignment through iterative row and column operations of the cost matrix, by identifying the least interference that a given receiver has to suffer in each pass. In each pass, through row and column operations, the minimum interference for each receiver is arrived at by systematically eliminating those receivers which have a possibility of getting a lower interference in subsequent iterations. This is ensured in steps 11 through 13 in the algorithm.

Algorithm 1 The Munkres Assignment Algorithm for Receiver Nonlinearity Aware Channel Assignment

1: FORMULATE: \( K \). Assign \( K' = K \cdot X = 0_{N \times N} \). 
2: ROW REDUCTION: \( \forall \ell, n \in [1, N], [K']_{\ell,n} = \min_n k^r_\ell \). 
3: COLUMN REDUCTION: \( \forall \ell, n \in [1, N], [K']_{\ell,n} = \min_n k^n_c \). 
4: Find a minimal set \( S \) of lines, to cover all zeros in \( K' \). 
5: if \(|S|\neq N\) then 
6: Identify the set of independent zeros in \( K' \), 
7: Formulate a set \( A = (\ell, n) \) representing the corresponding rows-column pair 
8: Optimal Assignment Found: \([x]_{\ell,n} = 1, \forall(\ell, n) \in A \) 
9: else 
10: Find \( k = \min_{\ell,n} K' \) such that \( k \) is not covered by any line in \( S \). 
11: Formulate \( K''_{\ell,n} = K_{\ell,n} - k, \forall(\ell, n) \) not covered by any line in \( S \). 
12: \( K''_{\ell,n} = K_{\ell,n} + k, \forall(\ell, n) \) covered by 2 lines in \( S \). 
13: Go to STEP 2 
14: end if 

2) Greedy Algorithm: We propose a greedy algorithm to iteratively find an assignment matrix \( X \) such that \( \text{tr}(XK) \) is minimized. In other words, we need to pick \( N \) elements of matrix \( K \) whose sum is the least, with the constraint that each of those elements is from a unique row and column. The following greedy algorithm is developed as a solution to the minimization problem.

Algorithm 2 Greedy Algorithm for Receiver Nonlinearity Aware Channel Assignment

1: FORMULATE: \( K \). 
2: INITIALIZE: \( X = 0_{N \times N} \). 
3: Define Sets \( \mathcal{C}_\ell = \{1, 2, \ldots, N\} \); \( \mathcal{C}_n = \{1, 2, \ldots, N\} \) 
4: for \( 1, 2, \ldots, N \) do 
5: \( (\ell^*, n^*) = \arg\min_{\ell,n} [K] \); \( \forall \ell \in \mathcal{C}_\ell \forall n \in \mathcal{C}_n \) 
6: \( [A]_{n^*, \ell^*} = 1 \). 
7: \( \mathcal{C}_\ell = \mathcal{C}_\ell \setminus \{\ell^*\}; \mathcal{C}_n = \mathcal{C}_n \setminus \{n^*\} \) 
8: end for

The intuition for this algorithm is that in each iteration, it greedily picks the least element of the matrix \( K \) and assigns that receiver (column index, \( n^* \)) to the corresponding channel (row index, \( \ell^* \)). All elements of this row and column are permanently excluded in the future iterations. This process is repeated until all receivers are assigned a channel. Note that the rows and columns of channel assignment matrix, \( X \) represent the receiver and channels; and vice versa for the adjacent channel interference matrix, \( K \). Thus, it warrants a flip of indices in the algorithm.

Remark: The \( q^{th} \) iteration of the algorithm (lines 3 to 7) involves finding the minimum among \((N - q + 1)^2 \) elements. Note that there is a dimensionality reduction of the search space for finding the minimum element in \( K \) in each iteration of the algorithm. The average computations for serial sorting is \( O((N - q + 1)^2) \) for the \( q^{th} \) iteration. Thus for \( N \) iterations, the computational complexity of the algorithm is \( O(N^3) \), which is efficient compared to the exponential complexity of the original problem.

E. Pre-Selector Spans a Factor of the Entire Band

In the preceding section, we made an assumption that the pre-selector filter of each receiver spanned the entire band of operation. In practice, different receivers have different pre-selector bandwidths. However, receivers do have to operate over the entire band. Consequently, receivers will have multiple pre-selector filters, each spanning an integer factor of the entire band as shown in Fig. 5.

Let \( M_n \) be the number of pre-selector filters for receiver \( n \). It is reasonable to assume that each pre-selector filter of receiver \( n \) spans an equal number of channels, and is a factor of \( N \). Thus, each pre-selector filter for receiver \( n \) spans \( \frac{N}{M_n} \) channels. This clearly changes the number of signals
producing intermodulation products at any given channel $\ell$ for a receiver $n$.

