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Date:
2022-07-01

Citation:
Dayarathna, S., Senanayake, R. & Evans, J. (2022). Sum-Rate Optimization in Flexible Half-Duplex Networks With Transmitter/Receiver Scheduling. IEEE Transactions on Wireless Communications, 21 (7), pp.4711-4724. https://doi.org/10.1109/TWC.2021.3132589.

Persistent Link:
https://hdl.handle.net/11343/311271

Sum-Rate Optimization in Flexible Half-Duplex Networks with Transmitter/Receiver Scheduling

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***Abstract*—In this paper, we focus on the problem of transmitter and receiver scheduling to maximize the achievable sum-rate of a flexible half-duplex network where nodes have the flexibility to either transmit, receive or be silent in a given time slot. We consider a network with multiple transmitters and receivers where each transmitter has specific information it needs to send to a set of receiving nodes. First, we conduct some structural analysis and show that the achievable sum-rate is maximized when each transmitter only transmits to a single receiver at a given time. Next, we consider one instance of the flexible network and by reducing the symmetric multiple receiver network to a single receiver network, we also show that the achievable sum-rate is maximized when either one transmitter or all the transmitters transmit. In fact, there exists a unique received signal-to-noise ratio at which the optimality changes from all-to-one. Finally, we design a novel low-cost algorithm that gives a sub-optimal solution to the achievable sum-rate maximization problem in a flexible half-duplex network. We also provide a comprehensive comparison of the proposed algorithm with respect to existing resource allocation techniques, and observe that our proposed algorithm provides significant sum-rate gains.**

***Index Terms*—Achievable sum-rate maximization, transmitter and receiver scheduling, flexible half-duplex, resource allocation.**

I. INTRODUCTION

In half-duplex mode of operation communication nodes can send data in both directions, but not simultaneously [1]. Thus, transmission and reception must be separated either in the time domain, which is commonly known as *time-division duplexing* (TDD) [2], [3] or in the frequency domain, which is commonly known as *frequency-division duplexing* (FDD) [4]. In TDD half-duplex networks, a node uses a single frequency band but can only transmit or receive data in a given time slot which is pre-defined. When this allocation between transmission and reception is not pre-defined the nodes have the flexibility to select when to transmit and when to receive. This concept, which is known as *flexible duplex*, introduces the ability to adapt the operation of transmission nodes depending on the traffic load. The added flexibility increases the diversity and enhances the rate/throughput region in flexible half-duplex networks [5], and it is one of the key technologies used to optimize resource utilization in fifth generation (5G) cellular networks [6]–[8].

Achievable sum-rate optimization in flexible half-duplex networks has been analyzed for networks where each transmitter or receiver has only one potential receiver or transmitter. However, with the advancement of new technologies such as device-to-device (D2D) and machine-to-machine (M2M) communications, wireless networks are required to support high data rate point-to-point communication links between multiple transmitting and receiving nodes [9]. As such, the transmitting nodes and the receiving nodes have to be carefully selected to manage interference and to improve the system performance. Interference management has been approached from several directions in the past. Under centralized resource allocation, power control as a method to manage interference has been commonly used [2], [10], [11]. This allows all links to coexist at the same time and simply reduce interference by changing the transmit power of the interfering nodes. On the other hand, different schemes have been proposed for decentralized interference management. For example, topological interference management [12] uses the specific network topology information available at the transmitting nodes to evaluate the degrees of freedom (DoF) for different network topology configurations. Taking a different approach, in [3], an on-off power control method is used where the authors show that either letting one link or all the links be active based on the cross gain parameter maximizes the achievable sum-rate. Similar to [3], in [13], an interference set scheduling scheme is used to manage interference by only allowing the non-interfering links to be active at a given time. Taking a step further, in [14], [15], the authors propose new distributed algorithms that allow a subset of interfering links to be active such that the respective interference is limited. This paper considers interference management via power control and focuses on the transmitter and receiver scheduling problem of flexible half-duplex networks with multiple transmitters and multiple receivers, and makes progress towards selecting the optimum transmitters and receivers when the objective is to maximize the achievable sum-rate.

We start the problem by focusing on the transmitter and receiver selection problem. In the area of transmitter and receiver scheduling, the base station selection problem was initially analyzed in [16] for a voice-oriented network, with the objective of minimizing the energy consumption. When the objective is to maximize the achievable sum-rate, which is the focus in most of today's data-oriented networks, the optimization problem is known to be difficult [17]. As such, in downlink multi-user scheduling most existing works either

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This work was supported by the Australian Research Council Discovery Project under Grant DP180101205 and Discovery Early Career Researcher Award under Grant DE180100501.

Manuscript received March 03, 2021; revised June 21, 2021 and October 03, 2021; accepted November 28, 2021.

consider orthogonal frequency division multiplexing (OFDM) channels to avoid interference [18], [19] or seek sub-optimal algorithms [11], [20]. In [19], the authors consider a Long-Term Evolution (LTE) cellular network with OFDM channel where all the users share equal power distribution. In [20], the authors consider the downlink of a cellular network with multiple users and base stations and provide a sub-optimal distributed iterative algorithm for base station selection and power control. In [11], the authors analyze the weighted sum-rate of a K-user Gaussian interference channel and propose an iterative algorithm based on the outer polyblock approximation. The low convergence rate, however, makes this algorithm not suitable for real-time implementation. In [21], the authors consider a downlink cellular network with multiple-input-multiple-output (MIMO) and try to analyse the throughput of a single cluster consisting of a single transmitter and multiple receivers in the presence of interference from other clusters. Within the cluster, active receivers are identified based on precoding and QoS weighted sum-rate. More recently, the power allocation problem in downlink multi-cell multi-user non-orthogonal multiple access (NOMA) network with minimum rate constraints is considered in [22].

In order to draw rigorous conclusions based on theoretical derivations, some papers have considered simplified networks [2] or symmetric channel models [3] and draw important conclusions about the optimal network behavior. In [2], the authors consider the uplink of a simple single-cell network and show, via the theory of majorization, that binary power allocation is optimum for a single-cell network with multiple transmitters. By binary we mean that the transmitting nodes transmit either at zero power, or maximum power P, without taking any value in the continuum of possible values between 0 and P. However, the authors do not identify the optimality of having a single transmitter or all the transmitters active since a non-symmetric network has been studied. In [3], the authors consider a symmetric network with multiple link pairs, where all desired gains are set to unity and all interfering gains among links are equal. It was shown that binary power allocation is optimum for all transmitters in such a network and the optimal choice is either one link or all the links being active.

Most research on the resource allocation in flexible half-duplex networks, focuses on dynamically adjusting the uplink/downlink time allocation based on traffic data and channel coefficients [23]–[27]. In [28], the authors use a rate splitting strategy by introducing a common time allocation that can be used by both uplink and downlink to reduce specified uplink/downlink time allocations. Uplink and downlink resource allocation for a flexible half-duplex network is proposed in [29] where the authors propose a successive approximation of fixed point and resource muting to reduce the probability of inter-mode interference. Optimization of two-way scheduling with topology graph and dynamic programming is proposed in [7], where the authors consider M pairs of nodes that communicate with each other. In [8], the authors present a fast instantaneous signal-to-interference-plus-noise-ratio (SINR) based mode selection for D2D devices within a flexible uplink/downlink TDD cellular network. In [5], the authors first analyze the feasibility of using available approximation techniques and then propose a sub-optimal iterative algorithm based on pattern search method to maximize the achievable sum-rate in a general flexible half-duplex network. Taking a different approach, in [10], the authors consider the reformulation of sum-rate optimization as a multi-convex optimization problem in order to solve the weighted sum-rate optimization problem.

In this paper, we consider a flexible half-duplex network with multiple transmitters and multiple receivers and analyze the transmitter and receiver scheduling problem to maximize the achievable sum-rate. The contributions of this paper are listed as follows.

- We first show that, in order to maximize the achievable sum-rate, it is optimal for each node to transmit only to one receiving node with the total transmit power instead of splitting the transmit power among potential receivers. This contribution is presented in Theorem 1.
- Under the special case of symmetric half-duplex network we show that the multiple receiver network can be simplified to a single receiver network, under which, we rigorously prove that it is optimal to let either one transmitter or all the transmitters be active, depending on the received signal-to-noise-ratio (SNR). In addition, we show that there exists a unique threshold value for switching between the two operating modes. This contribution is presented in Theorem 2.
- As the main contribution, the achievable sum-rate optimization problem for a general flexible half-duplex network is considered and a sub-optimal algorithm based on the pattern search method and tight lower bound approximation is proposed. This result is presented in Algorithm 1. Furthermore, the performance of our proposed sub-optimal algorithm is compared against the existing resource allocation techniques, revealing that the performance gap between proposed algorithm and existing techniques is larger for a denser network where cells are too close to each other.

The rest of the paper is organized as follows. In Section II, we provide the system model and the optimization problem formulation for a flexible half-duplex network with multiple transmitters and receivers. Then, the optimality of selecting a single receiver is proved in Section III followed by an analysis of a special symmetric network. Next, the proposed solution and the sub-optimal algorithm is given in Section IV with the numerical results in Section V. Finally, the conclusions are given in Section VI.

