Abstract—In this paper, we consider joint routing, scheduling, and resource allocation to maximize the throughput of OFDMA based wireless ad-hoc networks subject to MAC layer and network layer constraints. Comparing with previous work (e.g., Rashidi et al., ICC 2012) that assumes each subchannel to be orthogonally accessed by all network links through time sharing, we schedule the orthogonal multiple access (e.g., CDMA) among the outgoing links of each node to each subchannel and treat the interferences caused by other nodes as noise. We propose an iterative heuristic approach to decompose the original problem into subproblems, each of which can be solved approximately through linearization. Simulations demonstrate that, particularly in large networks, our proposed cross-layer design significantly outperforms the previously proposed “orthogonal-only” access.

I. INTRODUCTION

Throughput maximization is a fundamental goal of wireless ad-hoc networks. However, it is very challenging due to interference. Promising solutions require joint consideration of routing, scheduling and power allocations (JRSPA) across different communication layers.

Cross-layer design for throughput maximization has been investigated extensively over the past years. Based on the assumption of queueing incoming packets and considering different physical layer transmission schemes, Refs. [1], [2], [3] propose throughput optimal algorithms based on backpressure-type routing. Without queueing, some other works characterize the achievable rates of multi-hop wireless network with interference avoidance, e.g., [4], [5] and [6], where hard decisions are made to determine the interfering links either by comparing the geometric distances or the SIRs to the corresponding thresholds. In other literature, e.g., [7] and [8], the JRSPA problem is formulated as a convex optimization problem. Ref. [7] models the link capacity as a linear function of the SINR, which is only valid for the case of low SINRs on all the activated links. Ref. [8] models the link capacity as a convex function of power and bandwidth allocation variables or of time allocation variables. However, the model in [8] is based on the assumption that the link capacity depends only on the locally allocated resources while ignoring issues of interference, which is typically not fulfilled in practice.

In this paper, we explore cross-layer design for throughput maximization in Orthogonal Frequency Division Multiple Access (OFDMA) wireless ad-hoc networks. OFDMA allows the efficient use of spectrum in frequency-selective fading environments, and therefore is promising for wireless ad-hoc networking. Some papers have explored the cross-layer design of OFDMA-based wireless networks. For instance, resource allocation has been studied in [9] for multi-source, single destination, two-hop OFDMA relay networks subject to the restriction of exclusive (orthogonal) subchannel access, i.e., each subchannel can only be used once in the whole network. With the same subchannel access restriction, a heuristic approach has been proposed in [10] to maximize the throughput of OFDMA wireless mesh backhaul networks. Ref. [11] extends the framework to OFDMA ad-hoc networks; it allows all links in the network to access each subchannel through Time Division Multiple Access (TDMA). However, the model still assumes that each time-frequency resource can be used only once in the whole network. The original problem is finally transformed into a convex optimization problem.

Similar to [11], we focus on throughput maximization in OFDMA wireless ad-hoc network, using a similar network model and assuming that the outgoing links of each node are scheduled orthogonally. However, in contrast to [11], the outgoing links from different nodes need not to be orthogonal, and thus may cause interference to one another. The motivation for the change in setting is to expand the policy space for choosing the scheduling variables. Correspondingly, we can then trade off spatial frequency reuse with interference. The main contribution of this paper is to propose a linearization-based heuristic approach to tackle the new JRSPA problem. Simulation results demonstrate a significant throughput performance enhancement compared to the results of [11] in particular for large networks.

