IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 2, 2017, accepted August 27, 2017, date of publication August 30, 2017, date of current version October 12, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2747401

Balancing Interference and Delay in Heterogeneous Ad Hoc Networks With MIMO

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This work was supported in part by the Natural Science Foundation of China under Grant 61201255 and Grant 61372077, in part by the Science and Technology Program of Guangzhou under Grant 201707010490, in part by Shenzhen Science and Technology Programs under Grant ZDSYS 201507031550105 and Grant JCYJ20170302150411789, in part by the Guangdong Provincial Science and Technology Program under Grant 2016B090918080, and in part by the Innovation Project of Graduate School of South China Normal University.

ABSTRACT Heterogeneous ad hoc networks with MIMO links can significantly improve transmission performance of the entire distributed wireless communication system. In this paper, we investigate how to increase total system throughput and decrease end-to-end delay with the help of heterogeneous characteristics of the ad hoc networks. Even if there are lots of references about distributed scheduling control considering multiple antennas, channel state, and so on, it still needs to be addressed how to guarantee destination to receive packets with a short delay. To resolve this issue, we first propose an interference-delay tradeoff method using convex optimization, which adjusts transmission rate and power to balance interference and delay. We then develop a speed power interference-based topology resource control algorithm with delay constraint to further adjust transmission power for reducing energy consumption. Simulation results show that the proposed algorithms can outperform the existing ones in terms of throughput, end-to-end delay, and power consumption.

INDEX TERMS Heterogeneous ad hoc networks, convex optimization, MIMO.

I. INTRODUCTION

Recent increasing in demands of internet and portable computers has boosted the growth of mobile devices. Traditionally, most of devices which need network connections and provide data services are connected by fixed infrastructures, such as base stations. There are many practical difficult communication problems in places without fixed infrastructures. As a result, the future of wireless networks are heterogeneous and coexisting with various wireless LANs, e.g., WiFi, wireless MAN, WiMAX, public mobile network, and ad hoc networks. Thereinto, heterogeneous ad hoc networks consist of different types of terminal equipments, access technologies, number of antennas, transmission rate and power at different terminal nodes. They can provide flexibility for wireless communication, which results in new challenges for network design and optimization.

In addition, MIMO, as a core technology of 802.11 protocol, can significantly enhance transmission reliability and data transmission rate with multiple antennas. Therefore, the combination of MIMO and heterogeneous ad hoc networks has received increasing attention recently. Chu *et al.* proposed a distributed scheduling algorithm [1] to increase system throughout and decrease transmission delay by using diverse characteristics of heterogeneous wireless network with MIMO links [2]. Wireless networks with MIMO links are interference-limited rather than noise-limited, and interference from multiple antenna users is a key point for improving the performance limits of heterogeneous ad hoc network communications [3], [4]. Although some research works have spanned over several decades, except for multiple antennas, channel state, etc., it still needs to be addressed how to guarantee destination to receive packets with a short delay [5].

In this paper, we investigate how to guarantee terminal destination nodes to receive data packets efficiently and how to reduce transmission delay accordingly. To address these issues, Zhang et al. proposed an interference-based topology resource control algorithm with delay constraint (ITCD) according to signal-to-interference-plus-noise-ratio (SINR) of receiving nodes [6]. ITCD can guarantee terminal destination nodes to receive data packets successfully with a large probability and make end-to-end delay within a threshold by adjusting transmission power. However, in our paper, we develop a speed power ITCD (SPITCD) algorithm and then compare it with ITCD. Simulation results show that SPITCD by adjusting transmission power and rate through convex optimization can improve total system throughput, end-to-end delay, and power consumption obviously.

The main contributions of this paper are as follows. First, we propose an interference-delay optimization model using convex optimization method. Secondly, we propose a SPITCD which can guarantee terminal destination nodes to receive data packets efficiently by adjusting transmission rate and power of sending nodes while ensure end-to-end delay within a threshold.

The remainder of the paper is organized as follows. Section II provides problem formulations on study background. The proposed SPITCD algorithm is detailed in Section III and Section IV presents simulation results compared with the existing schemes. Finally, Section V concludes the paper.

II. PROBLEM FORMULATION

In this section, we describe the system and delay models adopted in this paper and then formulate an interference-delay optimization model for our resource management problem.

A. SYSTEM MODEL

In heterogeneous ad hoc networks with MIMO links [1], similar with [1, eq. (3)], the maximum achievable rate of a data stream can be expressed as,

$$\mathscr{C}(s) = \log\left(1 + P_s \boldsymbol{h}_s^* \left(N_0 \boldsymbol{I}_{N_{d(s)}^{ant}} + \sum_{q \epsilon I(s)} P_q \boldsymbol{h}_q \boldsymbol{h}_q^*\right)^{-1} \boldsymbol{h}_s\right), \tag{1}$$

where $\boldsymbol{h}_s$ and $\boldsymbol{h}_q$ are channel coefficient vectors of links s and q, respectively. P_s and P_q denote transmission power. N_0 is noise variance. $\boldsymbol{I}$ denotes interference set of data streams to corresponding destination nodes, which is an identity matrix in [1] and $N_{d(s)}^{ant}$ represents antenna number of receiving data streams from destination nodes. In addition, matrix $N_i^{ant} \times N_k^{ant}$ is used to denote channel state of each antenna pair between nodes n_i and n_k. From [1], channel coefficient h_q can be represented as follows,

$$h_q = \sqrt{\frac{k}{k+1}} \sigma_l e^{j\theta} + \sqrt{\frac{1}{k+1}} \mathcal{CN}(0, \sigma_l^2), \tag{2}$$

where k is called k-factor which is defined as power ratio of light-of-sight (LOS) path to scattered path [2]. For Rayleigh channel, $k = 0$. And for $k > 0$, it is Rician channel. Here, σ_l is cyclic complex random variable of link l and θ is angle variable which is $[0, 2\pi]$.