II. SYSTEM MODEL AND OPTIMIZATION PROBLEM FORMULATION

In this paper, we consider a flexible half-duplex network with a total of K nodes where transmitter k has specific information it needs to send to a set of multiple receiving nodes denoted by J_k. This is a common scenario that appears in flexible half-duplex cellular networks where, for example, users can be involved in both the cellular communication and

D2D/M2M communication using the same radio resources [6]–[8]. For such a network, the signal received at receiver j can be expressed as,

$$y_j = \sum_{k=1,k\neq j}^{K} h_{kj}\left(\sum_{i\in J_k} x_{ki}\right) + w_j, \tag{1}$$

where x_{ki} is the symbol transmitted by transmitter k which is intended for receiver i, $E\{|x_{ki}|^2\} = \alpha_{ki}P_k$ with P_k denoting the transmitted power and α_{ki} denoting the fraction of transmit power allocated for receiver i at the transmitter k, h_{kj} is the channel gain between transmitter k and receiver j and w_j is the additive white Gaussian noise at receiver j with mean zero and variance σ^2. In a flexible half-duplex network, a given node k can transmit, receive or be silent at any given time. Each of these states can be formulated in the form of binary variables as,

$$r_k = \begin{cases} 1 & \text{if node } k \text{ receives in the given time slot} \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

$$t_k = \begin{cases} 1 & \text{if node } k \text{ transmits in the given time slot} \\ 0 & \text{otherwise,} \end{cases} \tag{3}$$

$$s_k = \begin{cases} 1 & \text{if node } k \text{ is silent in the given time slot} \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

where a node can be only in one state in a given time slot, which can be written as, $r_k + t_k + s_k = 1,\ \forall k$ or equivalently as $r_k + t_k \in \{0, 1\},\ \forall k$. Hence, if $r_k + t_k = 0$, it means that node k is silent in the given time slot. In addition, as commonly used in literature [2], [3], [30], we assume that no cooperation is facilitated between the receiving nodes, and that single user decoding is performed at each receiver with interference treated as noise. As such, based on the above notation, the received SINR for the transmitting node k at the receiving node j in a flexible half-duplex network can be expressed as,

$$\mathrm{SINR}_{kj} = \frac{r_j\ P_k t_k \alpha_{kj}|h_{kj}|^2}{\sigma^2 + \sum_{l\neq k,j}^{K} P_l t_l |h_{lj}|^2 + \sum_{i\in J_k\backslash\{j\}} P_k t_k \alpha_{ki}|h_{kj}|^2}, \tag{5}$$

where $J_k\backslash\{j\}$ denotes the set of receiving nodes for transmitter k excluding node j. Therefore, we can write an expression for the achievable rate of transmitter k as,

$$R_k = \sum_{j\in J_k} \log_2\Big(1 + \mathrm{SINR}_{kj}\Big). \tag{6}$$

Thus, the achievable sum-rate of the entire network can be expressed as,

$$R = \sum_{k=1}^{K}\sum_{j\in J_k} \log_2\Big(1 + +\mathrm{SINR}_{kj}\Big). \tag{7}$$

The achievable sum-rate in (7) can be manipulated by the transmitter power allocation in terms of the total transmit power and the fraction of transmit power allocated for each receiver as well as the binary variables t_k, t_l and r_k. Therefore, we can formulate the following optimization problem to maximize the achievable sum-rate of the network as (8), given at the top of the next page, where P is the maximum transmit power of a given node. When transmitters and receivers are not fixed, the direction of the links are not fixed. Since, the sources and the destinations are not defined, source to destination links are also not defined and are subject to change. As a result, for the flexible half-duplex networks considered in this paper, it is harder to implement link scheduling for interference management. Therefore, we formulate the above optimization problem in such a way that the interference between transmitting nodes can be managed via power control. We note that the optimization problem (8) represents the achievable sum-rate maximization of a flexible half-duplex network via transmitter and receiver scheduling, transmit power control and node state optimization. To the best of our knowledge this problem has not been analyzed in the literature specially when multiple desired transmitters and receivers are allocated for each node in the network while nodes themselves have the flexibility to transmit or receive at a given instance.

Please note that, in the absence of any other constraints, treating a silent node as a receiving node would not decrease the sum-rate of the network. This is because, if a node is to receive from a silent node, its received SINR would be zero. This is the same as the SINR of a node that is trying receive from another receiving node. Also, the transmit power of a silent node is zero which is similar to the transmit power of a receiving node. Thus, by removing the last constraint, we set each node to either transmit or receive. After obtaining the optimum solution, we can obtain the silent nodes by redefining any receiving node with zero SINR as a silent node. As such, the simplified optimization problem can be given as (9), given at the top of the next page. Note that the formulation in (9) is a non-trivial optimization problem due to its non-convexity/non-linearity and the combinatorial nature. There is no known polynomial time algorithm to solve this problem and many standard numerical approaches fail to provide a solution. Therefore, we next proceed to perform some structural analysis to obtain analytical insights into the network behavior and then propose an iterative algorithm to solve the optimization problem in (9).

III. STRUCTURAL RESULTS AND SPECIAL CASES

We start our analysis by showing that it is optimal for each transmitter to transmit only to a single receiver using the total transmit power instead of splitting the transmit power among the potential receivers. First let us present the following preliminary result that will be used when deriving the main theorem presented in this section.

Lemma 1. *The optimization problem given in* (9) *has an optimal solution with equality* $\sum_{j\in J_i}\alpha_{ij} = 1$ *for each transmitter* i*.*

Proof. See Appendix A. □

The main result of this section is given by the following theorem.

$$
\begin{aligned}
\max_{P_k,\alpha_{kj},t_k,r_k\forall k,j}\ & \sum_{k=1}^{K}\sum_{j\in J_k}\log_2\left(1+r_j\frac{P_k t_k\alpha_{kj}|h_{kj}|^2}{\sigma^2+\sum_{l\neq k,j}^{K}P_l t_l|h_{lj}|^2+\sum_{i\in J_k\setminus\{j\}}P_k t_k\alpha_{ki}|h_{kj}|^2}\right)\\
\text{s.t}\ \ & 0\le P_k\le P\ \ \forall k,\\
& 0\le\alpha_{kj}\le 1\ \ \forall k,j,\\
& \sum_{j\in J_k}\alpha_{kj}\le 1\ \ \forall k,\\
& t_k,r_k\in\{0,1\}\ \ \forall k,\\
& t_k+r_k\in\{0,1\}\ \ \forall k.
\end{aligned}
\tag{8}
$$

$$
\begin{aligned}
\max_{P_k,\alpha_{kj},t_k,\forall k,j}\ & \sum_{k=1}^{K}\sum_{j\in J_k}\log_2\left(1+\frac{P_k t_k(1-t_j)\alpha_{kj}|h_{kj}|^2}{\sigma^2+\sum_{l\neq k,j}^{K}P_l t_l|h_{lj}|^2+\sum_{i\in J_k\setminus\{j\}}P_k t_k\alpha_{ki}|h_{kj}|^2}\right)\\
\text{s.t}\ \ & 0\le P_k\le P\ \ \forall k,\\
& 0\le\alpha_{kj}\le 1\ \ \forall k,j,\\
& \sum_{j\in J_k}\alpha_{kj}\le 1\ \ \forall k,\\
& t_k\in\{0,1\}\ \ \forall k.
\end{aligned}
\tag{9}
$$

$$
\begin{aligned}
\max_{\alpha_{kj}}\ & \prod_{k=1}^{K}\left[\left(1+\frac{P_k t_k(1-t_1)(1-\sum_{j\in J_k\setminus\{1\}}\alpha_{kj})|h_{k1}|^2}{\sigma_{k1}^2+P_k t_k(\sum_{j\in J_k\setminus\{1\}}\alpha_{kj})|h_{k1}|^2}\right)\prod_{j\in J_k\setminus\{1\}}\left(1+\frac{P_k t_k(1-t_j)\alpha_{kj}|h_{kj}|^2}{\sigma_{kj}^2+P_k t_k(1-\alpha_{kj})|h_{kj}|^2}\right)\right]\\
\text{s.t}\ \ & 0\le\alpha_{kj}\le 1\ \ \forall k,j,\\
& \sum_{j\in J_k\setminus\{1\}}\alpha_{kj}\le 1\ \ \forall k.
\end{aligned}
\tag{10}
$$

Theorem 1. *Consider a flexible-duplex network with K nodes where node k has information it needs to send to the subset $J_k, \forall k\in\{1,...,K\}$. For such a system where the achievable sum-rate maximization problem is given by* (9)*, the achievable sum-rate is optimized when each node selects at most one receiver among the set of possible receivers to transmit data, i.e, $\alpha_{kj}\in\{0,1\}$ with $\sum_{j\in J_k}\alpha_{kj}=1,\forall k$.*