The remainder of the paper is organized as follows. Section II describes the system model. Section III formulates the optimization problem and describes the linearization-based heuristic approach. Simulation results are provided in Section IV. The paper is concluded in Section V.
II. System Model

A. Network Settings

We consider an OFDMA wireless ad-hoc network with $N$ nodes denoted as set $\mathcal{N}$. The network operates over a frequency band equally divided into $K$ subchannels, denoted as set $\mathcal{K}$. Each subchannel has bandwidth $W$. Let $P_i$ represent the power budget of the $i$th node. We assume that the signal transmitted from any node $i$ can be overheard by all other nodes in the network at various strengths, depending on the channel gains. The network is thus fully connected. Let node pair $(i,j)$ represent the link from node $i$ to node $j$; $g_{ij}^k$ is the channel (power) gain of link $(i,j)$ on subchannel $k$.

Assume the $g_{ij}^k$ to be constant during multiple frames of transmission. This can be approximately true if the duration of communication is less than the coherence time of the wireless medium. We assume full channel state information (CSI) known by a centralized coordinator. Each node in the network can serve as source, relay and/or destination simultaneously; we allow each node to work in full-duplex mode\footnote{Note that recent researches\cite{12,13} have made full-duplex implementation practically feasible as well as theoretically interesting. The treatment of the half-duplex mode will be subject of future work.}, i.e., transmissions and receptions of a node can overlap in time without causing self-interference. Multiple data streams (“commodities”), indexed by $d \in D$ and intended for different destination nodes, may flow through the network concurrently.

B. System Constraints

In order to maximize the throughput of the network, we jointly schedule subchannel usage for each link, route the data streams, and allocate the power to each transmission, all subject to the constraints of different layers.

1) Scheduling Constraints: The scheduling of subchannels is characterized by the set of variables $\{c_{ij}^k\}$, where $i$ and $j$ are the transmitting and receiving node, respectively, and $k$ is the subchannel index.

First consider the case where the $c_{ij}^k$ are restricted to take binary values: $c_{ij}^k$ takes value 1 to indicate the exclusive usage of subchannel $k$ by link $(i,j)$, and 0 otherwise. In the OFDMA ad-hoc network, the constraints on the $c_{ij}^k$ are

$$\sum_{j : j \neq i} c_{ij}^k \leq 1, \forall i \in \mathcal{N}, k \in \mathcal{K},$$

(1)

$$c_{ij}^k \in \{0, 1\}, \forall i, j \in \mathcal{N}, j \neq i, k \in \mathcal{K}.$$  

(2)

Eq. (1) restricts each subchannel to be used by at most one of the outgoing links of each node.

With the binary $c_{ij}^k$, the JRSPA problem for a network with a general topology is an integer programming problem that falls into the category of NP-hard problems\cite{9}. To make the problem tractable, we relax the $c_{ij}^k$ to take values in the continuous interval $[0,1]$. Technologically, this models the application of multiple access techniques among the outgoing links of each transmitting node on each subchannel. Retaining (1), constraints (2) can then be replaced by

$$0 \leq c_{ij}^k \leq 1, \forall i, j \in \mathcal{N}, j \neq i, k \in \mathcal{K}.$$  

(3)

Then (1) and (3) imply that the outgoing links of each node access each subchannel orthogonally. Correspondingly, $c_{ij}^k$ represents the fraction that the amount of resource used by link $(i,j)$ on subchannel $k$ is divided by the total amount of resource under the multiple access scheme, e.g., the fraction of the time used under TDMA or the fraction of the spreading codes used under Code Division Multiple Access (CDMA).

In later parts of the paper, we adopt CDMA as the multiple access scheme to analyze, and briefly call the use of CDMA with the constraints (1), (3) the “local CDMA” scheme. The motivation is two fold:

a) As will be shown later, the interference can be characterized by the $c_{ij}^k$ and the power allocation variables in a closed form, c.f., (9). This makes our problem tractable.

b) For the transmission over each link $(i,j)$, all the signals overheard by node $j$ from nodes other than node $i$ on the same subchannel are whitened as noise. In contrast, under other local multiple access schemes, some interferers are possibly avoided because of being allocated with the resource, e.g., timeslots under “local TDMA”, orthogonal to the one allocated to link $(i,j)$. Therefore, applying local CDMA on each subchannel achieves a lower bound of the throughput of the OFDMA network.