For high SINR,

$$\mathscr{C}(s) \approx \log\left(P_s \boldsymbol{h}_s^* \left(N_0 \boldsymbol{I}_{N_{d(s)}^{ant}} + \sum_{q \epsilon I(s)} P_q \boldsymbol{h}_q \boldsymbol{h}_q^*\right)^{-1} \boldsymbol{h}_s\right). \tag{3}$$

B. DELAY MODEL

Assume a transmission path $\mathbf{p}$: $n_1, n_2, n_3, \cdots, n_{N-1}, n_N, n_i \epsilon \boldsymbol{A}$, $\boldsymbol{A}$ denotes the set of nodes in distributed heterogeneous ad hoc networks. Its end-to-end transmission delay $D_{\boldsymbol{p}}$ can be represented as [6],

$$D_{\boldsymbol{p}} = \sum_{i=1}^{N-1} (L_{(i)(i+1)} + C_i + Q_i), \tag{4}$$

where $L_{(i)(i+1)} = \frac{L}{B} + DIFS + T_{ACK} + SIFS$ is transmission delay between n_i and n_{i+1} (L is data packet length, B is data transmission rate), $DIFS$ is distributed inter-frame spacing, T_{ACK} is transmission delay of acknowledged frame, and $SIFS$ is short inter-frame spacing. C_i represents contention delay and Q_i denotes queuing delay.

C. INTERFERENCE-DELAY OPTIMIZATION MODEL

Denote s_i and r_i as transmitter and receiver, respectively. $P_{s_i r_i}$ and P_{max} are transmission power between nodes s_i and r_i and its maximum value. From [6], the SINR of destination node r_i can be expressed as,

$$SINR_{r_i} = \frac{P_{s_i r_i} \cdot \alpha_{s_i r_i}^2}{(P_{r_i}^I + \sigma_{r_i}^2) d_{s_i r_i}^{\beta}}, \quad i = 1, 2, \ldots, N, \tag{5}$$

$$P_{r_i}^I = c \cdot \sum_{s_i^{'} \neq s_i} \frac{P_{s_i^{'} r_i} \cdot \alpha_{s_i^{'} r_i}^2}{d_{s_i^{'} r_i}^{\beta}}, \tag{6}$$

where $\alpha_{s_i r_i}$ represents fading coefficient between s_i and r_i, $\sigma_{r_i}^2$ is thermal noise at destination node r_i, $d_{s_i r_i}$ denotes distance between nodes s_i and r_i, and β is signal strength decays exponentially with respect to transmission distance. In particular, $P_{r_i}^I$ is the received multiple interferences at node r_i and c is a constant coefficient. Thus, the interference-delay optimization model can be formulated as follows,

$$\begin{aligned} \min \quad & \sum_{s_i, r_i \epsilon \boldsymbol{A}, \boldsymbol{p}} P_{s_i r_i} + D_{\boldsymbol{p}}, \\ s.t. \quad & D_{T_{s_i}} \leq D_{max} \\ & 0 < P_{s_i r_i} \leq P_{max} \\ & SINR_{r_i} \geq \xi_{r_i} \\ & \sum_{s_i, r_i \epsilon \boldsymbol{A}, \boldsymbol{p}} x_{s_i} \leq \sum_{s_i, r_i \epsilon \boldsymbol{A}, \boldsymbol{p}} \mathscr{C}(s) \end{aligned} \tag{7}$$

where $D_{T_{s_i}}$ represents packet delay at transmitter node s_i and its value is limited to a threshold D_{max}. The packet will be discarded if delay exceeds the maximum value D_{max}. x_{s_i} represents transmission rate of s_i. In order to receive packets successfully, the SINR of destination node r_i should go beyond threshold parameter ξ_{r_i}. Our aim is to obtain the best transmission rate and power under the minimal value of objective function (7) in terms of power consumption and end-to-end delay.

In fact, the obtained interference-delay optimization model is a constrained optimization problem which can be transformed to a dual problem in order to be addressed easily. It can be also rewritten as $D : \min \sum_{\lambda,\mu\geq 0} D(\lambda,\mu)$, where the objective function of dual problem is $D(\lambda,\mu) = max_{x_{s_i,P_{s_ir_i}}} L(\lambda,\mu,x_{s_i,P_{s_ir_i}})$ and its corresponding Lagrangian function can be represented as,

$$L(\lambda,\mu,x_{s_i,P_{s_ir_i}}) = \sum_{s_i,r_i\epsilon \boldsymbol{A},\boldsymbol{p}} (P_{s_ir_i} + \sum_{i=1}^{N-1}(\frac{L}{x_{s_i}} + DIFS + T_{ACK} + SIFS + C_i + Q_i) + \lambda(\xi_{r_i} - \frac{P_{s_ir_i}\cdot\alpha^2_{s_ir_i}}{Z_{s_i'r_i}d^{\beta}_{s_ir_i}}) + \mu(x_{s_i} - \log(P_{s_ir_i}\boldsymbol{h}^*_{s_ir_i}(N_0\boldsymbol{I}_{N^{ant}_{d(s)}} + \sum_{s_i'r_i\in I(s_i)} P_{s_i'r_i}\hat{\mathbf{B}}_{s_i'r_i})^{-1}\boldsymbol{h}_{s_ir_i}))), \quad (8)$$

where λ and μ are two different dual variances whose values are no less than zero, $Z_{s_i'r_i} = P^I_{r_i} + \sigma^2_{r_i}$, and $\hat{\mathbf{B}}_{s_i'r_i} = \boldsymbol{h}_{s_i'r_i}\boldsymbol{h}^*_{s_i'r_i}$. More specifically, in order to simplify the calculation process and solve the optimization problem with different variances, the converted two dual sub-problems can be represented as follows,

$$D_1(\mu,x_{s_i}) = \sum_{s_i,r_i\epsilon \boldsymbol{A},\boldsymbol{p}} (\sum_{i=1}^{N-1}(\frac{L}{x_{s_i}} + DIFS + T_{ACK} + SIFS + C_i + Q_i) + \mu x_{s_i}) \quad (9)$$

$$D_2(\mu,\lambda,P_{s_ir_i}) = \sum_{s_i,r_i\epsilon \boldsymbol{A},\boldsymbol{p}} (P_{s_ir_i} + \lambda(\xi_{r_i} - \frac{P_{s_ir_i}\cdot\alpha^2_{s_ir_i}}{Z_{s_i'r_i}d^{\beta}_{s_ir_i}}) - \mu\log(P_{s_ir_i}\boldsymbol{h}^*_{s_ir_i}(N_0\boldsymbol{I}_{N^{ant}_{d(s)}} + \sum_{s_i'r_i\in I(s_i)} P_{s_i'r_i}\hat{\mathbf{B}}_{s_i'r_i})^{-1}\boldsymbol{h}_{s_ir_i})) \quad (10)$$