Proof. Based on Lemma 1, let us define $\sigma_{kj}^2=\sigma^2+\sum_{l\neq k,j}^{K}P_l t_l|h_{lj}|^2,\forall k,j$ and $\alpha_{k1}=1-\sum_{j\in J_k\setminus\{1\}}\alpha_{kj},\forall k$. Considering the monotonicity of the logarithmic function, we can re-write the optimization problem in (9) for a given transmit power vector $\mathbf{P}=[P_1,P_2,...,P_K]$ and a node state vector $[t_1,t_2,...,t_K]$ as (10), given at the top of the page. Let us define the objective function of (10) by $\hat{R}$, which is a variable of α_{kj}. Since the objective function and the inequality constraints are twice differentiable with respect to α_{kj}, we can rewrite (10) as an unconstrained optimization problem using the Lagrangian dual as,

$$
\begin{aligned}
\max_{\lambda_k,\forall k}\ & \left[\min_{\alpha_{kj},\forall k,j}\ -\hat{R}+\sum_{k=1}^{K}\lambda_k\left(\sum_{j\in J_k\setminus\{1\}}\alpha_{kj}-1\right)\right]\\
\text{s.t}\ \ & 0\le\alpha_{kj}\le 1\ \ \forall k,j,\\
& \lambda_k\ge 0\ \ \forall k,
\end{aligned}
\tag{11}
$$

where $\lambda_1,\lambda_2,...\lambda_K$ are the Lagrangian multipliers. Note that in (11), the minimization of the negative achievable sum-rate is considered. Therefore, the maximum achievable sum-rate for a given transmit power vector and node state vector is achieved when the objective function of (11) is minimized. In the following, we denote the objective function of (11) by L, which is again a variable of α_{kj}. Without the loss of generality, let us assume that $i\in J_l\setminus\{1\}$, i.e, α_{li} exists. The first derivative of L with respect to α_{li} can be computed for different values of t_l and t_i and can be conveniently expressed as (12), given at the top of the next page. Since, $\hat{R}\ge 1$ and $\lambda_l\ge 0$, for the first derivative to be zero, the term inside the brackets need to be negative or zero. Otherwise, the function L is either increasing or decreasing indicating that the achievable sum-rate is maximized at the corner points of $\alpha_{li},\forall l,i$. Based on the values of t_l and t_i, the second derivative of L with respect to α_{li} when the first derivative is zero can be expressed as (13), given at the top of the next page. Therefore, it can be seen that when the first derivative is zero, the second derivative is strictly negative, indicating that any existing critical point would be a maximum. Therefore, the achievable sum-rate is maximized at the corner points implying that $\alpha_{li}\in\{0,1\},\forall l,i$. However, since $\sum_{j\in J_l}\alpha_{lj}=1$ only one $\alpha_{li}=1,\forall l$ while rest are zero ($\alpha_{lj}=0,\forall j\neq i$). Since, this is valid for any given transmit

$$L^{'}(\alpha_{li}) = \hat{R}\left(\frac{P_l t_l(1-t_1)\,|h_{l1}|^2}{\sigma_{l1}^2 + P_l t_l |h_{l1}|^2 \sum_{j\in J_l\setminus\{1\}} \alpha_{lj}} - \frac{P_l t_l(1-t_i)\,|h_{li}|^2}{\sigma_{li}^2 + P_l t_l(1-\alpha_{li})|h_{li}|^2}\right) + \lambda_l. \tag{12}$$

$$\begin{aligned} L^{''}(\alpha_{li})_{|L^{'}(\alpha_{li})=0} =& \lambda_l\left(\frac{P_l t_l(1-t_1)\,|h_{l1}|^2}{\sigma_{l1}^2 + P_l t_l |h_{l1}|^2 \sum_{j\in J_l\setminus\{1\}} \alpha_{lj}} - \frac{P_l t_l(1-t_i)\,|h_{li}|^2}{\sigma_{li}^2 + P_l t_l(1-\alpha_{li})|h_{li}|^2}\right) \\ & - \hat{R}\left(\frac{P_l^2 t_l^2(1-t_1)^2\,|h_{l1}|^4}{(\sigma_{l1}^2 + P_l t_l |h_{l1}|^2 \sum_{j\in J_l\setminus\{1\}} \alpha_{lj})^2} + \frac{P_l^2 t_l^2(1-t_i)^2\,|h_{li}|^4}{(\sigma_{li}^2 + P_l t_l(1-\alpha_{li})|h_{li}|^2)^2}\right). \end{aligned} \tag{13}$$

power vector and node state vector, we can conclude that this result holds true even at the optimum solutions. Therefore, it is best for each node to transmit data symbols intended for at most one receiving node with the total transmit power instead of splitting the total transmit power among the set of possible receiving nodes. This completes the proof of Theorem 1. ☐

Based on Theorem 1, the symbols transmitted by each node would only be decoded at one receiving node. Therefore, the summation over the set J_k can be replaced by selecting $j \in J_k$ that maximizes the received rate and considering the achievable rate at that node. Next, due to the monotonicity of logarithmic function, we can re-write the optimization problem (9) as,

$$\begin{aligned} \max_{P_k, t_k\ \forall k} \ & \sum_{k=1}^{K} \log_2\left(1 + \max_{j\in J_k} \frac{P_k t_k (1-t_j)|h_{kj}|^2}{\sigma^2 + \sum_{l\neq k,j}^{K} P_l t_l |h_{lj}|^2}\right) \\ \text{s.t } & 0 \le P_k \le P \quad \forall i, \\ & t_k \in \{0,1\} \quad \forall k. \end{aligned} \tag{14}$$

We note that the optimization problem (14) is still a non-trivial optimization problem due to its non-convexity and there is no known polynomial time algorithm to solve this general problem. We also note that one instance of the flexible duplex network reduces to a general half-duplex network which can be represented by N transmitting nodes and M receiving nodes where $K = N + M$ and the cardinality of set $J_1 \cup J_2 \cup \ldots \cup J_N$ equals M. Therefore, we next proceed to consider a special half-duplex network with symmetric channels such that $h_{ij} = h_j\ \forall i$ and a common receiving node set such that $J_i = \{1, \ldots, M\}$, $\forall i$ to draw interesting insights.

Special Case: Symmetric Network

As a special case, we consider an instance of a special flexible half-duplex network where all channel gains to a particular receiver are identical, but they differ from one receiver to the next. Even though, the symmetric assumption greatly simplifies the problem, such simplified networks have been analyzed in the literature to obtain analytical insights into optimal network behavior [3], [31]. With this special symmetry condition, we can re-write the achievable sum-rate optimization given in (14) as,

$$\begin{aligned} \max_{P_1,\ldots,P_N} \ & \sum_{i=1}^{N} \log_2\left(1 + \max_{j\in\{1,\ldots,M\}} \frac{P_i |h_j|^2}{\sigma^2 + \sum_{k\neq i} P_k |h_j|^2}\right) \\ \text{s.t } & 0 \le P_i \le P \quad \forall i. \end{aligned} \tag{15}$$

Note that, under the symmetric network assumption, the achievable rate at each transmitter is increasing in h_j. Therefore, to maximize the achievable rate, the signal must be decoded at the receiver with the best channel fading gain, and this receiver is the same for all the transmitters. As such, a symmetric network with M receivers simplifies to a single receiver network where all of the transmitted signals are decoded at the receiver with the highest fading gain. Let $h = \max\{h_1, \ldots, h_M\}$. Then the optimization problem in (15) reduces to

$$\begin{aligned} \max_{P_1,\ldots,P_N} \ & \sum_{i=1}^{N} \log_2\left(1 + \frac{P_i |h|^2}{\sigma^2 + \sum_{k\neq i} P_k |h|^2}\right) \\ \text{s.t } & 0 \le P_i \le P \quad \forall i, \end{aligned} \tag{16}$$

which is equivalent to the achievable sum-rate maximization problem of a single receiver network. Therefore, we next analyze the achievable sum-rate maximization of a symmetric network with a single receiver, i.e., $M = 1$. First let us present the following preliminary results that will be used when deriving the main theorem presented in this section.

Lemma 2. *For $\gamma > 0$, the two functions $A(x)$ and $B(x)$, given by*

$$A(x) = \log\left(1 + \frac{\gamma}{1 + (x-1)\gamma}\right),$$

$$B(x) = \frac{x\gamma^2}{(1 + (x-1)\gamma)(1 + x\gamma)},$$

can only intersect at most once in the region $x \ge 1$.

Proof. See Appendix B. ☐

Lemma 3. *For $\gamma > 0$ and $N > 1$, the two functions $g_1(\gamma)$ and $g_N(\gamma)$, given by*

$$g_1(\gamma) = 1 + \gamma,$$

$$g_N(\gamma) = \left(1 + \frac{\gamma}{1 + (N-1)\gamma}\right)^N,$$

intersect only at one point.

Proof. See Appendix C. ☐

The main result of this section is given by the following theorem.

Theorem 2. *Consider a symmetric network with a single receiver and N transmitters, for which the achievable sum-rate* *maximization problem is given by* (16)*. For such a network, the achievable sum-rate is optimized when the number of active transmitters*

$$n = \begin{cases} N & \gamma \leq \gamma_N^*, \\ 1 & \gamma > \gamma_N^*, \end{cases}$$

where γ is the received SNR of an active node when it is transmitting at the maximum transmit power and γ_N^* is a unique threshold value of the received SNR. In order to maximize the achievable sum-rate each active transmitter will be transmitting in its maximum power.