We assume that the total number of orthogonal spreading codes generated to be sufficiently large such that the $c_{ij}^k$ can approximately take any values in interval $[0,1]$.

2) Power Allocation Constraints: Under the local CDMA scheme, let $p_{ij}^k$ represent the amount of power allocated to link $(i,j)$ for the transmission on subchannel $k$ if link $(i,j)$ used all the spreading codes. Then

$$\sum_k c_{ij}^k p_{ij}^k \leq P_i, \forall i \in \mathcal{N},$$

(4)

$$p_{ij}^k \geq 0, \forall i, j \in \mathcal{N}, j \neq i, k \in \mathcal{K},$$

(5)

where $c_{ij}^k p_{ij}^k$ is the actual amount of power allocated to link $(i,j)$ for the transmission on subchannel $k$. Eq. (4) describes the constraint of the power consumed by node $i$, summed over all outgoing links and all subchannels.

3) Routing Constraints: Let $s_i^d$ represent the exogenous input rate for commodity $d$ arriving at node $i$; let $x_{ij}^{(d)}$ represent the data rate for commodity $d$ that flows through link $(i,j)$ on subchannel $k$. Then the $s_i^d$ and the $x_{ij}^{(d)}$ satisfy:

$$x_{ij}^{(d)} \geq 0, \forall i, j \in \mathcal{N}, j \neq i, k \in \mathcal{K}, d \in D,$$

(6)

$$s_i^d \geq 0, \forall i \in \mathcal{N}, d \in D, i \neq d.$$  

(7)

Eq. (7) does not hold for $i = d$ since $s_i^d$ can be negative, which represents that data flows out of the network. Moreover, flow conservation requires that

$$\sum_k \sum_{j \neq i} x_{ij}^{(d)} - \sum_k \sum_{j \neq i} x_{ji}^{(d)} - s_i^d = 0, \forall i \in \mathcal{N}, d \in D.$$  

(8)

4) Link Capacity Constraints: Consistent with the scheduling constraints shown in (1) and (3), interference may exist among the transmissions over the links on the same subchannel.
but emanating from different nodes. Under the local CDMA scheme, different transmitting nodes use different sets of orthogonal spreading codes created, e.g., by multiplying a set of Walsh-Hadamard codes by m-sequence “scrambling” codes [14]. The result is that orthogonality among the spreading codes used on the outgoing links of each node can be guaranteed, while the spreading codes used to transmit by different nodes are non-orthogonal but distinguishable. The aggregate interference to each link \((i, j)\) on each subchannel \(k\) is

\[
\sum_{n \neq \hat{n}} \sum_{z \neq n} c_{n}^{k} p_{n}^{k} g_{nj}^{k}, \quad \forall i, j \in \mathcal{N}, \ k \in \mathcal{K}.
\]

(9)

Treating interferences as noise, it follows that the link capacities satisfy the following non-convex constraints:

\[
\sum_{d} x_{ij}^{(d)} \leq W c_{ij}^{k} \log_{2} \left( 1 + \frac{p_{ij}^{k} g_{ij}^{k}}{N_{0}W + \sum_{n \neq \hat{n}} \sum_{z \neq n} c_{n}^{k} p_{n}^{k} g_{nj}^{k}} \right),
\]

\[
\forall i, j \in \mathcal{N}, \ j \neq i, \ k \in \mathcal{K}, \ d \in \mathcal{D}, \ (10)
\]

where \(N_{0}W\) is the power of the additive white Gaussian noise.

### III. LINEARIZATION-BASED JRSPA OPTIMIZATION

The goal of this section is to determine the routing, scheduling and resource allocation variables, i.e., \(x_{ij}^{(d)}\), \(c_{ij}^{k}\) and \(p_{ij}^{k}\), respectively, to maximize the throughput of the network by formulating and approximately solving the JRSPA problem. 