As mentioned above, we can exploit a gradient descent algorithm to obtain the optimal rate $x^*_{s_i}$ and the optimal transmission power $P^*_{s_ir_i}$ with convex optimization method.

Lemma 1: The objective function of $D_1(\mu,x_{s_i})$ is a convex function.

Proof: With the help of Sherman-Morrison [7], we can easily obtain,

$$\frac{\partial^2 D_1(\mu,x_{s_i})}{\partial x^2_{s_i}} = \sum_{s_i,r_i\epsilon A}\sum_{i=1}^{N-1}\frac{2L}{x^3_{s_i}} > 0. \quad (11)$$

It shows that the second derivative of $D_1(\mu,x_{s_i})$ is more than zero and the objective function of $D_1(\mu,x_{s_i})$ is a convex function according to Convex Optimization of Boyd S [8]. ■

Lemma 2: The objective function of $D_2(\mu,\lambda,P_{s_ir_i})$ is a convex function.

Proof:

$$\frac{\partial^2 D_2(\mu,\lambda,P_{s_ir_i})}{\partial P^2_{s_ir_i}} = \mathbf{H}_{ss} = \sum_{s_i,r_i\epsilon \boldsymbol{A},\boldsymbol{p}} \lambda\cdot(\frac{2P^I_{r_i}\alpha^2_{s_ir_i}\sigma^2_{r_i}}{(Z_{s_i'r_i})^3 d^{\beta}_{s_ir_i}}) + \mu(\frac{1}{P^2_{s_ir_i}} + (\frac{\widetilde{\mathbf{B}}_{s_ir_i}}{1+(\sum_{s_i'r_i}P_{s_i'r_i})\widetilde{\mathbf{B}}_{s_i'r_i}})^2 - (\frac{\widetilde{\mathbf{B}}_{s_ir_i} - \hat{\mathbf{B}}_{s_ir_i}}{1+(\sum_{s_i'r_i}P_{s_i'r_i})\widetilde{\mathbf{B}}_{s_i'r_i} - (\sum_{s_i'r_i}P_{s_i'r_i})\hat{\mathbf{B}}_{s_i'r_i}})^2) \approx \sum_{s_i,r_i\epsilon \boldsymbol{A},\boldsymbol{p}} (\lambda\cdot(\frac{2P^I_{r_i}\alpha^2_{s_ir_i}\sigma^2_{r_i}}{(Z_{s_i'r_i})^3 d^{\beta}_{s_ir_i}}) + \mu\cdot\frac{1}{P^2_{s_ir_i}}). \quad (12)$$

where $\widetilde{\mathbf{B}}_{s_i'r_i} = \boldsymbol{h}^*_{s_i'r_i}\boldsymbol{h}_{s_i'r_i}$.

From [8], for all vectors $\mathbf{X}$, the Hessian matrix $\mathbf{H}_{ss}$ is indeed positive definite:

$$\mathbf{X}^T\mathbf{H}_{ss}\mathbf{X} > 0. \quad (13)$$

Thus, we can obtain that the objective function of $D_2(\mu,\lambda,P_{s_ir_i})$ is a convex function. ■

In the following, we will use gradient descent algorithm to obtain the optimal transmission rate $x^*_{s_i}$ and power $P^*_{s_ir_i}$.

$$\lambda(n+1) = [\lambda(n) + k_\lambda\cdot\frac{\partial L(\lambda,\mu,x_{s_i,P_{s_ir_i}})}{\partial\lambda}]^+ = [\lambda(n) + k_\lambda\cdot(\xi_{r_i} - \frac{P_{s_ir_i}\cdot\alpha^2_{s_ir_i}}{Z_{s_i'r_i}d^{\beta}_{s_ir_i}})]^+, \quad (14)$$

$$\mu(n+1) = [\mu(n) + k_\mu\cdot\frac{\partial L(\lambda,\mu,x_{s_i,P_{s_ir_i}})}{\partial\mu}]^+ = [\mu(n) + k_\mu\cdot(x_{s_i} - \log(P_{s_ir_i}\boldsymbol{h}^*_{s_ir_i}(N_0\boldsymbol{I}_{N^{ant}_{d(s_i)}} + \sum_{s_i'r_i\in I(s_i)} P_{s_i'r_i}\hat{\mathbf{B}}_{s_i'r_i})^{-1}\boldsymbol{h}_{s_ir_i}))]^+. \quad (15)$$