Proof. First we note that a non-symmetric network with a single receiver has been studied in detail in [2] where it was proved that binary power allocation is optimum when maximizing the achievable sum-rate. Thus, we reduce the optimization problem in (16) as,

$$\begin{aligned} &\max_{n} n \log_2 \left(1 + \frac{\gamma}{1+(n-1)\gamma}\right) \\ &\text{s.t } \ n \in \{1, ..., N\}, \end{aligned} \tag{17}$$

where n denotes the total number of active transmitters and $\gamma = P|h|^2/\sigma^2$ denotes the received SNR. Using the monotonicity of the logarithmic function, we can write (17) as,

$$\begin{aligned} &\max_{n} \left(1 + \frac{\gamma}{1+(n-1)\gamma}\right)^n \\ &\text{s.t } \ n \in \{1, ..., N\}. \end{aligned} \tag{18}$$

Next, we proceed to analyze the optimum number of transmitters that can be active such that the achievable sum-rate of the network is optimized for a given $\gamma > 0$. For the moment, we relax the integer constraint on n and consider the function

$$g(x) = \left(1 + \frac{\gamma}{1+(x-1)\gamma}\right)^x, \tag{19}$$

for $x \in \mathbb{R}$ with $1 \leq x \leq N$. The first derivative of $g(x)$ with respect to x can be conveniently expressed as,

$$g'(x) = (A(x) - B(x))\, g(x), \tag{20}$$

where

$$\begin{aligned} A(x) &= \log\left(1 + \frac{\gamma}{1+(x-1)\gamma}\right) \\ B(x) &= \frac{x\gamma^2}{(1+(x-1)\gamma)(1+x\gamma)}, \end{aligned}$$

As $g(x) \geq 1$, for the first derivative in (20) to be zero, $A(x)$ should be equal to $B(x)$. According to Lemma 2, $A(x)$ and $B(x)$ can only intersect at most once in the region $x \geq 1$. As such, $g(x)$ would have at most one critical point x^*, such that $g'(x) = 0$. The second derivative of $g(x)$ at x^* can be evaluated as,

$$g''(x^*) = g(x^*) \frac{\gamma^2 (x^*\gamma^2 - 2x^*\gamma + 2\gamma - 2)}{[1+(x^*-1)\gamma]^2 [1+x^*\gamma]^2}. \tag{21}$$

In order to show that (21) is positive, we define $\upsilon = \frac{\gamma}{(1+(x^*-1)\gamma)}$. Note that υ is always positive as $x^* \geq 1$ and $\gamma > 0$. Using the [32, eq. (3)] we can write

$$\frac{2\upsilon}{2+\upsilon} \leq \log(1+\upsilon), \forall \upsilon \geq 0, \tag{22}$$

based on which we write the following inequality at the critical point

$$\frac{2\gamma}{2(1+(x^*-1)\gamma)+\gamma} \leq \frac{x^*\gamma^2}{(1+(x^*-1)\gamma)(1+x^*\gamma)}. \tag{23}$$

After some mathematical manipulations the above inequality can be re-expressed as,

$$x^*\gamma^2 - 2x^*\gamma + 2\gamma - 2 \geq 0. \tag{24}$$

As such, all the terms in the numerator and the denominator of (21) are positive, and $g''(x^*) \geq 0$. This indicates that there is at most one global minimizer in $1 \leq x \leq N$. Therefore, within this range $g(x)$ is either increasing or decreasing or convex with respect to x. Hence, the maximum achievable sum-rate would be achieved in the corner points $(1, N)$ proving that it is best to either let one transmitter to be active or all the transmitters to be active. As discrete n is a subset of continuous x this results holds even for $n \in \{1, ..., N\}$.

Next, we analyze the threshold value of the received SNR, above which only one transmitter should be active to maximize the achievable sum-rate. Below this threshold value all the transmitters should be active. Treating γ as a random variable we define functions $g_1(\gamma)$ and $g_N(\gamma)$ to represent the value of $g(x)$ at $x = 1$ and $x = N$, respectively and write

$$\begin{aligned} g_1(\gamma) &= 1 + \gamma, \\ g_N(\gamma) &= \left(1 + \frac{\gamma}{1+(N-1)\gamma}\right)^N, \end{aligned}$$

According to Lemma 3, we can conclude that the two functions $g_1(\gamma)$ and $g_N(\gamma)$ intersect at one unique point in the region $\gamma > 0$ for any $N > 1$. Even though, a close form expression cannot be derived for this point of intersection, it can be found using the Newton Raphson method due to its uniqueness. In addition $\lim_{\gamma\to\infty} g_1(\gamma) \to \infty$, while $\lim_{\gamma\to\infty} g_N(\gamma)$ converges to the finite value $(N/(N-1))^N$. Therefore, it is clear that above this unique threshold point $g_1(\gamma) > g_N(\gamma)$ indicating that it is optimum for only one transmitter to be active. Similarly, below the threshold point $g_1(\gamma) < g_N(\gamma)$ indicating that it is optimum for all transmitters to be active. As such, the optimum number of active transmitters can be found as,

$$n = \begin{cases} N & \gamma \leq \gamma_N^*, \\ 1 & \gamma > \gamma_N^*, \end{cases} \tag{25}$$

where γ_N^* is the calculated threshold value of the received SNR which determines whether to activate one transmitter or all the transmitters to maximize the achievable sum-rate. Since, γ_N^* is a function of N, when the total number of links changes a new threshold value needs to be calculated. This completes the proof of Theorem 2. □

Even though, it is well known and intuitive that at the high SNR regime, the system is interference limited and so orthogonal multiple access schemes like time division multiple access (TDMA) are preferred, while at low SNR regime or noise-limited situations, a non-orthogonal access schemes like code division multiple access (CDMA) tend to be optimal [33], there is no known proof of a unique threshold point or non-existence of the middle ground for a symmetric network. In this paper we make this result precise and show that for a symmetric network no other mode would be optimal for any given SNR value and that there exists a unique threshold point where optimality change from all active mode to one active mode.

IV. PROPOSED SUB-OPTIMAL ALGORITHM

In this section, we focus on the combinatorial optimization problem in (14) and propose a novel iterative algorithm that maximizes the achievable sum-rate. We note that solving (14) is still hard due to its non-convexity/non-linearity and the combinatorial nature. Even when we relax the binary constraints, the relaxed problem is still non-convex and non-linear [5]. It is possible to obtain the optimal state of the nodes through an exhaustive search. However, for a network comprised of K nodes, there are $2^{K-1}+1$ possible combinations to search through and the computation complexity is quite high for large K. Therefore, we propose a sub-optimal algorithm to solve the optimization problem (14). We note that both the inner and the outer maximizations in (14) are interconnected. However, due to the complexity of the problem we approach this optimization problem in three steps.

First we consider the receiver selection problem for the transmitting node k with a given power vector $\mathbf{P} = [P_1, P_2, .., P_K]$ and node state vector $\mathbf{t} = [t_1, t_2, .., t_K]$ as,

$$\max_{j \in J_k} \frac{P_k t_k (1-t_j)|h_{kj}|^2}{\sigma^2 + \sum_{l \neq k,j}^{K} P_l t_l |h_{lj}|^2}. \tag{26}$$

Next, we consider the transmit power control problem for a given receiver assignment $\mathbf{j} = [j_1, j_2, ..., j_K]$ and node state vector $\mathbf{t} = [t_1, t_2, .., t_K]$ as,

$$\begin{aligned} &\max_{P_k \forall k} \sum_{k=1}^{K} \log_2 \left(1 + \frac{P_k t_k (1-t_{j_k})|h_{kj_k}|^2}{\sigma^2 + \sum_{l \neq k, j_k}^{K} P_l t_l |h_{lj_k}|^2} \right), \\ &\text{s.t} \quad 0 \leq P_k \leq P \quad \forall k. \end{aligned} \tag{27}$$

Finally, we consider the node state selection problem problem for a given receiver assignment $\mathbf{j} = [j_1, j_2, ..., j_K]$ and power vector $\mathbf{P} = [P_1, P_2, .., P_K]$ as,

$$\begin{aligned} &\max_{t_k, \forall k} \sum_{k=1}^{K} \log_2 \left(1 + \frac{P_k t_k (1-t_{j_k})|h_{kj_k}|^2}{\sigma^2 + \sum_{l \neq k, j_k}^{K} P_l t_l |h_{lj_k}|^2} \right), \\ &\text{s.t} \quad t_k \in \{0,1\} \quad \forall k. \end{aligned} \tag{28}$$

It is important to note that for a given transmit power vector and node state vector, the optimization problem (26) for a given node k does not depend on the receiver selection of the other nodes. Therefore, each transmitting node would compare its received SINR at each receiving node within the set of potential receivers and select the receiving node with the highest received SINR. However, solving the optimization problems (27) and (28) separately is still a challenging problem due to their non-convex/non-linear and the combinatorial natures. In the following, we solve the optimization problems in (27) and (28), separately, and then propose an iterative algorithm that combines the proposed solutions in order to provide a novel joint solution.

A. Power Control Problem

In (27), we consider the transmit power control problem. Due to the non-convex nature of (27), we consider the tight lower bound approximation in [34], [35] and approximate its objective function as (29), given at the top of the next page, that is tight at a chosen value $\bar{\mathbf{z}} = [\bar{z_1}, ..., \bar{z_K}]$ when the constants a_k and b_k are chosen as,

$$a_k = \frac{\bar{z}_k}{1+\bar{z}_k}, \qquad b_k = \log(1+\bar{z}_k) - \frac{\bar{z}_k}{1+\bar{z}_k}\log(\bar{z}_k).$$

By selecting $\bar{z}_k$ as the SINR_k achieved using the initial solution or the solution achieved via the previous iteration, we can re-write the achievable sum-rate optimization problem given in (27) as,

$$\begin{aligned} &\max_{P_k \forall k} \sum_{k=1}^{K} a_k \log \left(\frac{P_k t_k (1-t_{j_k})|h_{kj_k}|^2}{\sigma^2 + \sum_{l \neq k, j_k}^{K} P_l t_l |h_{lj_k}|^2} \right) + b_k \\ &\text{s.t} \quad 0 \leq P_k \leq P \quad \forall k. \end{aligned} \tag{30}$$

In order to convert this non-convex objective function into a convex function we use the variable transformation $P_k = e^{y_k}$ and reformulate the optimization problem as (31), given at the top of the next page. For a given receiver assignment and node state vector, the optimization problem (31) is concave. Therefore, in each iteration, we can compute the coefficients a_k and b_k based on the solution of the previous iteration and solve the above problem using any existing convex solver or by implementing a gradient decent algorithm. Since, the tight lower bound approximation considered here results in a monotonically improving objective, the sequence always converges [34], [35]. Therefore, (31) can be solved iteratively to find the optimum approximated achievable sum-rate for a given receiver assignment and node state vector.