#### A. Problem Formulation

Throughput performance can be expressed as maximizing the weighted summation of the supportable exogenous input rates \(s_{i}^{(d)}\) subject to the constraints (1), (3)-(8) and (10). The resulting optimization problem can be formulated as

\[
\max \left\{ s_{i}^{(d)}, c_{ij}^{k}, x_{ij}^{(d)}, p_{ij}^{k} \right\} \sum_{d \neq \hat{d}} \omega_{i}^{(d)} s_{i}^{(d)} \quad (11a)
\]

subject to:

Eq. (1), Eq. (3)-(8) and Eq. (10), \quad (11b)

where the \(\omega_{i}^{(d)}\) are non-negative constant weights.

The constraints (4) and (10) are non-convex, and therefore theoretically achieving the global optimum of the resulting problem (11) is not guaranteed. In this paper, we instead develop a heuristic approach to (11).

#### B. Linearization-based Approach

Our approach is to iterate a sequence of subproblems, each of which has a simpler form. We keep iterating, updating the parameters of each subproblem according to the solutions of the previous one, until they converge to a local optimum.

We aim to transform (4) and (10) into linear forms. To do this, we set \(\{c_{ij}^{k}\}\) and \(\{p_{ij}^{k}\}\) as two alternatively updating sets of parameters of the subproblems. We introduce the \(\Delta c_{ij}^{k}\) and \(\Delta p_{ij}^{k}\) as new variables, defined respectively as the changes in the \(c_{ij}^{k}\) and \(p_{ij}^{k}\) between two successive iterations, i.e.,

\[
c_{ij}^{k}[l + 1] = c_{ij}^{k}[l] + \Delta c_{ij}^{k}, \quad \forall i, j \in \mathcal{N}, \ i \neq j, \ k \in \mathcal{K}, \ l \geq 0,
\]

(12)

\[
p_{ij}^{k}[l + 1] = p_{ij}^{k}[l] + \Delta p_{ij}^{k}, \quad \forall i, j \in \mathcal{N}, \ i \neq j, \ k \in \mathcal{K}, \ l \geq 0,
\]

(13)

where \(l\) is the index of the iteration.

Updating the two sets of parameters \(\{c_{ij}^{k}[l]\}\) and \(\{p_{ij}^{k}[l]\}\) alternately forms two consecutive sub-steps in each iteration \(l\): the “scheduling update” and the “power allocation update”, denoted as sub-step \(l_{s}\) and \(l_{p}\), respectively. We define the update sequence of each iteration followed in this paper as: starting with \(\{c_{ij}^{k}[0]\}\) and \(\{p_{ij}^{k}[0]\}\), sub-step \(l_{s}\) updates \(\{c_{ij}^{k}[l]\}\) to \(\{c_{ij}^{k}[l + 1]\}\); then, continuing with \(\{c_{ij}^{k}[l + 1]\}\) and \(\{p_{ij}^{k}[l]\}\), sub-step \(l_{p}\) updates \(\{p_{ij}^{k}[l]\}\) to \(\{p_{ij}^{k}[l + 1]\}\). Having clarified the update sequence, in the remainder of this subsection and for notational convenience, we omit the iteration indices in reformulating certain constraints.

By replacing the \(c_{ij}^{k}\) in (4) by \(c_{ij}^{k} + \Delta c_{ij}^{k}\), the power constraint in sub-step \(l_{s}\) becomes linear:

\[
\sum_{k : j \neq i} (c_{ij}^{k} + \Delta c_{ij}^{k}) p_{ij}^{k} \leq P_{s}, \quad \forall i \in \mathcal{N}. \quad (14)
\]