Let $\frac{\partial D_1(\mu,x_{s_i})}{\partial x_{s_i}} = 0$, we can obtain,

$$x_{s_i}(n+1) = \sum_{s_i,r_i\epsilon \boldsymbol{A},\boldsymbol{p}}\sum_{i=1}^{N-1}\sqrt{\frac{L}{\mu(n+1)}}, \quad (16)$$

$$P_{s_ir_i}(n+1) = [P_{s_ir_i}(n) + k_p\cdot\frac{\partial D_2(\mu,\lambda,P_{s_ir_i})}{\partial P_{s_ir_i}}]^+ = [P_{s_ir_i}(n) + k_p\cdot(\sum_{s_i,r_i\epsilon \boldsymbol{A},\boldsymbol{p}}(1-\lambda(n)\cdot(\frac{\alpha^2_{s_ir_i}\cdot Z_{s_i'r_i} - P_{s_ir_i}(n)\cdot\alpha^2_{s_ir_i}\cdot S_A}{(Z_{s_i'r_i})^2\cdot d^{\beta}_{s_ir_i}})$$

$$
\begin{aligned}
&-\mu(n)\cdot(\frac{1}{P_{s_ir_i}(n)} \\
&+\frac{\widetilde{\mathbf{B}}_{s_ir_i}-\hat{\mathbf{B}}_{s_ir_i}}{1+(\sum_{s_i^{\prime}r_i}P_{s_i^{\prime}r_i})\widetilde{\mathbf{B}}_{s_i^{\prime}r_i}-(\sum_{s_i^{\prime}r_i}P_{s_i^{\prime}r_i})\hat{\mathbf{B}}_{s_i^{\prime}r_i}} \\
&-\frac{\widetilde{\mathbf{B}}_{s_ir_i}}{1+(\sum_{s_i^{\prime}r_i}P_{s_i^{\prime}r_i})\widetilde{\mathbf{B}}_{s_i^{\prime}r_i}})))]^+, \qquad (17)
\end{aligned}
$$

where k_λ, k_μ, and k_p are step factors, respectively. The objective function can obtain a minimum value when λ and μ iterate to their optimal values. Hence, the optimal value x_{s_i} and $P_{s_ir_i}$ can be obtained.

III. ALGORITHM

A. SPITCD ALGORITHM

In order to receive data packets efficiently and control transmission delay within a threshold, SPITCD algorithm, as shown in Alg.1, can satisfy the above constraints and reduce power as much as possible by adjusting transmission rate and power of senders. For every path $\boldsymbol{p}$, every sending node selects receiver with the highest SINR among neighboring nodes. However, the transmission delay $D_{T_{r_i}}$ between sending and receiving nodes can not exceed their connection time and mobility of terminal nodes will not destroy data transmission (line 2). Following this, SPITCD algorithm iterates the optimal rate and power according to each link's SINR under constraints of interference and delay (line 3-6). Then, transmission power of each link will be decreased as much as possible under the distributed wireless network circumstance. When the actual transmission time T_i satisfies $T_i < D_{max}$ and the initial value of t_b is zero, transmission power can be decreased by increasing $D_{max} - T_i$ (line 12-14). On the other hand, if T_i exceeds D_{max}, transmission power can be increased by factor $(1 + w)$ which enables delay under the constraint of D_{max} (line 17-19). However, since increasing transmission power means increasing transmission range, it will bring in interference from nearby sending nodes. Therefore, a trade-off between increasing power and decreasing delay needs to be considered.

Algorithm 1 SPITCD

1: Path P: $S, ..., i-1, i, i+1, ..., R$; $P_{pre} = P_{max}$;
2: Forwarder i selects stable links which satisfy $D_{T_{r_i}} < T_{M_{r_i}}$
3: $\lambda_{s_i}(n+1) = [\lambda_{s_i}(n) + k_\lambda.\frac{\partial L(\lambda,\mu,x_{s_i},P_{s_ir_i})}{\partial\lambda}]^+$;
4: $\mu_{s_i}(n+1) = [\mu_{s_i}(n) + k_\mu.\frac{\partial L(\lambda,\mu,x_{s_i},P_{s_ir_i})}{\partial\mu}]^+$;
5: $x_{s_i(n+1)} = \sum_{s_ir_i\in A}\sum_{i=1}^{N-1}\cdot\sqrt{\frac{L}{\mu_{s_i}(n+1)}}$;
6: $P_{s_ir_i}(n+1) = [P_{s_ir_i}(n) + k_P.\frac{\partial D_2(\lambda,\mu,P_{s_ir_i})}{\partial P_{s_ir_i}}]^+$;
7: **while** $(P_{s_ir_i} \le P_{max})$ and $(D_{T_{s_ir_i}} \le D_{max})$ do
8: { minimizing the power consumption while satisfying the interference constrain }
9: $SINR_{r_i} = \frac{P_{s_ir_i}.\alpha^2_{s_ir_i}}{(P^I_{r_i}+\sigma^2_{r_i})d^\beta_{s_ir_i}}$;
10: $P_{s_ir_i} = P_{s_ir_i}\cdot\frac{\xi_{r_i}}{SINR_{r_i}}$;
11: { adjusting D_{max} with the balancing factor t_b}
12: if $(T_i < D_{max})$ then
13: $t_b+ = D_{max} - T_i$;
14: $D_{max}+ = t_b$;
15: end if
16: { link(s_i, r_i) can not meet the requirement for delay, $D_{T_{s_ir_i}} > D^r_s$, and increase the transmission range. }
17: if $(D_{T_{s_ir_i}} > D_{max})$ or $(T_i > D_{max})$ then
18: $P_{s_ir_i} = min(P_{s_ir_i}(1+w), P_{pre})$;
19: $P_{pre} = P_{s_ir_i}$;
20: end if
21: **end while**