B. Node State Selection Problem

In (28), we consider the node state selection problem. Let us define the desired channel fading gain matrix ($\mathbf{D}$) and interference channel fading gain matrix ($\mathbf{I}$) as,

$$\mathbf{d_k} = \left[0, 0, \ldots, 0, \frac{P_k |h_{k,j_k}|^2}{\sigma^2}, 0, \ldots, 0\right], \tag{32}$$

$$\begin{aligned} \mathbf{i_k} = \Bigg[&\frac{P_1 |h_{1,j_k}|^2}{\sigma^2}, \ldots, \frac{P_{j_k-1} |h_{j_k-1,j_k}|^2}{\sigma^2}, 0, \frac{P_{j_k+1} |h_{j_k+1,j_k}|^2}{\sigma^2}, \\ &\ldots, \frac{P_{k-1} |h_{k-1,j_k}|^2}{\sigma^2}, 0, \frac{P_{k+1} |h_{k+1,j_k}|^2}{\sigma^2}, \ldots \frac{P_K |h_{K,j_k}|^2}{\sigma^2} \Bigg], \end{aligned} \tag{33}$$

$$\sum_{k=1}^{K} \log_2\left(1+\frac{P_k t_k(1-t_{j_k})|h_{kj_k}|^2}{\sigma^2+\sum_{l\neq k,j_k}^{K} P_l t_l |h_{lj_k}|^2}\right) \geq \sum_{k=1}^{K} a_k \log\left(\frac{P_k t_k(1-t_{j_k})|h_{kj_k}|^2}{\sigma^2+\sum_{l\neq k,j_k}^{K} P_l t_l |h_{lj_k}|^2}\right)+b_k. \tag{29}$$

$$\begin{aligned} &\max_{y_k \forall k} \sum_{k=1}^{K} a_k y_k + a_k \log\left(t_k(1-t_{j_k})|h_{kj_k}|^2\right) + b_k - a_k \log\left(\sigma^2 + \sum_{l\neq k,j_k}^{K} e^{y_l} t_l |h_{lj_k}|^2\right) \\ &\text{s.t} \quad y_k \leq \log(P) \ \ \forall k. \end{aligned} \tag{31}$$

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where $\mathbf{d_k}$ is the k^{th} column of the matrix $\mathbf{D}$. All the elements in $\mathbf{d_k}$ are zero except for the k^{th} element, which represents the normalized SNR at node j_k from node k. Similarly, $\mathbf{i_k}$ is the k^{th} column of $\mathbf{I}$. In $\mathbf{i_k}$ the elements k and j_k are zero and each non-zero element l represents the normalized SNR at node j_k from node l. Based on these definitions, we can re-write the optimization problem (28) as,

$$\begin{aligned} &\max_{t_k,\forall k} \sum_{k=1}^{K} \log_2\left(1+\frac{(1-t_{j_k})\ \mathbf{t}\ \mathbf{d_k}}{1+\mathbf{t}\ \mathbf{i_k}}\right) \\ &\text{s.t} \quad t_k \in \{0,1\} \ \ \forall k. \end{aligned} \tag{34}$$

The reformulated optimization problem in (34) can be solved by using the pattern search algorithm proposed in [5] and it has a complexity $3K^3 + 2K^2$. While the pattern search algorithm has a third order complexity, it is important to note that it achieves significantly better results while maintaining low complexity compared to the alternative exhaustive search which has exponential complexity.

By solving the three optimization problems (26), (34) and (31) iteratively, as given in Algorithm 1, we can achieve a new sub-optimal solution to the achievable sum-rate optimization problem in (14). At the start of Algorithm 1, we initialize the transmit power vector $\mathbf{P}$ to the maximum power vector and the approximated maximum achievable sum-rate R^* to zero. We also initialize the receiver assignment vector $\mathbf{j}$ to the vector resulting in performing receiver assignment based on the received SNR. In each iteration, we first solve (34) for a given receiver assignment and transmit power vector by adopting the pattern search algorithm in [5] which converges to a sub-optimal solution. After the first iteration, we compare the achievable sum-rate achieved by the solution of the pattern search algorithm with R^* and update the optimum node state vector only if the solution of the pattern search algorithm improves the achievable sum-rate. Therefore, after the first iteration, the node state vector is changed at iteration n only if the resultant achievable sum-rate is higher for a different node state vector under the new transmit power vector and the receiver assignment. Next, we solve the optimization problem (26) for a given transmit power vector and node state vector. This can be solved to produce the optimal solution for each transmitting node, independently, by assigning the receiving node with the highest received SINR for each transmitting node. In each iteration the solution of (26) would change from the solution of the previous iteration, only if the achievable sum-rate can be improved under new transmit power and node state vectors. Finally, we proceed to iteratively solve the power control problem based on the tight lower bound approximation. In the m^{th} iteration, we solve the optimization problem (31) and assign the solution to vector $\mathbf{Y}^{(m)} = [y_1, y_2, \ldots, y_K]$. Then the calculated relative error e is compared against a user defined threshold e_{th}. The tight lower bound approximation monotonically improves the objective function and always converges [35]. Thus, the achievable sum-rate improves within each iteration of the inner loop and the transmit power vector is changed at iteration n only if the resultant achievable sum-rate is higher for a different transmit power allocation under the new node state vector and the receiver assignment. Therefore, in the n^{th} iteration of the outer loop, the achievable sum-rate improves monotonically until it converges to a solution. We note that the optimization problem (14) is non-convex and hence there might exist multiple local optima. Since the objective function monotonically improves in each iteration it eventually converges to one of the local solutions. We consider the proposed algorithm to be sub-optimal as we cannot guarantee that the converged solution is the global optimum solution. In implementation, we stop the algorithm and consider it to have converged when the relative difference between the achievable sum-rate in n^{th} iteration and $(n+1)^{\text{th}}$ iteration is less than a user defined threshold.

V. NUMERICAL AND SIMULATION RESULTS

In this section, we present simulation results to evaluate the performance of the proposed sub-optimal algorithm.

We consider a network with $D_A \times D_A$ m^2 coverage and divide it into N_{BS} smaller cells. We place one base station (BS) at the center of each cell and N_{UE} user equipments (UEs) at random locations within the cell. In a given cell, we consider that the BS wants to send data to the UEs in the same cell while the UEs want to send data to the BS as well as to each other. Therefore, in each cell all nodes transmit and receive data to/from the other nodes. If we consider $N_{UE} = 2$, then there are six potential communication links within a cell. However, only two can take place at a given moment due to the half-duplex nature. In addition, we assume that the channels between transmitting and receiving nodes have a Rayleigh distribution and the mean of the channel gain is calculated using the standard path-loss model [36] as,

$$E|h_L|^2 = \left(\frac{c}{4\pi f_c}\right)^2 d_L^{-\beta}, \tag{35}$$

```
Algorithm 1: Proposed Sub-Optimal Algorithm
Input  : Channel state information (CSI), $P$, and
         $J_k \ \forall k$ and transmitting nodes list $\mathbf{K_{Tx}}$
Output: Approximated maximum achievable sum-rate:
         $R^*$, optimum node status vector: $\mathbf{t}^*$, optimum
         receiver assignment $\mathbf{j}^*$ and optimum power
         allocation vector $\mathbf{P}^*$
$n = 1, \mathbf{P}^* \leftarrow P, \mathbf{t}^* \leftarrow 0, R^* \leftarrow 0$, $\mathbf{j}^* \leftarrow$ receiver
  selection based on received SNR
while true do
    for j=each node in $\mathbf{K_{Tx}}$ do
        $k \leftarrow j$, $\mathbf{t_{pattern}} \leftarrow$ starting point with only
          node j transmitting
        while true do
            index $\leftarrow$ best node to transmit with
              $\mathbf{t_{pattern}}$ as identified via pattern search
            if index == $k$ then
                break
            $\mathbf{t_{pattern}}$(index) $\leftarrow 1$, $k \leftarrow$index
        end
        $R_{max}(j) \leftarrow$ sum-rate from (34) for
          $\mathbf{t_{pattern}}$, $\mathbf{t_{max}}(j) \leftarrow \mathbf{t_{pattern}}$
    end
    $\mathbf{t^{(n)}} \leftarrow$ relevant $\mathbf{t_{max}}$ for maximum
      $R_{max}$, $R^{(n)} \leftarrow$ sum-rate with $\mathbf{P}^*$,$\mathbf{j}^*$ and $\mathbf{t^{(n)}}$
    if $R^{(n)} \geq R^*$ then
        $\mathbf{t}^* \leftarrow \mathbf{t^{(n)}}$, $R^* \leftarrow R^{(n)}$
    $\mathbf{j}^* \leftarrow$ solution to problem (26) with $\mathbf{P}^*$ and
      $\mathbf{t}^*$, $m = 0$
    while true do
        $m \leftarrow m + 1$, $\mathbf{Y}^{(m)} \leftarrow$ solution to problem (31)
          with $\mathbf{j}^*, \mathbf{t}^*$
        $e \leftarrow |\ \mathbf{Y}^{(m)} - \mathbf{Y}^{(m-1)}\ |/|\mathbf{Y}^{(m)}|$
        if $e < e_{th}$ then
            break
    end
    $\mathbf{P}^{(n)} = e^{\mathbf{Y}^{(m)}}$, $R^{(n)} \leftarrow$ sum-rate with $\mathbf{P}^{(n)}$,$\mathbf{j}^*$ and
      $\mathbf{t}^*$
    if $(R^{(n)} - R^*)/R^{(n)} > e_{th}$ then
        $\mathbf{P}^* \leftarrow \mathbf{P}^{(n)}$, $R^* \leftarrow R^{(n)}$, $n \leftarrow n + 1$
    else
        break
end
```

