Channel Aware Distributed Scheduling For Exploiting Multi-Receiver Diversity and Multiuser Diversity in Ad-Hoc Networks: A Unified PHY/MAC Approach

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***Abstract*—We study channel aware distributed scheduling in ad hoc networks where many links contend for the common channel using random access, and the focus here is on the model where each transmitter node has multiple intended receivers. In such a network, channel probing takes place in two phases: 1) in phase I, all transmitters contend for the channel using random access to reserve the channel, and the probing to accomplish a successful channel contention takes a *random duration*; and 2) in phase II, subsequent probings are carried out to estimate the link conditions from the successful transmitter in phase I to its intended receivers, according to specific probing mechanisms, and the probing for each receiver takes a *constant duration*. In this paper, we shall study various probing mechanisms for utilizing multi-receiver diversity in phase II and multiuser diversity in phase I for ad hoc (peer-to-peer) communications.**

Clearly, further probing increases the likelihood of seeing better channel conditions for exploiting diversities, but at the cost of additional time. Therefore, channel probing must be done efficiently to balance the tradeoff between the throughput gain from better channel conditions and the probing cost. One main objective of this study is to characterize this tradeoff in a stochastic decision making framework. Specifically, we cast network throughput optimization as an optimal stopping problem, and then explore channel aware distributed scheduling to leverage multi-receiver diversity and multiuser diversity in a joint manner. We show that the optimal scheduling policies for all proposed probing mechanisms exhibit threshold structures, indicating that they are amenable to easy distributed implementation. We show that the optimal thresholds and the maximum network throughput can be obtained off-line by solving fixed point equations. We further develop iterative algorithms to compute the optimal thresholds and the throughput.

I. Introduction

The optimal design of wireless ad-hoc networks faces a number of unique challenges in wireless communications, including co-channel interference and time varying channel conditions. The combination of interference and channel fading may result in a higher order of packet losses in wireless networks. More specifically,

1) *Co-channel interference*: The shared nature of wireless medium may result in transmission failure due to co-channel interference from other transmissions. Collision resolution and interference management are regarded as the functionalities of the medium access control (MAC) layer, and are typically handled by scheduling or random access protocols.

2) *Channel Fading*: Fading is the time variation of the wireless channel due to two effects: large-scale path loss and shadowing effects that cause the signal to attenuate with distance; and multipath scattering effects that result in delayed copies of the signal adding up constructively or destructively at the receiver. Fading is often mitigated at the physical layer using coding/modulation and diversity techniques.

The traditional approach for wireless network design intends to separate link losses caused by fading from those by interference. That is, the PHY layer addresses the issues of fading, while the MAC layer addresses the issue of contention. This hope for separation of point-to-point link reliability and multiple access functionality between the PHY and MAC layers relies on the implicit assumption that the PHY layer works perfectly and hides fading from MAC. However, it is difficult to determine if packet losses are due to MAC-layer variation or channel variation. Indeed, as shown in [3] and our experimental measurements [8], fading can often adversely affect the MAC layer in many realistic scenarios. In a nutshell, channel fading and interference occur on the same time scales.

The coupling between the timescales of fading and MAC calls for a unified PHY/MAC design for wireless ad-hoc networks, in order to achieve greater operational efficiencies vis-a-vis throughput and latency. Indeed, joint PHY/MAC diversities, including multiuser diversity, multi-receiver diversity, time diversity and spatial diversity, are available for exploitation in a wide range of wireless scenarios by using channel-aware scheduling. It is therefore of critical importance to develop a rigorous understanding of MAC-layer scheduling that can resolve contention and mitigate interference efficiently while exploiting diversities. There is a consensus that channel-aware distributed scheduling will help to propel significant advances towards providing better QoS in ad hoc networks.