Define \(I_{ij}^{k} \triangleq \sum_{n \neq \hat{n}} \sum_{z \neq n} c_{n}^{k} p_{n}^{k} g_{nj}^{k}\). We perform Taylor expansion on (10) with the \(c_{ij}^{k}\) replaced by the \(c_{ij}^{k} + \Delta c_{ij}^{k}\), and keep the constant and linear terms. The link capacity constraints in sub-step \(l_{c}\) are approximately

\[
\sum_{d} x_{ij}^{(d)} \leq W \Delta c_{ij}^{k} \log_{2} \left( 1 + \frac{p_{ij}^{k} g_{ij}^{k}}{N_{0}W + I_{ij}^{k}} \right) - (\ln 2) \left( N_{0}W + I_{ij}^{k} + p_{ij}^{k} g_{ij}^{k} \right) \left( N_{0}W + I_{ij}^{k} \right),
\]

\[
\forall i, j \in \mathcal{N}, \ j \neq i, \ k \in \mathcal{K}. \quad (15)
\]

Additionally, we use a parameter \(\eta\) to control the approximation accuracy by restricting the ranges of the \(\Delta c_{ij}^{k}\) relative to the \(c_{ij}^{k}\) according to the following relations:

\[
\sum_{n : j \neq i} \sum_{z \neq n} \Delta c_{n}^{k} p_{n}^{k} g_{nj}^{k} \leq \eta (N_{0}W + I_{ij}^{k}),
\]

(16a)

\[
\forall i, j \in \mathcal{N}, j \neq i, k \in \mathcal{K}.
\]

\[
|\Delta c_{ij}^{k} p_{ij}^{k} g_{ij}^{k}| \leq \eta (N_{0}W + I_{ij}^{k} + p_{ij}^{k} g_{ij}^{k}),
\]

(16b)

\[
\forall i, j \in \mathcal{N}, j \neq i, k \in \mathcal{K}.
\]

Similarly, the power budget constraints in sub-step \(l_{p}\) are

\[
\sum_{k : j \neq i} c_{ij}^{k} (p_{ij}^{k} + \Delta p_{ij}^{k}) \leq P_{s}, \quad \forall i \in \mathcal{N}. \quad (17)
\]
The link capacity constraints in sub-step \( l_p \) are approximately
\[
\sum_d x_{ij}^{(d)} \leq \frac{W c_{ij}^d \Delta p_{ij}^k}{(\ln 2)} (N_0 W + I_{ij}^k + p_{ij}^k g_{ij}^k)
\]
and the corresponding range restrictions on the \( \Delta p_{ij}^k \) are
\[
\sum_{n:n \neq i, z \neq n} c_{n}^k \Delta p_{n}^k g_{n}^k \leq \eta (N_0 W + I_{ij}^k),
\]
for all \( i, j \in \mathcal{N}, j \neq i, k \in \mathcal{K}, \) (18)

Based on (14)-(19), the two subproblems corresponding to sub-steps \( l_c \) and \( l_p \), respectively, are formulated as follows:

1) Optimization Subproblem of Sub-step \( l_c \):
\[
\text{max} \left\{ s_i^{(d)}, x_{ij}^{(d)} \right\} \sum_d \sum_{i \neq d} \omega_i^{(d)} s_i^{(d)}
\]
subject to:
Eq. (6)-(8) and Eq. (14)-(16),
\[
\sum_{j: j \neq i} (c_{ij}^k + \Delta c_{ij}^k) \leq 1, \forall i \in \mathcal{N}, k \in \mathcal{K},
\]
(20b)
\[
c_{ij}^k + \Delta c_{ij}^k \geq 0, \forall i, j \in \mathcal{N}, j \neq i, k \in \mathcal{K}.
\]
(20d)

2) Optimization Problem of Sub-step \( l_p \):
\[
\text{max} \left\{ s_i^{(d)}, x_{ij}^{(d)} \right\} \sum_d \sum_{i \neq d} \omega_i^{(d)} s_i^{(d)}
\]
subject to:
Eq. (6)-(8) and Eq. (17)-(19),
\[
p_{ij}^k + \Delta p_{ij}^k \geq 0, \forall i, j \in \mathcal{N}, j \neq i, k \in \mathcal{K}.
\]
(21c)

It can be seen that both (20) and (21) are linear programs. We conclude that the original problem (11) can be tackled by iteratively solving these linear programming subproblems with controllable approximations. Since the original problem is non-convex, convergence to a global optimum cannot be guaranteed. However, the simulations in Sec. IV show that for some special cases where an optimum solution can be found analytically, the solution of our iterative approach is close to the global optimum.