where c is the speed of light, f_c is the carrier frequency, d_L is the distance between the transmitter and the receiver of link L, β is the path loss exponent and h_L is the instantaneous channel fading gain of link L. For these examples, we set $f_c = 1.9$ GHz, $\beta = 3.5$ and transmit bandwidth is 200 kHz. We also set the user defined threshold value for Algorithm 1 as $e_{th} = 10^{-3}$ for all the simulation examples.

We compare the performance of the proposed algorithm with five reference techniques, namely the highest SNR scheme, ITLinQ based Algorithm, conventional TDD scheme, interfering scheme and frequency reuse scheme. Under the highest SNR scheme, in each cell only the link which has the highest SNR would communicate while creating interference between cells. For the ITLinQ based algorithm, we implemented the centralized algorithm with the condition given in [15, (2)]. However, since this algorithm required fixed transmitter and receiver pairs, we made two modifications. First, in order to accommodate flexible duplexity while avoiding two pairs being selected with same node in transmitting and receiving ends, we consider that each node is a full-duplex node with infinite self interference. Next, in order to ensure that multiple links with the same transmitter are not selected, once a link is selected we remove any other low priority links with the same transmitter from the priority list. Under the conventional TDD scheme all potential communications happen within a cell but over different time slots. Under the interfering scheme all potential communications happen over multiple time slots where only several communications that are possible at once happen in a given time slot. For example, when $N_{UE} = 2$, we consider that at the first time slot UE1 receives from both BS and UE2, at the second time slot UE2 receives from both BS and UE1 and at the third time slot BS received from both UE1 and UE2. Finally, under the frequency reuse scheme, we assume that four frequency bands are available, so that the given frequency band would only be used by non-adjacent cells. This removes the interference caused by adjacent cells, but reduces the number of active transmissions for the considered resource block. Within the cell we consider that communication take place over conventional TDD scheme. Since, we consider the instantaneous performance, we consider the average over multiple time slots whenever the TDD based scheme is used.

Figure 1 plots the achievable sum-rate versus the maximum transmit power P, when network area $D_A \times D_A = 1$ km^2, $N_{BS} = 25$ and $N_{UE} = 2$. From the plot, we observe that when the transmit power is small all techniques have similar performance. However, as the transmit power increases, all reference techniques start to deviate from the proposed solution with the proposed algorithm having comparatively better performance. We also note that at the high transmit power regime, the highest SNR scheme has better performance than ITLinQ based algorithm and the other reference techniques which uses conventional TDD. This is because at the high transmit power regime the effect of interference is significant, therefore, it is optimum for only single communication to take place within a cell. This is captured by both the highest SNR scheme and the proposed algorithm where as the randomized priority order and the limited interference allowed by the ITLinQ based algorithm introduce some sub-optimality. Since the proposed algorithm has the ability to iteratively update its selection with the consideration of interference from other cells it outperforms the highest SNR scheme as well.

Figure 2 plots the achievable sum-rate versus the dimensions of the considered area when the transmission power is fixed at 10 dBm, $N_{BS} = 25$ and $N_{UE} = 2$. As D_A increases, the cell size increases. Initially, this reduces the interference caused by the nearby cells thus, increasing the achievable sum-rate. However, when the cell size is increased further, the average

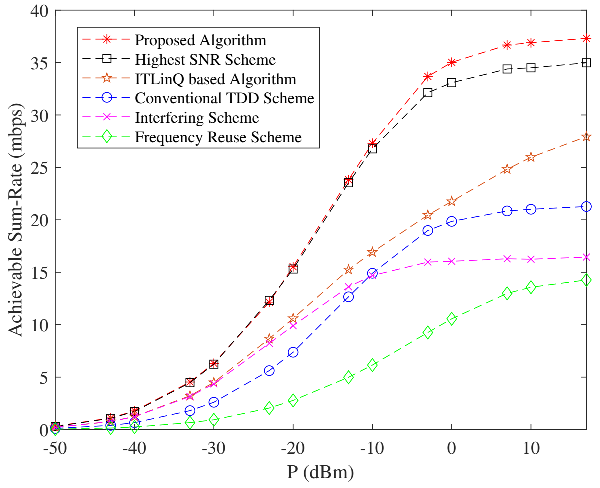


Figure 1: Achievable sum-rate versus transmit power

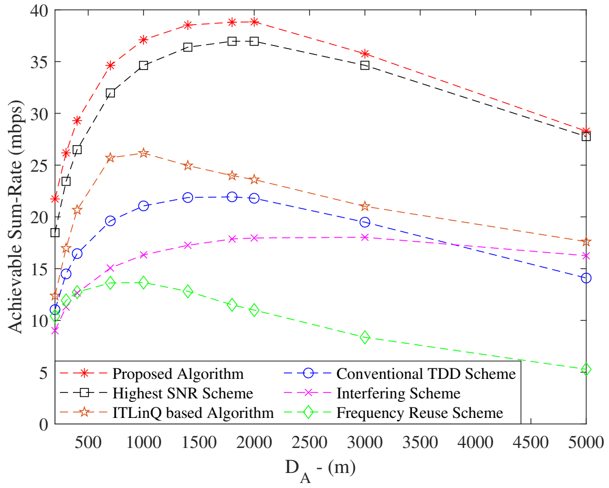


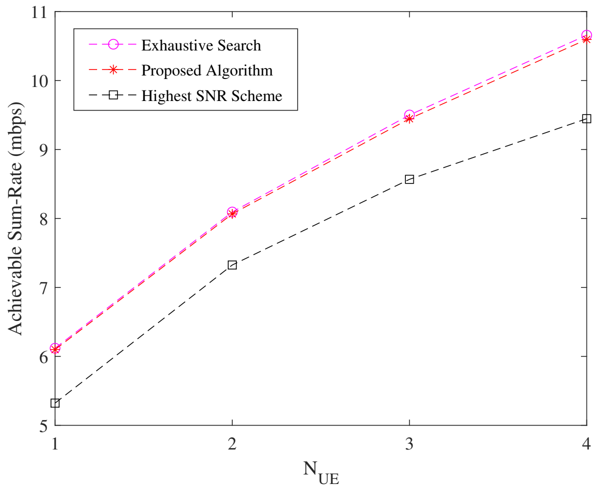
Figure 2: Achievable sum-rate versus area dimension

distance between the BS and UEs as well as between two UEs increases resulting in a reduction in the achievable sum-rate even with less interference. From the plot, we observe that the proposed algorithm has better performance than the reference techniques in a denser area while both proposed method and the highest SNR method have similar and comparatively better performance as D_A increases. Lower performances of other reference techniques can be explained by their inability to completely get rid of interference. In addition, we can observe that the frequency reuse scheme has similar performance to the conventional TDD scheme in denser areas. But as we increase the cell size it becomes worse because of the under-utilization of resources. Therefore, we can conclude that the proposed algorithm improves the overall network throughput in denser networks where cells are too close to each other.

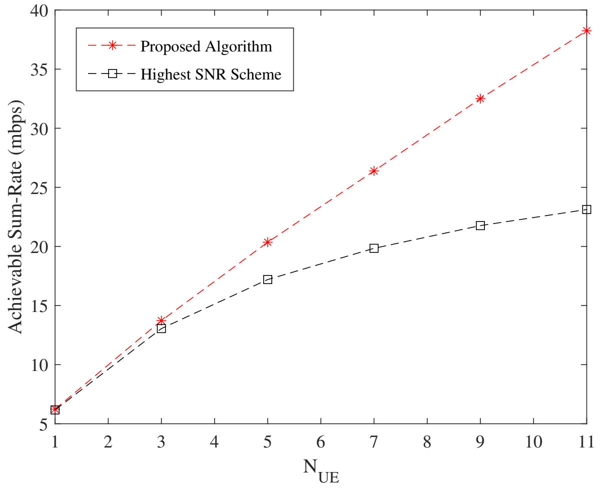
Figures 1 and 2 clearly illustrate that the proposed scheme is much better than the ITLinQ based algorithm, the conventional TDD scheme, the interfering scheme and the frequency reuse scheme. However, we note that for the example considered in Figure 1 and 2, the gap between the proposed algorithm and the highest SNR scheme is quite small. Therefore, we next compare the performance of the proposed algorithm and the highest SNR scheme when the number of UEs within a cell changes. In addition to the highest SNR scheme we compare the performance of our proposed algorithm with the potential exhaustive search. We note that the exhaustive search here does not mean the optimal solution, but a close approximation to the optimal solution where the power control and the receiver selection are iteratively solved using the tight lower bound approximation and the SINR comparison, respectively for all possible transmission directions. Since, this exhaustive search was unable to handle a larger number of nodes, in Figure 3a, we plot the achievable sum-rate versus the number of UEs in a cell N_{UE}, when network area $D_A \times D_A = 1\ \text{km}^2, N_{BS} = 4$ and $P = 10$ dB. From the figure, we observe that in smaller networks, the performance gap between this sub-optimal exhaustive search and the proposed algorithm is quite small compared to the performance gap between the proposed algorithm and the highest SNR scheme. In addition, we also observe that as we increase N_{UE}, the performance gap increases between the proposed algorithm and the highest SNR scheme. Figure 3b plots the achievable sum-rate versus the number of UEs in a cell N_{UE} for larger networks, when network area $D_A \times D_A = 3\ \text{km}^2, N_{BS} = 9$ and $P = 10$ dB. From the plot, we observe that when there are smaller number of UEs within a cell, then both the highest SNR scheme and the proposed algorithm have close performance. This can be explained by the limited communications that can happen within a cell due to the half-duplex nature of the nodes. However, as we increase N_{UE}, the achievable sum-rate of the proposed algorithm increases more significantly while that of the highest SNR scheme increases in a diminishing rate. When the number of UEs increases, that also increases the number of possible communication within a cell and as such, having multiple communications become more optimum which cannot be captured by the highest SNR scheme.