Any given channel $\ell \in [1,N]$ maps to a frequency bin $\ell_n \in [1,M_n]$ in the pre-selector of receiver $n$. The frequency bin to which a given channel is mapped can be obtained as,

$$\ell_n = (\ell - 1) \mod M_n + 1,$$

where $a \mod b = a - b\lfloor a/b \rfloor$ is modulo operation. The number of intermodulation products at a given channel $\ell$ for a receiver $n$ with $M_n$ pre-selector filters is given by,

$$\kappa^p_\ell = |\Psi_{\ell_n,M_n}| + |\Upsilon_{\ell_n,M_n}|,$$

where $|\cdot|$ is the cardinality of the set. The computations, approximations, and framework for receiver nonlinearity aware channel allocation of the preceding sections can be now be used for receivers with difference pre-selector filters with this modification to calculate the number of intermodulation products.

### IV. GENERIC FRAMEWORK FOR MULTIPLE TRANSMITTER-RECEIVER PAIRS

In this section, we consider a network of $N$ transmitters and $N$ receivers ($N$ Tx-Rx pairs) communicating over $N$ distinct adjacent channel links. As before, we assume the network is a multi-RAT system with disparate receiver front-ends. We assume the transmitters and receivers are distributed in a geographical area and the network topology is known to the centralized controller. We also assume that all the transmitters have omni-directional antennas. Each channel has the center frequency $f_\ell$, $\ell \in [1,N]$ and bandwidth $W$. Each receiver $n \in [1,N]$ has a unique front-end nonlinearity described by its third order intermodulation intercept point, IIP$_3n$. We consider the channel allocation for the $N$ links with an objective to maximize the sum rate of the network.

#### A. Adjacent Channel Interference Formulation

In this section, we formulate the adjacent channel interference encountered by the receiver $n \in [1,N]$. We initially assume that the pre-selector filters of all receivers span the entire band of operation with bandwidth $NW$ for simplicity, and later relax this assumption. Thus, each receiver receives $N$ signals (one of which is desired), but the power of each of those signals is dependent on the distance of all the transmitters from the given receiver $n$.

We define an indicator function for channel allocation,

$$x_{nl} = \mathbb{1}\{\text{Channel } \ell \text{ is allocated to receiver } n, \text{ denoted as } \ell \rightarrow n\}.$$  

We define an indicator function to denote all the adjacent channel bins $\{i,j,k\} \in \Psi_{\ell,N}$ causing pair-wise intermodulation distortion for a given channel $\ell$ as,

$$y_{\ell}^{i,j,k} = \mathbb{1}\{\{i,j,k\} \in \Psi_{\ell,N}\}.$$  

Now the adjacent channel interference due to pair-wise intermodulation at channel $\ell$, given that received signal amplitude in channels $j,k$ are respectively given by $A_j,A_k$ can be written as,

$$\rho_{\ell}^{2\text{tone}} = \alpha_3 \sum_{j=1}^{N} \sum_{k=1}^{N} y_{\ell}^{i,j,k} A_j^2 A_k.$$  

We define an indicator function to denote all the adjacent channel bins $\{i,j,k\} \in \Psi_{\ell,N}$ causing triple intermodulation distortion for a given channel $\ell$ as,

$$z_{\ell}^{i,j,k} = \mathbb{1}\{\{i,j,k\} \in \Psi_{\ell,N}\}.$$  

Now the adjacent channel interference due to tri-pair intermodulation at channel $\ell$, given that received signal amplitude in channels $i,j,k$ are respectively given by $A_i,A_j,A_k$ can be written as,

$$\rho_{\ell}^{3\text{tone}} = \alpha_3 \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} z_{\ell}^{i,j,k} A_i A_j A_k.$$  

Let $d_{n,j}$ denote the distance between receiver $n \in [1,N]$ and transmitter $j \in [1,N]$. The received power at receiver $n$ from transmitter $j$ is then given by $P_{R_{n,j}} = P_{T_j} d_{n,j}^{-\mu}$ where $P_{T_j}$ is the transmit power of transmitter $j$ and $\mu$ is the propagation loss exponent. The total nonlinear adjacent channel interference due to intermodulation distortion for a given link with receiver $n$ is given in $31$.

Evidently, equation (31), as shown at the top of the next page, is a cumbersome formulation. We thus seek to re-formulate the adjacent channel interference due to nonlinear distortions using matrices to provide a simpler representation. For this, we first formulate a distance vector and a diagonal distance matrix for receiver $n$ with respect to the transmitters as,

$$d_n = \begin{bmatrix} d_{n1}^{-\mu/2} \\ d_{n2}^{-\mu/2} \\ \vdots \\ d_{nj}^{-\mu/2} \end{bmatrix}; \quad D_n = \begin{bmatrix} d_{n1}^{-\mu/2} & 0 & \cdots & 0 \\ 0 & d_{n2}^{-\mu/2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & d_{nj}^{-\mu/2} \end{bmatrix}.$$  