Channel aware opportunistic scheduling was first developed for the downlink transmissions in cellular wireless networks (see, e.g., [2], [4], [6], [7], [16], [17], [20], [21], [22]), assuming that the scheduler has knowledge of the instantaneous channel conditions for all links. That is to say, the scheduling is *centralized*. Opportunistic scheduling originates from a holistic view: roughly speaking, in a multiuser wireless network, at each moment it is likely that there exists a user with good channel conditions; and by picking the instantaneous on-peak user for data transmission, opportunistic scheduling can utilize the wireless resource more efficiently. More recently, channel aware random access has been investigated for the uplink

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transmissions in a many-to-one network [1], [18], where the channel probing can be realized by broadcasting pilot signals from the base station.

Needless to say, channel-aware distributed scheduling for ad hoc networks is much more challenging, because the distributed nature of ad hoc communications dictates that each link has no knowledge of other links' channel conditions. Indeed, little work has been done on developing channel-aware distributed scheduling to reap rich diversity gains in wireless ad-hoc networks. In [24], we have taken some initial steps in this direction by studying distributed opportunistic scheduling. Simply put, we consider a single-hop random access network with many links, each with one transmitter and one receiver. In such a network, distributed opportunistic scheduling involves a process of joint channel probing and distributed scheduling. A key observation is that in case of poor channel conditions, further channel probing may result in higher throughput. The desired tradeoff between the throughput gain from better channel conditions and the cost for further channel probings boils down to judiciously choosing the optimal stopping rule for channel probing. In [24], we have provided a systematic characterization of this tradeoff for the single-receiver case (i.e., each transmitter has one receiver only).

In many wireless applications, it is very likely that a node may have multiple channels [9], [13], [19] or multiple intended receivers [8], [15]. For example, the existing IEEE 802.11a/b standards have already specified multiple frequencies for data communications, and the cutting-edge RF technologies can serve multiple receivers in future wireless systems. To fully exploit the multi-receiver/multiuser capability gives rise to significant challenges for upper-layer protocol design. Particularly, it is of great interest to leveage such degrees of freedom for MAC layer design. One unique challenge in exploiting multi-receiver/multiuser diversities is that in ad-hoc networks nodes have limited knowledge about time-varying channel conditions. Clearly, probings are needed to discover channel conditions so that data transmissions could be carried out over favorable channel conditions. Recent studies [9], [13], [19] have explored optimal channel probing for a single link system with multiple channels, and the schemes therein are designed for point-to-point communications. In contrast, this paper considers ad-hoc networks with many links, and the focus here is to develop optimal channel-aware distributed scheduling for network throughput optimization by leveraging multi-receiver/multiuser diversities and time diversity in a joint manner.

The rest of the paper is organized as follows. Section II-B gives a brief review on the distributed opportunistic scheduling for the single receiver model, and presents the problem formulation on channel-aware distributed scheduling for the network model where each transmitter has multiple receivers. In Section III, we study channel aware distributed scheduling for two important applications, namely, the unicast traffic and the multicast traffic. In particular, Section III-A, the main focus of this study, presents four probing mechanisms for the unicast application, and investigates the corresponding optimal scheduling policies. Section III-C presents the study for the multicast application. In Section IV, we develop iterative algorithms for computing the optimal thresholds and the maximum throughput. The numerical examples in Section V corroborate the theoretic findings. Finally, Section VI concludes the paper. Due to space limitation, most details of the proofs are omitted in this conference version, and can be found in [23].

II. Background and Problem Formulation

A. Network model

Building on [24], we consider a single-hop ad-hoc network with M transmitter nodes, each with multiple intended receivers. We assume that each transmitter node m contends for the channel using random access with probability p_m, $m = 1, \ldots, M$. A collision model is assumed for channel contention, where a channel contention of a node is said to be successful if no other nodes transmit at the same time. Accordingly, the overall successful contention probability is given by $\sum_{m=1}^{M}(p_m \prod_{i \neq m}(1-p_i))$, denoted as p_s; and the number of slots (denoted as K) needed to accomplish a successful channel contention is a Geometric random variable, i.e., $K \sim Geometric(p_s)$. Let τ denote the duration of mini-slot for channel contention.