Figure 4 plots the percentage of rate distribution among the cellular communication (between BS and UEs) and D2D communication (between two UEs) in each cell for a transmission period of 100 time slots. From the plot, we observe that in some cells the proposed algorithm either allows only cellular communication or D2D communication to take place. This is because based on the network realization, if two UEs are too far from each other it is best to allow only the cellular communication, to increase the achievable sum-rate. On the other hand, if the two UEs are close to each other but at the cell edge, then it is best to only allow D2D communication to increase the achievable sum-rate. Therefore, the proposed algorithm is most suitable in sensor networks where communication path does not matter.

We next analyze the complexity of the proposed algorithm in terms of number of iterations for convergence and computation time. Figure 5a plots the total number of iterations including both inner and outer loops of Algorithm 1 versus the number of nodes K when $D_A \times D_A = 3\ \text{km}^2$ and



(a) $N_{BS} = 4$ with $D_A \times D_A = 1$ km^2



(b) $N_{BS} = 9$ with $D_A \times D_A = 3$ km^2

Figure 3: Achievable sum-rate versus number of users per cell

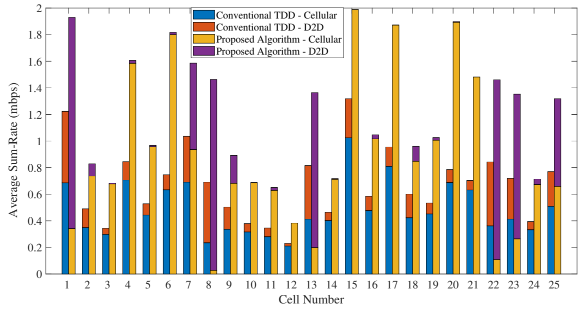


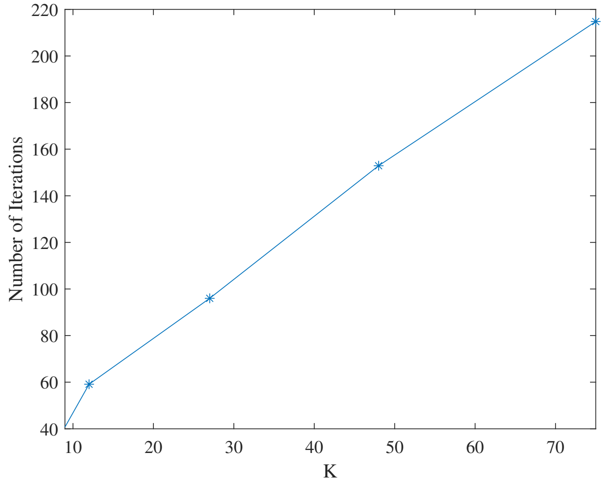
Figure 4: Cellular and D2D sum-rate distribution for each cell

$P = 10$ dB. K is increased by increasing N_{BS} while keeping $N_{UE} = 2$. From the figure, we can observe that as K increases, the number of iterations increases as well. Since, the increment in the number of iterations is linear, we can conclude that the proposed algorithm has linear complexity with respect to the total number of iterations. Figure 5b plots the average computation time of Algorithm 1 versus the number of nodes K when $D_A \times D_A = 1$ km^2 and $P = 10$ dB. Since, the exhaustive search was unable to handle a larger number of nodes, we increased K by increasing N_{UE} while keeping $N_{BS} = 4$. From the figure, we can observe that as K increases, the computation time of exhaustive search is linearly increasing in logarithmic scale thus implying that it has an exponential complexity with respect to K. On the other hand, the computation time of the proposed algorithm is significantly lower compared to the exhaustive search and only slightly increases in the logarithmic scale. We also note that the computation times of the ITLinQ based algorithm and the highest SNR scheme are significantly smaller than our proposed algorithm. As such, there is a clear trade-off between the complexity and the achievable sum-rate performance.

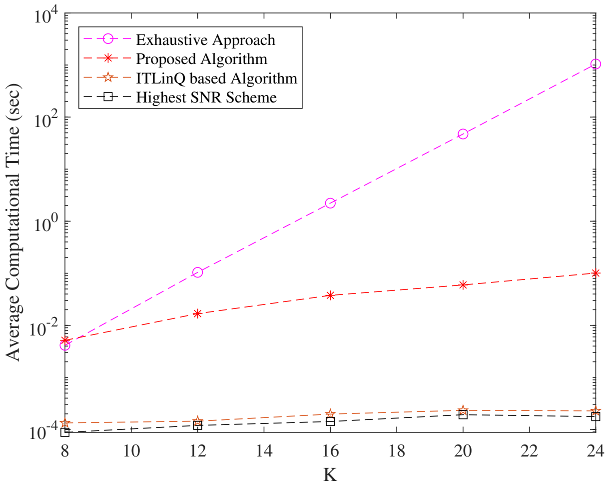
VI. CONCLUSION

Transmitter and receiver scheduling in flexible half-duplex networks is analyzed in terms of the achievable sum-rate optimization. First, it is shown that when maximizing the achievable sum-rate, it is optimal for each transmitter to transmit to at most one receiver. Next, the optimal transmitter scheduling problem of a symmetric network is analyzed and it is shown that a single instance of the symmetric network with multiple receiving nodes can be simplified to a single receiver node network. Then, by considering a symmetric network with a single receiver it is proved that the optimum transmitter scheduling is to let either one transmitter or all the transmitters to be active depending on the value of the received SNR. Further, it is shown that for a network with a fixed number of receivers, there exists a unique threshold value of the received SNR at which the optimality changes from all to one. Finally, an iterative sub-optimal algorithms is proposed to maximize the achievable sum-rate of a flexible network with transmitter and receiver scheduling by separating the optimization problem into three sub problems. Numerical examples are used to further illustrate accuracy of the results and the performance of the proposed algorithm.

An extension to fair scheduling in a flexible half-duplex network with transmitter and receiver selection would formulate another challenging problem. While in [10], the authors consider the fair scheduling problem in a flexible full-duplex network it is only for a network where there is one potential receiver or transmitter. In addition, this work considers centralized interference management using transmit power control. Therefore, the consideration of distributed interference management via link scheduling or interference avoidance via OFDMA channels would be another interesting future extension.



(a) Number of iterations for convergence.



(b) Average computation time

Figure 5: Complexity of proposed algorithm versus number of nodes

APPENDIX A
PROOF OF LEMMA 1

In this section, we provide the proof of Lemma 1. Let R^* denote the optimum achievable sum-rate that results from the transmit power vector $[P_1^*, ..., P_K^*]$ where P_k^* denotes the optimum transmit power of node k, the transmit power fraction vector $[\alpha_{kj}^*]$, $\forall j \in J_k$ where α_{kj}^* denotes the optimum transmit power fraction of node k allocated for node j and the node state vector $[t_1^*, ..., t_K^*]$ where t_k^* denoted the optimum state of the node k. Therefore, the optimum achievable sum-rate R^* can be written as (36), given at top of the next page. Without loss of generality, let us consider that node 1 is transmitting and assume that $\sum_{j\in J_1} \alpha_{1j}^* < 1$ and choose a set of small increments $[\delta_{1j}]$, $\forall j \in J_1$ such that $\delta_{1i}\alpha_{1j}^* = \delta_{1j}\alpha_{1i}^*$. Next, we define a new fractional vector for node 1 where $\hat{\alpha}_{1j} = \alpha_{1j}^* + \delta_{1j}$ such that $\sum_{j\in J_1} \hat{\alpha}_{1j} \leq 1$. The resulting achievable sum-rate can be expressed as (37) with Δ_j expressed as (38), given at top of the next page.