(32)
\[ \rho_n = \alpha_3 \sum_{\ell=1}^{N} x_{n\ell} \left( \sum_{j_1=1}^{N} \sum_{k_1=1}^{N} \sum_{u_1=1}^{1} \sum_{v_1=1}^{1} \sum_{j_2=1}^{N} \sum_{k_2=1}^{N} \sum_{u_2=1}^{1} \sum_{v_2=1}^{1} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{u=1}^{1} \sum_{v=1}^{1} \eta_{j_1,k_1}^{j_2,k_2} x_{u_1,j_1} x_{v_1,k_1} P_{T_{u_1}} \sqrt{P_{T_{v_1}}} d_{n u v_1}^{-\mu/2} d_{n u v_2}^{-\mu/2} + \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{u=1}^{1} \sum_{v=1}^{1} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{u=1}^{1} \sum_{v=1}^{1} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{u=1}^{1} \sum_{v=1}^{1} \eta_{i,j}^{j_2,k_2} x_{u_2,j_2} x_{v_2,k_2} P_{T_{u_2}} P_{T_{v_2}} d_{n u v_2}^{-\mu/2} d_{n u v_2}^{-\mu/2} \right) \] (31)

We now define the ‘amplitude’ vector \( A = [\sqrt{T_{T_1}}, \sqrt{T_{T_2}}, \ldots, \sqrt{T_{T_N}}]^T \) and the diagonal matrix \( G = \text{diag}(P_{T_1}, P_{T_2}, \ldots, P_{T_N}) \) on the same lines as in Section II. Now, \( d_n^A G^{1/2} \) and \( D_n A \) give the received amplitude values at receiver \( n \) from all the transmitters. This can be used to compute the adjacent channel interference.

However, it is to be noted that channel assignment itself impacts the adjacent channel interference power since received powers on each channel is different and nonlinear adjacent channel interference is dependent on relative spectral locations of interfering signals. Thus, evaluation of adjacent channel interference cannot be agnostic to channel allocation and has to be inclusive of it. We define the channel allocation permutation matrix \( X = [x_{n\ell} : n, \ell = 1, \ldots, N] \) with rows representing the channels and columns representing the receivers.

1) System Model Representation for Two-Tone Intermodulation: The two-tone intermodulation distortion at frequency bin \( n \), \( \rho_n^{2\text{tone}} \), can be formulated as [30]–[32],

\[ \rho_n^{2\text{tone}} = \alpha_3 \sum_{\ell=1}^{N} x_{n\ell} \left( \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{u=1}^{1} \sum_{v=1}^{1} \eta_{j,k}^{j_2,k_2} x_{u,j_1} x_{v,k_1} \sqrt{P_{T_{u_1}}} \sqrt{P_{T_{v_1}}} d_{n u v_1}^{-\mu/2} d_{n u v_2}^{-\mu/2} \right) \] (32)

where, \( I \) is a \( 1 \times N \) row vector of all ones,

\[ L_n^A = \sum_{\ell=1}^{N} e_{\ell} e_{\ell}^T, \text{ and } L_n^B = \sum_{\ell_1, \ell_2} e_{\ell_1} e_{\ell_2}^T. \] (33)

and \( \Phi_n \) is given by (3), \( \Theta_n \) is given by (4), and \( e_i \) denotes the unit basis vector.

2) System Model Representation for Three-Tone Intermodulation: The three-tone intermodulation distortion at frequency bin \( n \), \( \rho_n^{3\text{tone}} \), can be formulated as [30]–[32],

\[ \rho_n^{3\text{tone}} = 2\alpha_3 \sum_{\ell=1}^{N} x_{n\ell} \left( \sum_{\ell_1, \ell_2} A_{\ell_1, \ell_2} \right) \] (34)

where,

\[ L_{n,i}^A = \sum_{\ell_1, \ell_2} e_{\ell_1} e_{\ell_2}^T, \text{ and } L_{n,i}^D = \sum_{\ell_1, \ell_2} e_{\ell_1} e_{\ell_2}^T. \] (35)

and \( \Theta_n \) is given by (5).

Note: We henceforth drop \( N \), the total number of channel spanned by pre-selector filter in the subscript notation for convenience.

3) Overall System Model Representation for Intermodulation Distortion: The total intermodulation distortion for receiver \( n \) is given by the sum of two-tone and three-tone intermodulation given by,

\[ \rho_n = \alpha_3 \left( 1 \left( L_n^A G L_n^B A \right) + 2 \sum_{\ell=1}^{N} A_{\ell_1, \ell_2} \right) \] (36)

Note that the above equation was formulated to provides flexibility to include the channel allocation information by manipulating the amplitude vector \( A \) and diagonal matrix \( G \) by pre and post multiplying with the channel allocation matrix \( X \) [31], [32]. Also, small scale fading can be incorporated in a straightforward manner.

Thus, we formulate the total amplitude of adjacent channel interference encountered by receiver \( n \) accounting for intermodulation products, network topology and channel allocation as,

\[ \rho_n(X) = \alpha_3 \left( 1 \left( L_n^A X d_n^T G X^T L_n^B X D_n A \right) + 2 \sum_{\ell=1}^{N} A_{\ell_1, \ell_2} \right) \] (37)

where the manipulations due to pre and post multiplications are underlined for ease in reading.