Different from the model where each transmitter is associated with one single receiver only, the probing in the multi-receivers case takes place in two phases (see Fig. 5 for example): 1) In phase I, all transmitters contend for the channel using random access to reserve the channel (e.g., by sending RTS), and the probing in this phase to accomplish a successful channel contention takes a *random duration of* $K\tau$; and 2) In phase II, subsequent probings are carried out to estimate the channel conditions from the successful transmitter in phase I to its intended receivers, according to specific probing mechanisms, and for each receiver the probing for channel condition incurs a *constant duration of* τ. In particular, we shall study four probing mechanisms, namely, 1) the random selection (RS) mechanism, 2) the exhaustive sequential probing with recall (ESPWR) mechanism, 3) the sequential probing without recall (SPWOR) mechanism, and 4) the sequential probing with recall (SPWR) mechanism.

Suppose that after channel probing, the link condition of the probed receiver can be obtained accurately. Due to channel fading, the link condition corresponding to each channel probing can be either good or bad. (We shall make this precise.) Clearly, the chance of seeing better channel conditions increases if further probing is performed. However, each probing incurs a certain amount of time that could be used for data transmission. Therefore, there exist fundamental tradeoffs between the throughput gain from better channel conditions and the probing cost. In this paper, we take a systematic approach to characterize this tradeoff by appealing to optimal stopping theory [11], [12], and explore channel-aware distributed scheduling to exploit multi-receiver diversity in phase II and multiuser diversity in phase I for ad-hoc communications. For all four probing mechanisms, we characterize the corresponding optimal scheduling policies; and show that the optimal scheduling boils down to joint execution of channel probing using an optimal stopping rule and then data transmission.

B. Distributed Opportunistic Scheduling: The Single Receiver Case

In [24], we have studied the network model where every transmitter has one receiver only. Simply put, we have casted the problem as a maximal rate of return problem [12], where the rate of return refers to the average network throughput. Let $R_{n,s(n)}$ denote the instant channel rate at the n-th successful channel contention (or channel probing) when link $s(n)$ has successfully occupies the channel, and $T_n = \sum_{j=1}^{n} K_j\tau + T$ denote the total time that includes the contention duration and the data transmission time (see Fig. 1).

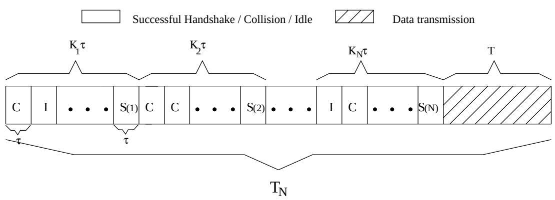

Fig. 1. A sample realization of the distributed opportunistic scheduling.

Let $(\Omega, \mathcal{F}, (\mathcal{F}_n)_{n\geq 0}, P)$ denote the probability space, where $(\mathcal{F}_n)_{n\geq 0}$ is understood to be the natural filtration generated by $\{R_{n,s(n)}, T_n, n = 1, 2, \ldots\}$. The scheduling problem can then be described as follows: given observations of $\{R_{n,s(n)}, T_n\}$, the objective is to find a stopping time N^* for maximizing the network throughput. That is, distributed opportunistic scheduling boils down to characterizing N^* and x^*:

$$N^* \triangleq \arg\max_{N\in Q} \frac{E[R_{N,s(N)}T]}{E[T_N]}, \quad x^* \triangleq \sup_{N\in Q} \frac{E[R_{N,s(N)}T]}{E[T_N]}, \tag{1}$$

where

$$Q \triangleq \{N : N \geq 1, E[T_N] < \infty\}. \tag{2}$$

Assume that the rates $\{R_{n,s(n)}, n = 1, 2, \ldots, \}$ are independent with finite second moments. Define $\delta \triangleq \frac{\tau}{T}$. We have the following result [24].