Based on the monotonicity of the logarithmic function and the fact that $\delta_{1i}\alpha_{1j}^* = \delta_{1j}\alpha_{1i}^*$, it can be shown that $\Delta_j \geq 0, \forall j$. As such, $R \geq R^*$. Since, R^* denotes the maximum achievable sum-rate for the optimum transmit power vector and the optimum node state vector, the above inequality must be satisfied with the equality. Therefore, we can increase the values of $[\delta_{1j}]$, $\forall j \in J_1$ until the constraint $\sum_{j\in J_1} \hat{\alpha}_{1j} \leq 1$ is satisfied with the equality while achieving the same optimum achievable sum-rate R^*. Thus, there exists an optimum solution with $\sum_{j\in J_1} \hat{\alpha}_{1j} = 1$, which completes the proof of Lemma 1.

APPENDIX B
PROOF OF LEMMA 2

In this section, we provide the proof of Lemma 2. Let us first define a new function $f(x)$ such that, $f(x) = A(x) - B(x)$. The two functions given by $A(x)$ and $B(x)$ can only intersect when $f(x) = 0$. First we note that, when $x = 1$,

$$f(1) = \log(1+\gamma) - \frac{\gamma^2}{1+\gamma}, \tag{39}$$

and when $x \to \infty$ we can show that $\lim_{x\to\infty} f(x) = 0$. Then, we derive the first derivative of $f(x)$ with respect to x as

$$f'(x) = \frac{\gamma^2\left(2(\gamma-1) - x\gamma(2-\gamma)\right)}{(1+(x-1)\gamma)^2(1+x\gamma)^2}, \tag{40}$$

from which we learn that $f(x)$ has only one critical point, at $\bar{x} = \dfrac{2(\gamma-1)}{\gamma(2-\gamma)}$. Next, we analyze the behaviour of $f(x)$ under all possible scenarios of $\bar{x}$.

Firstly, when $\gamma = 2$, $\bar{x}$ does not exist, $f(1)$ is -0.23 and the first derivative $f'(x)$ is positive $\forall x \geq 1$. Thus $f(x)$ starts with a negative value and strictly increases with x. Since $\lim_{x\to\infty} f(x) = 0$, according to the monotone convergence theorem the function never crosses zero in $x \geq 1$. Secondly, when $\gamma < \sqrt{2}$, $\bar{x}$ is outside the region of interest, i.e., $\bar{x} < 1$. $f(1)$ is positive and the first derivative $f'(x)$ is negative $\forall x \geq 1$. Thus $f(x)$ starts with a positive value and strictly decreases with x. Since $\lim_{x\to\infty} f(x) = 0$, the function never crosses zero in $x \geq 1$. Thirdly, when $\gamma \geq 2$, $\bar{x}$ is again outside the region of interest, i.e., $\bar{x} < 1$. $f(1)$ is negative and the first derivative $f'(x)$ is positive $\forall x \geq 1$. Thus $f(x)$ starts with a negative value and strictly increases with x. Since $\lim_{x\to\infty} f(x) = 0$, the function never crosses zero in $x \geq 1$. Finally, when $\sqrt{2} \leq \gamma < 2$, $\bar{x}$ is within the region of interest, i.e., $\bar{x} \geq 1$. The second derivative of $f(x)$ at $\bar{x}$ can be derived as,

$$f''(\bar{x}) = \frac{-\gamma^3(2-\gamma)}{(1+(x-1)\gamma)^2(1+x\gamma)^2}, \tag{41}$$

which is negative $\forall x \geq 1$. As such, $f(x)$ can have at most one critical point which is a maximum in the region of $x \geq 1$. Since $\lim_{x\to\infty} f(x) = 0$, $f(x) = 0$ can have real and finite roots in the region $x \geq 1$ only if $f(\bar{x}) > 0$ and $f(1) \leq 0$. This is further illustrated in Figure 6 for an example of $\gamma = 1.6$. Substituting $\gamma = 1.6$ in the expression for $\bar{x}$ we find one

$$R^* = \sum_{k=1}^{K}\sum_{j\in J_k}\log_2\left(1+\frac{P_k^* t_k^*(1-t_j^*)\alpha_{kj}^*|h_{kj}|^2}{\sigma^2+\sum_{l\neq k,j}^{K}P_l^* t_l^*|h_{lj}|^2+\sum_{i\in J_k\setminus\{j\}}P_k^* t_k^*\alpha_{ki}^*|h_{kj}|^2}\right). \tag{36}$$

$$\begin{aligned} R &= \sum_{j\in J_1}\log_2\left(1+\frac{P_1^* t_1^*(1-t_j^*)\hat{\alpha}_{1j}|h_{1j}|^2}{\sigma^2+\sum_{l\neq 1,j}^{K}P_l^* t_l^*|h_{lj}|^2+\sum_{i\in J_1\setminus\{j\}}P_1^* t_1^*\hat{\alpha}_{1i}|h_{1j}|^2}\right) \\ &\qquad +\sum_{k=2}^{K}\sum_{j\in J_k}\log_2\left(1+\frac{P_k^* t_k^*(1-t_j^*)\alpha_{kj}^*|h_{kj}|^2}{\sigma^2+\sum_{l\neq k,j}^{K}P_l^* t_l^*|h_{lj}|^2+\sum_{i\in J_k\setminus\{j\}}P_k^* t_k^*\alpha_{ki}^*|h_{kj}|^2}\right) \\ &= R^* + \sum_{j\in J_1}\Delta_j, \end{aligned} \tag{37}$$

$$\begin{aligned} \Delta_j &= \log_2\left(1+\frac{P_1^* t_1^*(1-t_j^*)\hat{\alpha}_{1j}|h_{1j}|^2}{\sigma^2+\sum_{l\neq 1,j}^{K}P_l^* t_l^*|h_{lj}|^2+\sum_{i\in J_1\setminus\{j\}}P_1^* t_1^*\hat{\alpha}_{1i}|h_{1j}|^2}\right) \\ &\qquad -\log_2\left(1+\frac{P_1^* t_1^*(1-t_j^*)\alpha_{1j}^*|h_{1j}|^2}{\sigma^2+\sum_{l\neq 1,j}^{K}P_l^* t_l^*|h_{lj}|^2+\sum_{i\in J_1\setminus\{j\}}P_1^* t_1^*\alpha_{1i}^*|h_{1j}|^2}\right). \end{aligned} \tag{38}$$

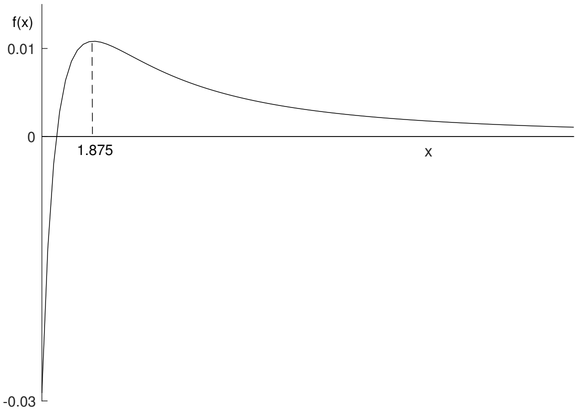


Figure 6: $f(x)$ with respect to x

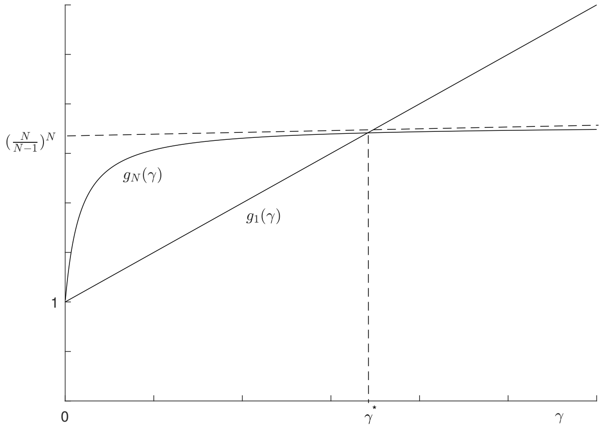


Figure 7: $g_1(\gamma)$ and $g_N(\gamma)$ with respect to γ

critical point $\bar{x} = 1.875$. Given that $f''(\bar{x})$ in (41) is negative at $\gamma = 1.6$, we conclude that there is a maximum point at $x = 1.875$. Therefore, $f(x)$ will intersect the x-axis in the region $1 \leq x < \bar{x}$. When $x > \bar{x}$, $f(x)$ strictly decreases and since there are no other critical points it does not cross the x-axis again.

APPENDIX C
PROOF OF LEMMA 3

In this section, we provide the proof of Lemma 3. We start by noting that $g_1(0) = g_N(0) = 1$. As such, both functions start at the same point. However, $\lim_{\gamma\to\infty} g_1(\gamma) \to \infty$, while $\lim_{\gamma\to\infty} g_N(\gamma)$ converges to a finite value $(N/(N-1))^N$. We also note that the first derivative of $g_1(\gamma)$ with respect to γ has a constant value of 1, while the first derivative of $g_N(\gamma)$ is a positive but decreasing function of γ and can be expressed as,

$$g'_N(\gamma) = \frac{\left(\frac{1}{N}+\gamma\right)^{N-1}}{N\left(\frac{1}{N}+(1-\frac{1}{N})\gamma\right)^{N+1}}. \tag{42}$$

Since $g'_N(0) = N$ with $N > 1$, the starting incremental rate of $g_N(\gamma)$ is larger than that of $g_1(\gamma)$. Therefore, we can conclude that the two functions intersect in the region $\gamma > 0$. In addition, having one function with a constant increment and the other with a decreasing increment implies that these two functions will only intersect at one point. This is clearly illustrated in Figure 7.

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