B. Framework for Channel Assignment

The intermodulation distortion power for receiver \( n \) is given by \( P_{\text{ACI}_n}(X) = \rho_n(X) \). If \( \eta \) is AWGN, the rate for receiver \( n \) and network-wide sum rate is given by,

\[ R_n = W \log_2 \left( 1 + \frac{P_{T_n} d_n^{\mu}}{P_{\text{ACI}_n}(X) + \eta} \right), \] (38)

\[ R = W \sum_{n=1}^{N} \log_2 \left( 1 + \frac{P_{T_n} d_n^{\mu}}{P_{\text{ACI}_n}(X) + \eta} \right). \] (39)

The network sum-rate maximization problem can now be formulated as,

\[ J_3 = \max_X \sum_{n=1}^{N} \log_2 \left( 1 + \frac{P_{T_n} d_n^{\mu}}{P_{\text{ACI}_n}(X) + \eta} \right) \] (40)

s.t \( \sum_{\ell=1}^{N} x_{n\ell} = 1 \); \( \sum_{n=1}^{N} x_{n\ell} = 1. \) (41)
This is non-convex, nonlinear, NP-hard, mixed binary integer optimization problem and has an inconvenient form. The Signal-to-Noise-plus-Interference-Ratio for receiver \( n \) is,

\[
\text{SINR}_n = \frac{P_{T_n} d_{n}^{-\mu}}{P_{\text{ACI}_n}(X) + \eta}.
\]

The maximization problem can now be written in terms of the permutation matrix as,

\[
J_3 = \max_X W \sum_{n=1}^{N} \log_2 \left( 1 + \frac{P_{T_n} d_{n}^{-\mu}}{P_{\text{ACI}_n}(X) + \eta} \right)
\]

subject to \( \sum_{\ell=1}^{N} x_{n\ell} = 1 \); \( \sum_{n=1}^{N} x_{n\ell} = 1 \); \( x_{n\ell} \in \{0,1\} \). (48)

We can lower bound the objective function and use similar arguments as presented in Section III-B to transform the sum-rate maximization problem into sum interference minimization, \( \min \sum_{n=1}^{N} | \rho_{n}^2(X) | \), where \( \rho_{n}(X) \) is given by equation (41). However, this will not give any advantage unlike with the case with co-located transmitters to design fast algorithms owing to the complexity of the underlying phenomena. Research on possible ways to develop optimal algorithms for this problem is beyond the scope of this paper. Thus, we develop a fast heuristic algorithm for this optimization problem and analyze the results.

C. Heuristic Algorithm: Simulated Annealing

In the preceding subsection, we developed the framework for receiver nonlinearity-aware network sum-rate maximization. As was evident, the maximization problem is highly complex. Development of optimal or approximation algorithms for the proposed framework is beyond the scope of this paper. The objective of this paper is to demonstrate the benefits of receiver-centric spectral access and co-existence in next-generation wireless systems. Thus, we employ a heuristic technique and develop a fast algorithm based on Simulated Annealing (SA) and demonstrate that there exist such meta-heuristic approaches to solve the proposed framework and obtain an approximation of the global optimum.

SA is a meta-heuristic probabilistic technique to approximate the global optimum solution of a given objective. Its utility is pronounced especially when the problem is exceedingly complex with the exponentially scaling search space. It was first proposed by [40] and [41] gives a comprehensive review. It has been previously applied to channel allocation in [42]–[44]. In addition we also used genetic algorithm in our experiments, but SA was found to outperform genetic algorithm as also was reported in [44]. For brevity, we report results only using SA in this paper.

The channel assignment problem at hand is essentially a combinatorial optimization problem of finding the best permutation out of the \( N! \) possible assignments. We define the set \( S = \{s_1, s_2, \cdots, s_N\} \) to represent the channels allocated to users \( \{1,2,\cdots,N\} \) respectively. Clearly, \( s_i \in [1,N] \) are unique. The idea behind simulated annealing is to start with a random state and check the value of the objective function at a neighboring state. If the neighboring objective is greater, update to the neighboring state else, update with a certain probability. Updating to the neighboring state with a certain probability even when it yields a lower objective is to ensure that the solution does not get stuck in a local minima. However, with the increasing iterations, the probability of updating to the neighboring state yielding lower objective is decreased ensuring convergence. This process of gradual decrease in the probability which leads to convergence was inspired by the controlled cooling of materials to reduce lattice defects in metallurgy and hence the name Simulated Annealing.

The SA based channel assignment is described in Algorithm 3. The initialization includes formulating the several network topology matrices, initializing a random channel assignment state \( S \), formulating the channel assignment permutation matrix \( X \), computing adjacent channel interference power \( P_{\text{ACI}} \) and the sum rate. Further, the initial temperature \( T \), cutoff temperature \( T_{\min} \) and the update constant \( \lambda \) are set.