B. DISTRIBUTED RESOURCE SCHEDULING ALGORITHM WITH SPITCD

In distributed resource scheduling algorithm, firstly, we should estimate information of channel state, antenna number, and size of data streams. And then, we ask the transmitter to select the best transmission pattern according to its demodulation ability. Finally, source node transmits data streams to destination via different resource scheduling strategies. Here, transmission nodes are sorted into poor nodes when $X^{TX}_i < T^{TX}_i$ and rich nodes when $X^{TX}_i >= T^{TX}_i$. Poor nodes can be transmitters and receivers but rich nodes are only receiving nodes. $X^{TX}_i = (\bar{\mathscr{P}}_i - \hat{\mathscr{P}}_i)/\bar{\mathscr{P}}_i + \gamma_i$ represents an indication of whether a node n_i can be selected as a transmitting node. $\mathscr{P}(s_{iq})$ is the priority of the q-th data stream of node n_i and $\mathscr{P}_i = \sum_{s_{iq}\in S_i}\mathscr{P}(s_{iq})/|S_i|$. $\bar{\mathscr{P}}_i = \sum_{j=1}^{N_j^{active}}\mathscr{P}_i/N_j^{active}$ denotes the average priority of all active nodes in neighbor node set of n_i. N_j^{active} is the set of active neighbor nodes of n_i. $\hat{\mathscr{P}}_i$ is the average priority of all streams which are transmitted to neighbor nodes and γ_i represents a random number whose range is [0,1]. Moreover, $T^{TX}_i = \{1, min_{j\in\mathscr{V}_i}(\mathcal{N}^{rc}_j/\mathcal{N}^a_j ctive)\}$ denotes the capacity of neighbor nodes of n_i, where $\mathcal{N}^{rc}_j$ represents the maximum value of receiving data streams of n_j and $\mathscr{V}_i$ is the set of neighbor nodes of n_i. Obviously, the greater of T^{TX}_i, the bigger demodulation ability of n_i. In this case, the node with the highest priority looks for the optimal receiving nodes among its neighboring nodes and chooses an appropriate transmission pattern (poor slot or rich slot) to fulfill its communication.

As shown in Alg.2, $A_i{}^{res}$ is the remaining antenna set of n_i and A_i is its full set of n_i. N_i^{res} represents the residual stream number to assign and N_i^{allo} denotes the stream number of n_i assigned to transmit. $DES^j_i(q)$ represents the q-th stream of destination node n_i with the j-th highest priority level (j=1 is the highest level). N_k^{dec} is the number of data streams and N_k^{rc} is the maximum receiving data streams of n_k. The transmitter selects poor slot or rich slot to transmit data streams according to the demodulation ability of its receiving node n_k (line 3-9). When $N_k^{rc} - N_k^{dec} > 0$, it is proven that n_k can receive all

Algorithm 2 Distributed Scheduling Algorithm Equipped With SPITCD

1: **Initialize**:$j = 1$, $\{A_i\}^{res} = \{A_i\}$, $N_i^{res} = N_i^{allo}$
2: **while** $N_i^{res} > 0$
3: **if** $|\{DES_i^j\}| \leq N_i^{res}$
4: $OPP\_ALLOC(\{A_i\}^{res}, \{DES_i^j\}, |\{DES_i^j\}|, N_i^{res})$
5: $N_i^{res} = N_i^{res} - |\{DES_i^j\}|$
6: **else**
7: $OPP\_ALLOC(\{A_i\}^{res}, \{DES_i^j\}, N_i^{res}, 0)$
8: $N_i^{res} = 0$
9: **end if**
10: $j \Leftarrow j + 1$
11: **end while**
12: **end**

Algorithm 3 OPP_ALLOC($\{A_i\}^{res}$, $\{DES_i^j\}$, k, N_i^{res})

1: **Initialize:** $l = 0$
2: $W_i^j = \{\mathscr{C}(i, DES_i^j(q), A_i^{res}(p))|A_i^{res}(p) \in \{A_i\}^{res},$
3: $DES_i^j(q) \in \{DES_i^j\}, p = 1, \ldots, |\{A_i\}^{res}|, q =$ $1, \ldots, |\{DES_i^j\}|$
4: **while** $l < k$
5: $W_{max} \Leftarrow maxW_i^j$, $\{A_{max}, DES_{max}\} \Leftarrow argmax\ W_i^j$
6: $W_i^j \Leftarrow W_i^j \backslash \{W(A_{max}), DES_i^j(q))|DES_i^j(q)) \in$ $\{DES_i^j\}, q =$
7: $1, \ldots, |\{DES_i^j\}|\}$; if there is no other stream target for the
8: receiver node DES_{max}, also remove
9: $\{W(A_i^{res}(p), DES_{max})|A_i^{res}(p) \in \{A_i\}^{res}, p =$
10: $1, \ldots, |\{A_i\}^{res}|\}$;
11: Allocate the stream for the receiver DES_{max} to antenna
12: A_{max}, every antenna uses $x_{s_i}^*$ and $P_{s_i}^*$ to transmit
13: **if** DES_{max} has sent indicator of weak channel
14: **if** $N_i^{res} > 0$
15: $k \Leftarrow k - 1, l \Leftarrow l + 1, N_i^{res} \Leftarrow N_i^{res} - 1$;
16: **else** $\{N_i^{res} = 0\}$
17: $k \Leftarrow k - 1$
18: **end if**
19: **end if**
20: $\{A_i\}^{res} \Leftarrow \{A_i\}^{res} \backslash A_{max}$
21: $l \Leftarrow l + 1$
22: **end while**

data streams which are sent by n_i and n_i can choose rich slot to transmit data streams. Otherwise, n_i only uses poor slot. Line 4-5 and line 7-8 are poor and rich slots, respectively, which is implemented by OPP_ALLOC, as shown in Alg.3.

In Alg.3, at first, the transmitter chooses data stream with the highest priority to its destination with the highest priority too (line 4-6). W_i^j represents the data stream set with the j-th highest priority of n_i. k is the number of antennas with the j-th highest priority and l is the number of antennas currently allocated. A_{max}^* denotes the selected optimal antenna. It is worth mentioning that two cases should be removed. One situation is that $A_i{}^{res}$ has the highest priority but $DES_i^j(q)$ is not. The other situation is that $DES_i^j(q)$ has the highest priority and $A_i{}^{res}$ is not. Then, the selected antennas send data streams to their receivers with the optimal rate $x_{s_i}^*$ and the optimal power $p_{s_i}^*$ which is iterated by SPITCD algorithm (line 11-12).

Specially, similar to 802.11, transmitters should ensure the channel busy or not by carrier sense multiple access with collision detection (CSMA/CA). In line 14-18, when receiving node is in the weak channel, we can reduce an antenna to increase the transmission powers of the residual antennas to reduce loss probability of packets. After that, it will search for the next highest priority data stream until all data streams of source node can be scheduled reasonably. This algorithm will take channel conditions and other issues into account and adopt appropriate treatments to further improve the quality of communication.