C. Implementation of the Iterative Approach

In this section, we describe certain considerations that arise in the algorithmic implementation.

1) Setting the Initial Values of the \( c_{ij}^k \) and \( p_{ij}^k \): We must avoid setting inappropriate initial values of the \( c_{ij}^k \) and \( p_{ij}^k \), which would increase the likelihood of convergence to a “small value” local maximum. We set the initial values of the \( c_{ij}^k \) and \( p_{ij}^k \) to zeros so as not to bias the optimization process.

2) Confirming the Stopping Criterion: Because of the approximation error arising from linearization, results achieved by the subproblems can keep fluctuating as the iteration evolves and no theoretical convergence is guaranteed. Therefore, we choose a threshold value \( T \) and a positive integer \( L \) to parameterize the termination of the iterations. Specifically, as the algorithm iterates, we keep monitoring and updating the maximum peak-to-peak variation of the throughput values achieved in the latest \( L \) consecutive iterations, denoted as \( V(l, \cdots, l-L+1) \), where \( l \) is the index of the latest iteration. Whenever \( V(l, \cdots, l-L+1) \) falls below the threshold \( T \), we stop the iterations and output the throughput value of iteration \( l \) as the desired one. By setting \( L > 2 \), we avoid falsely terminating the iteration when the two latest achieved throughput values are accidentally similar.

3) Reducing the Iteration Count: A small value of \( \eta \) in (16) and (19), guarantees a high linear approximation accuracy in each iteration but increases the iteration count, i.e., the number of required iterations. Therefore, we use a set of monotonically decreasing parameters \( \{\eta_m\}_{m=1}^M \), matched with a set of monotonically decreasing threshold values \( \{T_m\}_{m=1}^M \). Then the \( \eta_m \) and \( T_m \) are traversed as the iterations evolve. Together, the use of the \( \eta_m \) and \( T_m \) reduces the overall iteration count and controls the final approximation accuracy.

The pseudo code of the linearization-based approach, denoted as L-JRSPA, can be summarized as follows:

```plaintext
Set \( l = 0; \) Set \( \{c_{ij}^k[0]\} \) and \( \{p_{ij}^k[0]\} \) to zeros; Set the values of \( \{\eta_m\}_{m=1}^M \), \( \{T_m\}_{m=1}^M \) and \( L; \) for \( 1 \leq m \leq M \) do while \( V(l, \cdots, l-L+1) \geq T_m \) do
   Optimize (20) with \( \eta_m \), \( \{c_{ij}^k[l]\} \) and \( \{p_{ij}^k[l]\}; \)
   Update \( \{c_{ij}^k[l]\} \) to \( \{c_{ij}^k[l+1]\}; \)
   Optimize (21) with \( \eta_m \), \( \{c_{ij}^k[l+1]\} \) and \( \{p_{ij}^k[l]\}; \)
   Update \( \{p_{ij}^k[l]\} \) to \( \{p_{ij}^k[l+1]\}; \)
   \( l \leftarrow l+1; \)
end while
Output \( \{s_i^{(d)}[l]\}, \{c_{ij}^k[l]\}, \{x_{ij}^{(d)}[l]\}, \{p_{ij}^k[l]\}. \)
```