### Algorithm 3 SA Based Receiver Nonlinearity Aware Channel Assignment

**INITIALIZATIONS**

1. Formulate: Network topology matrices \( A, G, d_n, D_n \)
2. Initial State: Random Assignment, \( S = \{s_1, s_2, \cdots, s_N\} \)
3. Formulate: Channel Assignment Permutation Matrix, \( X(S) \)
4. Compute: \( \rho_{n}, \forall n \in [1,N] \) using equation (41) and \( P_{\text{ACI}_n}(X) = |\rho_{n}|^2 \)
5. Evaluate: \( R = W \sum_{n=1}^{N} \log_2 \left( 1 + \frac{P_{T_n} d_{n}^{-\mu}}{P_{\text{ACI}_n}(X) + \eta} \right) \)
6. Initialize: Initial Temperature, \( T \), Cutoff Temperature, \( T_{\min} \), Update Constant, \( \lambda \in (0,1) \)

**ITERATIONS**

7. while \( T > T_{\min} \) do
8. Generate two random integers \( i \in [1,N], j \in [1,N] : i \neq j \)
9. Update to neighboring state by swapping the channel assignment of receivers \( i,j \) in \( S \):
   \( S_{\text{new}} = S(\text{swap}(s_i,s_j)) \)
10. Formulate new Channel Assignment Permutation Matrix, \( X(S_{\text{new}}) \)
11. Compute \( \rho_{n}, \forall n \in [1,N] \) using equation (41) and \( P_{\text{ACI}_n}(X) = |\rho_{n}|^2 \)
12. Evaluate \( R_{\text{new}} = W \sum_{n=1}^{N} \log_2 \left( 1 + \frac{P_{T_n} d_{n}^{-\mu}}{P_{\text{ACI}_n}(X) + \eta} \right) \)
13. Compute \( \delta_c = R_{\text{new}} - R \); and \( p_{\delta_c} = \exp \left( \frac{-\delta_c}{T} \right) \)
14. if \( \delta_c > 0 \) then
15. \( R = R_{\text{new}} \); and \( S = S_{\text{new}} \)
16. else
17. Generate a random number \( \zeta \sim \text{Unif}(0,1) \)
18. if \( \zeta \leq p_{\delta_c} \) then
19. \( R = R_{\text{new}} \); and \( S = S_{\text{new}} \)
20. \end if
21. \end if
22. Update \( T = \lambda T \)
23. \end while
Through the iterations, to update to a neighboring state, two unique random integers in the range $[1, N]$ are chosen. The channel assignment of those two receivers are swapped, thus creating a new assignment state. The network sum rate of this new assignment and the difference, $\delta_e$ between the current and new network sum rate are computed. If the new rate is higher ($\delta_e > 0$), then the new assignment is retained. If the new rate is lower, the new assignment is retained with a probability of $p_{\delta_e} = \exp \left( \frac{\delta_e}{\rho} \right)$. This is implemented by generating a uniform random number between 0 and 1 and comparing it with $p_{\delta_e}$.

D. Pre-selector Spans a Factor of the Entire Band

In the preceding discussions, we assumed that a single pre-selector filter spans the entire band of operation for all receivers. However, this assumption may not hold as receivers may have multiple pre-selectors spanning the band of operation to minimize the adjacent channel signals entering the front end as shown in Fig. 5.

As detailed in Section III-E, we assume receiver $n$ has $M_n$ pre-selector filters, each spanning $\frac{N}{M_n}$ channels. A given channel $\ell \in [1, N]$ for a receiver $n$ maps to a frequency $\ell_n = ((\ell - 1) \mod M_n) + 1$ as before. However, to compute the adjacent channel interference, we need to evolve different steps. This is because, the received amplitude on each channel for a given network is different and dependent on the channel allocation itself due to the nature of network topology.

For a given channel $\ell$ the pre-selector filter for a receiver $n$ spans the channels $[\ell - \ell_n, \ell - \ell_n + M_n]$. With this we now define a filter matrix for each channel for a given receiver $n$ as,

$$F_{n,\ell} = \begin{bmatrix} 0 & I & 0 & \ldots & 0 \\ M_n \times (\ell - \ell_n) & M_n \times M_n & M_n \times (N + \ell_n - \ell - M_n) \end{bmatrix}, \quad (49)$$

where $0$ is a zero matrix and $I$ is an identity matrix. Thus, $F_{n,\ell}$ is a characteristic of a given receiver. Along with that, the matrices $L_{n,i}^A, L_{n,i}^B, L_{n,i}^C, L_{n,i}^D$ are now defined for the pre-selector filter width $M_n$. To use the formulation in equation (41), we need the radio-environment matrices. For a given channel assignment matrix $X$ with channel $\ell$ assigned to receiver $n$, and the network topology matrix $D_n$, we formulate,

$$A'_{n,\ell} = F_{n,\ell} X D_n A; \quad G'_{n} = \text{diag}(A'_n) = F_{n,\ell} X d_n^T G X^T F_{n,\ell}^T. \quad (50)$$