IV. RESULT ANALYSIS

In this paper, 100 nodes are distributed over a 1250 m × 1250 m area randomly which forms an ad-hoc network. The transmission range of mobile nodes is set to be 250m and the maximum power of node is 0.8 W. One data packet is 1000 bytes. In case of SINR (ξ_i) is no less than 10, the data packets can be received correctly.

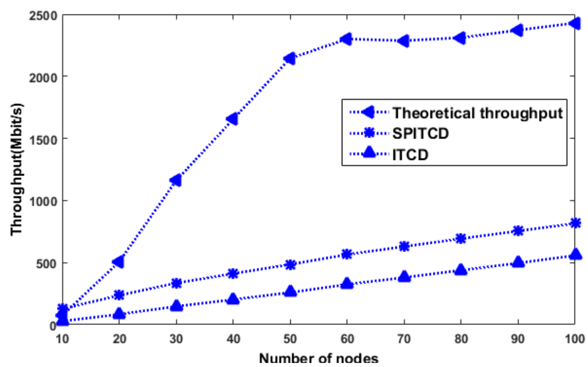

FIGURE 1. Impact of node density on throughput.

1) IMPACT OF MEAN ANTENNA ARRAY SIZE

As shown in Fig.1, the theoretical value of system throughput is higher than SPITCD and ITCD algorithm. The reason is that both SPITCD and ITCD consider whether data packets can be received successfully. The system throughput rises as increasing of nodes which will bring out increasing number of links. At the beginning, the theoretical value of throughput is rising when the number of nodes increases. However, at last, it reaches to saturation since the number of nodes has got to a bottleneck. Furthermore, the system throughput of SPITCD is 32% higher than ITCD when adjusting transmission rate and power properly. Similarly, in Fig.2, the transmission power consumption of SPITCD is 15% less than ITCD and the end-to-end delay of SPITCD is 30% less than ITCD as shown in Fig.3.

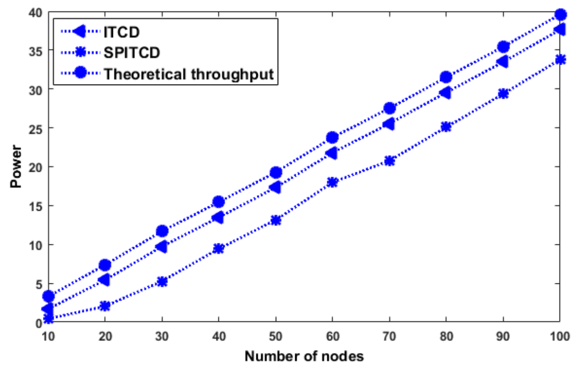

FIGURE 2. Impact of node density on power consumption.

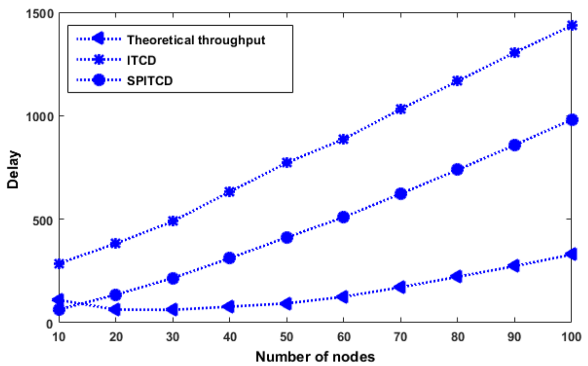

FIGURE 3. Impact of node density on delay.

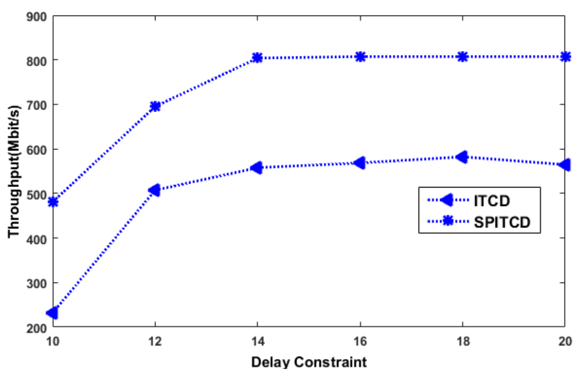

FIGURE 4. Impact of delay constraint on throughput.

2) IMPACT OF DELAY CONSTRAINT

The delay constraint affects whether destination node can receive data packets successfully which will also have impact on system throughput and transmission power consumption. As increasing delay constraint, the probability of receiving data packets efficiently by adjusting transmission power is decreased, resulting in that transmission power is decreasing and system throughput is increasing, as shown in Fig.4 and Fig.5. In addition, in Fig.4, transmission power consumption of SPITCD is 31% less than ITCD. And for the same reason, in Fig.5, the end-to-end delay of SPITCD is 18% less than ITCD.

The above simulation results testify that both node density and delay constraint effect the system performance.

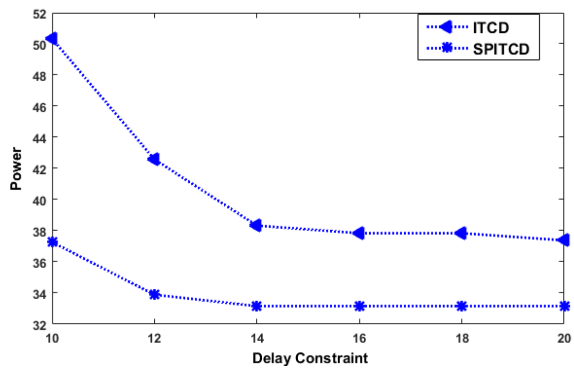

FIGURE 5. Impact of delay constraint on power consumption.

By adjusting transmission rate and power into proper values, our proposed SPITCD can obtain better system throughput, end-to-end delay, and power consumption obviously. If it is not the case, lots of antenna data flows will quit the transmission directly according to interference policy.