IV. Simulation Results

The JRSPA proposed in [11] assumes each subchannel to be accessed at a given time by only a single link in the network, and sharing of this channel among links through TDMA (we call this setting as the global TDMA scheme). In contrast, our proposed L-JRSPA assumes the use of the local CDMA
Fig. 1. Line network topology, $K = 8$, $d = N$

Fig. 2. Throughput of a line network as function of number of nodes, $N$

Fig. 3. An optimum set of reuse patterns for 8 subchannels in an infinite-node line network

compensated with spatial reuse. As $N$ increases from 2 to 4, the throughput decreases significantly due to allocating subchannels among more links. After $N$ increases beyond 4, two transmissions far apart can use the same subchannel without causing significant interference to each other, which gradually becomes a dominant factor in preventing further throughput decrease as $N$ increases.

In Fig. 2, we experientially set the parameter $L = 10$ for both of the two curves plotted under L-JRSPA, but they have different sets of controlling parameters $\{\eta_m\}_{m=1}^M$ and $\{T_m\}_{m=1}^M$. One has $[\eta_1, \eta_2] = [0.1, 0.01]$ and $[T_1, T_2] = [0.02, 0.005]$; the other has $[\eta_1, \eta_2, \eta_3] = [0.2, 0.1, 0.01]$ and $[T_1, T_2, T_3] = [0.2, 0.02, 0.005]$. Note that the two curves do not completely overlap. This can be explained by the fact that iterations with different $\{\eta_m\}_{m=1}^M$ evolve along different paths in the policy space and finally converges to distinct local optima. However, the solutions are very close numerically.

Since the throughput achieved under L-JRSPA approaches a constant as the network size grows, it is interesting to explore the difference between our (numerically obtained) stable throughput and the maximum throughput (under the local CDMA assumption) that can be achieved as the number of nodes goes to infinity. The analytically computed throughput of an infinite-node line network with settings in Sec. IV-A is 6.225, which is shown as the height of the horizontal line in Fig. 2; the corresponding optimal set of reuse patterns for the 8 subchannels are shown in Fig. 3, where the numbers represent subchannel indices. For details, see [15]. It can be seen in Fig. 2 that the obtained stable throughput is very close to the maximum throughput of the infinite-node line network.

B. Throughput of Networks with Irregular Topologies

In this subsection, we first simulate a network with the topology shown as Fig. 4. The network has 12 nodes with node 1 being the source and node 12 being the destination; the position information $(X, Y)$ coordinates) of all the nodes is listed by the following set $G$:

$$G = \{(1.0, 0.5), (1.0, 2.0), (3.0, 1.0), (2.0, 3.0), (4.5, 1.0), (3.3, 4.2), (4.7, 4.0), (5.3, 1.8), (6.0, 2.7), (7.0, 1.7), (8.0, 3.0), (7.0, 4.1)\}.$$  

Additionally, assume the network has 4 subchannels to use, each of which experiences pathloss with coefficient $\alpha = 3.5$ and independent Rayleigh fading. The mean SNR at unit distance on each subchannel is no more than 20dB. We assume that the communication duration is smaller than the coherence time of the wireless medium in the network. For the iterations, we set $L = 10$, $[\eta_1, \eta_2, \eta_3] = [0.2, 0.1, 0.01]$ and $[T_1, T_2, T_3] = [0.2, 0.02, 0.005]$.
We find that the throughput performance can be enhanced significantly when compared with the strategy of accessing each subchannel orthogonally among all links, particularly in large networks. Moreover, simulations on line networks with increasing sizes show the throughput convergence to a constant value close to the theoretical maximum throughput of a line network with infinite number of nodes.

L-JRSPA implicitly assumes centralized knowledge of the channel states and centralized control. This can be realized when the channel shows little or no time variance, since then the relative overhead for feedback and control signaling is negligible. Such situations occur, e.g., in fixed-terminal mesh networks and industrial wireless sensor networks. Distributed versions of our algorithm are topics for future research.

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REFERENCES