The adjacent channel interference due to intermodulation distortion is now calculated as,

$$\rho_n = \alpha_{3n} \left( 1 \left( L_n^A G_n' L_n^B A'_n \right) + 2 \sum_{\forall i \in T_n} A_n'^T L_{n,i}^C G_n'^{1/2} L_{n,i}^D A_n' \right). \quad (51)$$

Thus, to evaluate the adjacent channel interference $\rho_n$ on step 11 of Algorithm 3, we follow the steps shown in Algorithm 4. The rest of the algorithm remains the same for channel assignment.

Algorithm 4 Steps to Compute $\rho_n$ When Pre-selector Spans a Factor $N$

1. Note the channel assigned to receiver $n$ as, $\ell = i : s_i = n, s_i \in S$
2. Compute $\ell'_n = ((\ell - 1) \mod M_n) + 1$
3. Compute $A'_{n,\ell} = F_{n,\ell} X D_n A$
4. Formulate $G'_n = \text{diag}(A'_n)$
5. Compute $\rho_n$ using equation $(51)$

V. Modeling Transmitter Masks and OOBE

In the discussion thus far we ignored the adjacent channel interference due to the Out-Of-Band Emission (OOBE) of transmitters. However, transmitter leakage into adjacent bands is an important aspect that needs to be modeled for next-generation wireless network design. Assume the link $n \in [1, N]$ is assigned channel $c \in [1, N]$. Let $e_{cc}^p$ denote the fraction of the power emitted by transmitter on link $n$ on channel $\ell$ when assigned channel $c$, as illustrated in Fig. 7. For $c = \ell$, this represents the in-band power and hence, $e_{cc}^n = e^n, \forall c \in [1, N]$ where $e^n$ is the fraction of in-band power emitted. Let $E_n$ represent the emission matrix for transmitter $n$ whose columns $c \in [1, N]$ represent its transmit mask when assigned to that channel,

$$E_n = \begin{bmatrix} e_{11}^n & e_{12}^n & \cdots & e_{1N}^n \\ e_{21}^n & e_{22}^n & \cdots & e_{2N}^n \\ \vdots & \vdots & \ddots & \vdots \\ e_{N1}^n & e_{N2}^n & \cdots & e_{NN}^n \end{bmatrix}. \quad (52)$$

If $P = [P_1 \ P_2 \ \cdots \ P_N]^T$ represents the vector of transmit powers of the $n$ transmitters, and $X$ is the channel assignment permutation matrix, the ‘transmit power profile’ of the network denoted by the vector $P_{Tx}$

$$P_{Tx} = \sum_{n=1}^{N} E_n X L_{Tx}^n X P,$$

where the rows represent the $N$ channels can be formulated as, $L_{Tx}^n = e_n e_n^T$, $e_n$ is the unit basis vector in $\mathbb{R}^N$. This formulation gives the total contribution of each transmitter on a given channel. The transmit amplitude vector is given by,

$$A_{Tx} = [P_{Tx}]^{1/2}. \quad (54)$$

Using this transmit amplitude vector $A_{Tx}$, the adjacent channel interference for receiver $n$ can be computed using the formulation,

$$\rho_n = \alpha_{3n} \left( 1 \left( L_n^A d_n^T G_{Tx} X L_n^B D_n A_{Tx} \right) + 2 \sum_{\forall i \in T_n} [A_{Tx}^T]^T L_{n,i}^C d_n^T G_{Tx} L_{n,i}^D A_{Tx} \right). \quad (55)$$

The adjacent channel interference power is computed as $P_{ACi,n} = |\rho_n|^2$. If the pre-selector filter for the given receiver $n$ spans a factor of the entire operational bandwidth, the adjacent
channel interference can be computed using Algorithm 4 by replacing step 3 as $A_{\tau_1,\ell} = F_{n,\ell} \cdot D_n \cdot A_{\tau_1}^T$

In addition, there is co-channel interference caused by overlapping OOB E from adjacent channel transmitters. For a given receiver $n$, this can be computed as,

$$P_{\text{OOBE}_n} = e_n \left( X^T P_{\text{Tx}} - P \right).$$

The total interference, $P_{\text{INT}_n}$ due to ACI and OOB E for receiver $n$ is then given by $P_{\text{INT}_n} = P_{\text{ACI}_n} + P_{\text{OOBE}_n}$. Channel Assignment can then be optimized using Algorithm 3 using $P_{\text{INT}_n}$ (in place of $P_{\text{ACI}_n}$) to compute the network rate.

VI. SIMULATION RESULTS

A. Single Transmitter, Multiple Receivers

In this section, we present the simulation of the case with single (or co-located) transmitter gateway downlink with multiple receivers described in Section III. The simulations are performed assuming the receivers to be uniformly distributed inside a circle of radius 50 m with the transmitter located at the centre of the circle. The transmit power is equal for all channels and is set to 30 dBm.