V. CONCLUSION

To improve resource efficiency and transmission reliability of distributed heterogeneous ad hoc networks with MIMO links, we have proposed an interference-delay optimization model that can get the optimal transmission rate and power via convex optimization method under balancing of interference and delay. On the basis of delay constraints, a novel SPITCD algorithm was presented by readjusting transmission power and rate under the proposed interference-delay optimization model. Simulation results have shown that SPITCD improves the system throughput, end-to-end delay, and power consumption compared with ITCD and performs well in our distributed wireless ad hoc networks with MIMO links.

APPENDIX A
CONVERGENCE ANALYSIS OF POWER CONTROL

It will be proven that the objective function must have continuous property of Lipschitz constant when the norm of Hessian matrix has upper bound [9]. Thus, the power control scheme is convergent. The upper bound can be written as follows,

$$\|H\|_2 \leq \sqrt{\|H\|_1 \|H\|_\infty} \tag{18}$$

where $\|H\|_1 = \max_j \sum_i \mid H_{ij} \mid$ and $\|H\|_\infty = \max_i \sum_j \mid H_{ij} \mid$.

The Hessian matrix of $D_2(\mu, \lambda, P_{s_ir_i})$ can be represented as,

$$\begin{aligned}\mathbf{H}_{ss} = &\sum_{s_i, r_i \epsilon A} \lambda \cdot \Big(\frac{2P^I_{r_i}\alpha^2_{s_ir_i}\sigma^2_{r_i}}{(Z_{s_i^{'}r_i})^3 d^{\beta}_{s_ir_i}}\Big) + \mu\Big(\frac{1}{P^2_{s_ir_i}} \\ &+ \Big(\frac{\widetilde{\mathbf{B}}_{s_ir_i}}{1+(\sum_{s_i^{'}r_i} P_{s_i^{'}r_i})\widetilde{\mathbf{B}}_{s_i^{'}r_i}}\Big)^2 \\ &- \Big(\frac{\widetilde{\mathbf{B}}_{s_ir_i} - \hat{\mathbf{B}}_{s_ir_i}}{1+(\sum_{s_i^{'}r_i} P_{s_i^{'}r_i})\widetilde{\mathbf{B}}_{s_i^{'}r_i} - (\sum_{s_i^{'}r_i} P_{s_i^{'}r_i})\hat{\mathbf{B}}_{s_i^{'}r_i}}\Big)^2\Big),\end{aligned} \tag{19}$$

$$\mathbf{H}_{sj} = \sum_{j_i \neq s_i} -\lambda \cdot \Big(\frac{-\alpha^2_{s_ir_i} \cdot P^{I'}_{r_i}}{(Z_{s'_ir_i})^2 d^{\beta}_{s_ir_i}} + \frac{2\alpha^2_{s_ir_i} \cdot P^{I}_{r_i} \cdot P^{I'}_{r_i} \cdot P_{s_ir_i}}{(Z_{s'_ir_i})^3 d^{\beta}_{s_ir_i}} \Big) - \mu\Big(\frac{(\widetilde{\mathbf{B}}_{s_ir_i})(\widetilde{\mathbf{B}}_{j_ir_i})}{(1+(\sum_{s'_ir_i} P_{s'_ir_i})\widetilde{\mathbf{B}}_{s'_ir_i})^2} - \frac{(\widetilde{\mathbf{B}}_{s_ir_i} - \hat{\mathbf{B}}_{s_ir_i})(\widetilde{\mathbf{B}}_{j_ir_i} - \hat{\mathbf{B}}_{j_ir_i})}{(1+(\sum_{s'_ir_i} P_{s'_ir_i})\widetilde{\mathbf{B}}_{s'_ir_i} - (\sum_{s'_ir_i} P_{s'_ir_i})\hat{\mathbf{B}}_{s'_ir_i})^2} \Big), \quad (20)$$

where $P^{I'}_{r_i} = c \cdot \sum_{j_i \neq s_i} \frac{\alpha^2_{j_ir_i}}{d^{\beta}_{j_ir_i}}$.

Eventually, the power control scheme is convergent when step factor k_p satisfies $\varepsilon \leq k_p \leq (2-\varepsilon)/L$, where $\varepsilon > 0$ and L is Lipschitz constant which can be represented as,