1) Varying IIP3 Diversity: In this section, we consider a small network of $N = 8$ nodes on downlink over 8 distinct channels with each channel spanning $B = 8$ MHz. The pre-selector is assumed to span the entire operating bandwidth of $B = 8$ MHz. The IIP3 of all the devices are uniformly distributed in the range $IIP_3 \sim \text{Unif}(IIP_{3_{\text{min}}}, IIP_{3_{\text{max}}})$. In order to vary the diversity of devices, we fix $IIP_{3_{\text{min}}} = -30$ dBm and vary $IIP_{3_{\text{max}}}$ from $-20$ dBm to $+10$ dBm in steps of 5 dB. For each $IIP_3$ range, Monte-Carlo simulations are carried out and the results are averaged over 10,000 network realizations and network sum rate is plotted as a function of the $IIP_3$ standard deviation as shown in Fig. 8. The transmit power for each user is was selected as $P_T = 30$ dBm. We compare the optimal assignment for the sum rate maximization obtained through the Munkres assignment algorithm and greedy algorithm proposed in this paper. A randomized channel assignment without receiver characteristics is used as baseline for comparison [26]. Without the knowledge of receiver characteristics, there is no way to compare the difference between assignments since all users are operating on distinct channels. Hence, a randomized assignment is chosen as the baseline [26]. Firstly, receiver-centric channel assignment significantly increases the network sum rate – an order of magnitude improvement is seen. Secondly, the assignment of the proposed greedy algorithm is very close to the optimal solution when averaged over large network realizations, for small networks.

2) Impact on Scalability: An important consideration while studying heterogeneous and diverse RAT systems is to assess the scalability of co-existence in such operations. The density of connected devices is expected to exponentially increase in next generation wireless networks. Thus, it is important to study the impact of receiver-centric awareness in such dense networks with diverse devices. We consider a total bandwidth, $B = 10$ MHz with nodes uniformly distributed in a circular area with radius 50 m. The density of nodes is varied from 0.001 nodes per m² (∼ just 1 node) to 0.05 nodes per m² (∼ 400 nodes). Each node is allocated a channel spanning $W = \frac{B}{4}$ Hz, where $N$ is the number of nodes in the network. Simulations with the proposed framework and algorithms are carried out for channel assignment for 10,000 network realizations and the results are presented. For each realization, $IIP_3$ is uniformly distributed between $-30$ dBm and $+10$ dBm for the nodes, and pre-selector is assumed to span the entire 10 MHz for all nodes. As the node density increases, the number of adjacent channel interferers increase causing a drop in the network sum rate. This is where receiver-centric channel assignment can potentially yield very high spectral efficiency gains. Fig. 9 shows that gain of several orders of magnitude is obtained due to to receiver-centric channel assignment with increasing node density, with the Munkres assignment algorithm providing the optimal solution.

We next carry out simulations with the same setup, except for the pre-selector filter span. We relax the assumption that the pre-selector filter for all nodes (receivers) are equal (spanning the entire bandwidth as assumed before). Instead, pre-selector filter for each node is a uniform random factor of $N$ (the total number of channels) in each network realization. This is in addition to the random $IIP_3$ of each receiver. The results are as shown in Fig. 10. Naturally, when the pre-selector filter spans less than the entire band of possible channels, the amount of adjacent channel interfering signals that impact the desired channel is less. Thus, we see a better overall network sum
rate, irrespective of receiver-centric assignment compared to Fig. 9. However, the spectral efficiency with receiver-centric allocations that takes into account the vulnerabilities of all receiver nodes in the network is orders of magnitude better than receiver agnostic allocations. The absence of ‘smoothness’ in the curves despite 10,000 network realizations is due to the fact that network sum rate depends on the number of choices available for pre-selector filter bandwidths, which numerically vary significantly for different numbers ranging from $N \approx 1$ to $N \approx 400$ (e.g. Prime numbers do not have any divisors, while even numbers generally have large number of divisors).

B. Multiple Transmitter-Receiver Pairs

In this section, we present the simulation results for the general setting of $N$ Tx-Rx pairs communicating over $N$ adjacent channels over a geographic area as described in Section IV. The simulations are performed assuming the transmitters and receivers are uniformly distributed inside a circle of radius 500 m. The transmit power for a given transmitter is randomly chosen between 10 dBm and 80 dBm.