$$\begin{aligned}(L)^2 = max_j &\sum_{s_i,r_i \epsilon A} \Big(-\lambda \cdot \Big(\frac{-\alpha^2_{s_ir_i} \cdot S'_A}{(Z_{s'_ir_i})^2 d^{\beta}_{s_ir_i}} + \frac{2\alpha^2_{s_ir_i} \cdot S_A \cdot S'_A \cdot P_{s_ir_i}}{(Z_{s'_ir_i})^3 d^{\beta}_{s_ir_i}}\Big) - \mu\Big(\frac{(\widetilde{\mathbf{B}}_{s_ir_i})(\widetilde{\mathbf{B}}_{j_ir_i})}{(1+(\sum_{s'_ir_i} P_{s'_ir_i})\widetilde{\mathbf{B}}_{s'_ir_i})^2} - \frac{(\widetilde{\mathbf{B}}_{s_ir_i} - \hat{\mathbf{B}}_{s_ir_i})(\widetilde{\mathbf{B}}_{j_ir_i} - \hat{\mathbf{B}}_{j_ir_i})}{(1+(\sum_{s'_ir_i} P_{s'_ir_i})\widetilde{\mathbf{B}}_{s'_ir_i} - (\sum_{s'_ir_i} P_{s'_ir_i})\hat{\mathbf{B}}_{s'_ir_i})^2}\Big) \\
&+ \mid \lambda \cdot \Big(\frac{2S_A\alpha^2_{s_ir_i}\sigma^2_{r_i}}{(Z_{s'_ir_i})^3 d^{\beta}_{s_ir_i}}\Big) + \Big(\frac{1}{P^2_{s_ir_i}} + \Big(\frac{\widetilde{\mathbf{B}}_{s_ir_i}}{1+(\sum_{s'_ir_i} P_{s'_ir_i})\widetilde{\mathbf{B}}_{s'_ir_i}}\Big)^2 - \Big(\frac{\widetilde{\mathbf{B}}_{s_ir_i} - \hat{\mathbf{B}}_{s_ir_i}}{1+(\sum_{s'_ir_i} P_{s'_ir_i})\widetilde{\mathbf{B}}_{s'_ir_i} - (\sum_{s'_ir_i} P_{s'_ir_i})\hat{\mathbf{B}}_{s'_ir_i}}\Big)^2 \mid\Big) \\
\times max_s &\sum_{s_i,r_i \epsilon A} \Big(-\lambda \cdot \Big(\frac{-\alpha^2_{s_ir_i} \cdot S'_A}{(Z_{s'_ir_i})^2 d^{\beta}_{s_ir_i}} + \frac{2\alpha^2_{s_ir_i} \cdot S_A \cdot S'_A \cdot P_{s_ir_i}}{(Z_{s'_ir_i})^3 d^{\beta}_{s_ir_i}}\Big) - \mu\Big(\frac{(\widetilde{\mathbf{B}}_{s_ir_i})(\widetilde{\mathbf{B}}_{j_ir_i})}{(1+(\sum_{s'_ir_i} P_{s'_ir_i})\widetilde{\mathbf{B}}_{s'_ir_i})^2} - \frac{(\widetilde{\mathbf{B}}_{s_ir_i} - \hat{\mathbf{B}}_{s_ir_i})(\widetilde{\mathbf{B}}_{j_ir_i} - \hat{\mathbf{B}}_{j_ir_i})}{(1+(\sum_{s'_ir_i} P_{s'_ir_i})\widetilde{\mathbf{B}}_{s'_ir_i} - (\sum_{s'_ir_i} P_{s'_ir_i})\hat{\mathbf{B}}_{s'_ir_i})^2}\Big) \\
&+ \mid \lambda \cdot \Big(\frac{2S_A\alpha^2_{s_ir_i}\sigma^2_{r_i}}{(Z_{s'_ir_i})^3 d^{\beta}_{s_ir_i}}\Big) + \Big(\frac{1}{P^2_{s_ir_i}} + \Big(\frac{\widetilde{\mathbf{B}}_{s_ir_i}}{1+(\sum_{s'_ir_i} P_{s'_ir_i})\widetilde{\mathbf{B}}_{s'_ir_i}}\Big)^2 - \Big(\frac{\widetilde{\mathbf{B}}_{s_ir_i} - \hat{\mathbf{B}}_{s_ir_i}}{1+(\sum_{s'_ir_i} P_{s'_ir_i})\widetilde{\mathbf{B}}_{s'_ir_i} - (\sum_{s'_ir_i} P_{s'_ir_i})\hat{\mathbf{B}}_{s'_ir_i}}\Big)^2 \mid\Big).\end{aligned} \quad (21)$$

APPENDIX B
CONVERGENCE ANALYSIS OF RATE CONTROL

When μ converges to the optimal value μ^*, x_{s_i} converges to the optimal value $x^*_{s_i}$ correspondingly. Thus, μ and x_{s_i} have the same convergence characteristics. We will prove that rate control scheme is convergent when k_μ satisfies $0 < k_\mu < 2/k$, where k denotes Lipschitz constant [10], as follows.

One of the dual variances is $\mu = (\mu_1, \mu_2, \mu_3, \cdots \mu_L)^T$. Taking a derivative to dual problem $D(\lambda, \mu)$ with respect to μ, we can obtain,

$$\nabla_\mu D = Rx_{s_i} - \log(P_{s_ir_i}\boldsymbol{h}^*_{s_ir_i}(N_0\boldsymbol{I}_{N^{ant}_{d(s)}} + \sum_{s'_ir_i \in I(s)} P_{s'_ir_i}\hat{\mathbf{B}}_{s'_ir_i})^{-1}\boldsymbol{h}_{s_ir_i}), \quad (22)$$

where $\boldsymbol{R}$ denotes route matrix. The corresponding links will transmit data streams when element of matrix R_{ij} is equal to 1. Furthermore,

$$\|\nabla D(\mu(n)) - \nabla D(\mu(n+1))\|_2 \leq S_R\|x_{s_i}(\mu^s(n)) - x_{s_i}(\mu^s(n+1))\|_F. \quad (23)$$

From the above expression, $\|\cdot\|$ represents matrix norm and $S_R = \|R\|$, $\|\cdot\|_F$ is F-norm. $\mu(n)$ also is called congestion price and $\mu^s(n) = \sum_{s_i,r_i \epsilon A} \mu(n)$ is the sum of congestion price. In this paper, we define $t^1 = \mu^s(n)$, $t^2 = \mu^s(n+1)$, $x_{s_i}(n) = \sum_{s_i,r_i \epsilon A} \sum_{i=1}^{N-1} \sqrt{\frac{L}{\mu(n)}}$ and $V^t_s(t) = f(\mu^s(n))$. Thus, we can obtain,

$$\|x_{s_i}(\mu^s(n)) - x_{s_i}(\mu^s(n+1))\|_F \leq max \mid V'_s(t^{max}_s) \mid \cdot \|t^1 - t^2\|_F, \quad (24)$$

$$\|t^1 - t^2\|_F \leq 2S_R max(S_R) max \mid V'_s(t^{max}_s) \mid \cdot \|\mu(n) - \mu(n+1)\|_2, \quad (25)$$

$$\|\nabla D(\mu(n)) - \nabla D(\mu(n+1))\|_2 \leq 2S_R max(S_R) \cdot max \mid V'_s(t^{max}_s) \mid \cdot \|\mu(n) - \mu(n+1)\|_2. \quad (26)$$

Finally, we can obtain that $k = 2S_R max(S_R) \times 2max \mid V'_t(t^{max}) \mid$ and our proposed rate control scheme is convergent.

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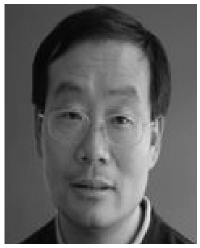

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