1) Varying $IIP_3$ Diversity: In this section, we consider a network of $N = 8$ Tx-Rx pairs over 8 distinct channels with each channel spanning $W = 1$ MHz. The pre-selector is assumed to span the entire operating bandwidth of $B = 8$ MHz. The $IIP_3$ of all the devices are uniformly distributed in the range $IIP_3 \sim \text{Unif}(IIP_{3\text{min}}, IIP_{3\text{max}})$. In order to vary the diversity of devices, we fix $IIP_{3\text{min}} = -30$ dBm and vary $IIP_{3\text{max}}$ from $-20$ dBm to $+10$ dBm in steps of 5 dB. As the $IIP_3$ variance increases, diversity of receiver performance also increases. For each range, Monte-Carlo simulations are carried out, and the results are averaged over 10,000 network realizations. Network sum rate is plotted as a function of the $IIP_3$ standard deviation as shown in Fig. 11. We compare the optimal the sum rate maximization obtained through exhaustive search, to the sum rate from randomized channel assignment without receiver characteristics (baseline for comparison [26]) and demonstrate the impact of utilizing receiver characteristics in channel assignments. As evident from the simulations, receiver-centric channel assignment significantly increases the network sum rate, by orders of magnitude. As the diversity of devices increase, an increase in network sum rate is anticipated, owing to an increase in receivers with ‘good’ characteristics. However, receiver-centric assignment significantly increases the network sum rate in comparison, primarily because ‘receiver characteristic awareness’ can protect vulnerable receivers from interference, while boosting the rate to ‘good’ receivers.

2) Simulated Annealing Algorithm: In this section, we present the results of the proposed heuristic algorithm based on Simulated Annealing (SA) for the channel assignment problem. We consider a network of $N = 8$, Tx-Rx pairs over 8 distinct channels with each channel spanning $W = 1$ MHz. The pre-selector is assumed to span the entire operating bandwidth of $B = 8$ MHz. The $IIP_3$ of all the devices are uniformly distributed in the range $IIP_3 \sim \text{Unif}(IIP_{3\text{min}}, IIP_{3\text{max}})$. We plot the convergence of the simulated annealing algorithm, and compare its performance against the optimal obtained through exhaustive search. The convergence for a sample network realization is shown in Fig. 12. Average rate of convergence was found to be...
Fig. 12. Sample convergence of proposed Simulated Annealing (SA) algorithm for $N = 8$: The solution obtained is close to optimum (within an order of magnitude).

Fig. 13. Sample convergence of proposed Simulated Annealing (SA) algorithm for $N = 100$: $\sim 17,000$ iterations to converge.

about $122$ iterations with a standard deviation of about $30$ (rounding off to nearest decimal) over $10,000$ network realizations. Monte-Carlo simulations indicated the solution obtained was close to the optimum (within an order of magnitude), with the mean performance after $150$ iterations over $10,000$ network realizations found to be $93.41\%$ of the optimal value. Fig. 13 shows the sample convergence for a network with $N = 100$ nodes.

3) Impact of Scalability: In this section, we present a final result of network simulations and examine the gains of receiver-centric framework with increasing node density with varying $\text{IIP}_3$ characteristics. We consider a total bandwidth, $B = 20$ MHz. The density of nodes is varied from $0.001$ nodes per m$^2$ to $0.05$ nodes per m$^2$. Each node is allocated a channel, spanning $W = \frac{B}{N}$ Hz, where $N$ is the number of nodes in the network for a given density. Simulations with the proposed SA based assignment algorithm are carried out for $10,000$ network realizations for each node density and the results are presented. For each realization, $\text{IIP}_3$ is uniformly distributed between $-30$ dBm and $+10$ dBm for each node, and the pre-selector is assumed to span an integer factor of the entire bandwidth of $20$ MHz, selected uniformly at random for each node. As the node density increases, the number of adjacent channel interferers increase causing a drop in the network sum rate. With receiver-centric assignments, co-existence of diverse nodes can be ensured with relatively high spectrum efficiency at high node density. Fig. 14 shows that gains of several orders of magnitude are obtained due to receiver-centric channel assignment at higher node densities.

VII. CONCLUSIONS

In this paper, we demonstrated that receiver-centric spectrum access and network optimization will substantially increase spectrum efficiency in next generation diverse-RAT dense wireless networks. Spectrum efficiency gains of several orders of magnitude were observed for dense wireless networks with receiver diversity through extensive network simulations with centrally controlled receiver-centric channel assignment frameworks compared to receiver agnostic assignment. We proposed computationally efficient network optimization frameworks and algorithms to account for receiver front-end nonlinearities and transmitter out-of-band emission masks. This approach yields high network performance gains and promotes harmonious co-existence of dense wireless networks with receiver diversity. The impact of adjacent channel interference on diverse and heterogeneous networks is demonstrated in this paper. Next generation spectrum access and network optimization frameworks should account for RF front-end nonlinearity and imperfections.

This work has the potential to pave way for new research frontiers in receiver-centric frameworks and algorithms for efficient spectrum access and network management. Computationally efficient algorithms with analytical performance guarantees need to be developed for the proposed receiver-centric frameworks. Development of downlink power control algorithms with channel allocation can further increase network performance. The assumption of fixed channel bandwidths for all users can be relaxed and computational algorithms to obtain bounded approximations for demand based resource allocations is a promising area of future research.

REFERENCES


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