Proposition 2.1: **(The Single Receiver Case)** a) The optimal stopping rule N^* for distributed scheduling exists, and is given by

$$N^* = \min\{n \geq 1 : R_{n,s(n)} \geq x^*\}. \tag{3}$$

b) The maximum throughput x^* is an optimal threshold, and is the unique solution to

$$E(R_{n,s(n)} - x)^+ = \frac{x\delta}{p_s}. \tag{4}$$

The above result reveals that the optimal stopping rule N^* is a pure threshold policy [24], and the stopping decision depends on the current rate only. Accordingly, the optimal channel probing and scheduling mechanism takes the following simple form: If the successful link discovers that the current rate $R_{n,s(n)}$ is higher than the pre-computed threshold x^*, it transmits the data using the current rate $R_{n,s(n)}$; otherwise, it skips the transmission opportunity, and the links re-contend [24].

C. Summary of Main Results

In this paper, we consider a network model with each transmitter has multiple intended receivers and study channel aware distributed scheduling for exploiting multi-receiver/multiuser diversities, for both unicast traffic and multicast traffic.

1) For the unicast case, we show that the optimal scheduling policies for all four probing mechanisms exhibit threshold structures, and that the stopping decisions are based on the thresholds and the local channel conditions. Particularly, we show that for the RS and ESPWR probing mechanisms, the corresponding optimal scheduling policies are single threshold policies, where the maximum network throughput is an optimal threshold. In contrast, the optimal scheduling policies for both SPWOR and SPWR are multi-stage threshold policies, where the optimal thresholds are functions of the number of probed receivers. Furthermore, we show that the optimal thresholds and the maximum network throughput can be obtained off-line by solving fixed point equations. Therefore, the optimal scheduling policies are amenable to easy distributed implementation. Interestingly, we observe that the optimal thresholds for SPWOR monotonically decrease, whereas the optimal thresholds for SPWR first increase and then decrease.

2) For multicast traffic, we show that the probing process can be treated the same as the ESPWR mechanism. As a result, the optimal scheduling developed for the ESPWR mechanism is applicable to the multicast case under consideration. Needless to say, the optimal thresholds depend on the specific rewards of interest, and we study two different cases: 1) the reward is the number of ready users; and 2) the reward is the sum rate.

3) We develop iterative algorithms to obtain the optimal thresholds by appealing to the technique of fractional maximization [5]. We establish the convergence of the iterative algorithms, and show that the convergence rate is quadratic. Particularly, we derive iterative algorithms to compute the optimal thresholds for the four probing mechanisms for the continuous rate case.

III. Channel Aware Distributed Scheduling for Exploiting Multi-Receiver Diversity and Multiuser Diversity

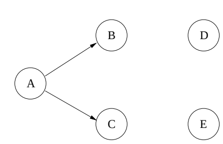

Fig. 2. A sketch of a transmitter with multiple receivers.

In this section, we generalize the above study to a network model where each transmitter node has multiple receivers (see Fig. 2), and the objective is to maximize the overall network throughput. For ease of exposition, we first consider a homogeneous network where all transmitters have the same number (say L) of receivers, and the channel condition follows the same distribution $F_R(r)$ [1]. We will generalize the study to heterogenous networks in Section III-B. Without loss of optimality, we assume that the probing order for each transmitter is based on a specific numbering of the receivers, numbered 0 to $L-1$.

Let $t(n)$ denote the transmitter accomplishing a successful channel contention in the n-th round, and $R_{n,t(n),j}$ be the corresponding rate after receiver j is probed, $j = 0, 1, \ldots, L-1$. In wireless communications, $R_{n,t(n),j}$ depends on the time varying channel condition. Following the standard assumption on block fading in wireless communications [14], we assume that the rate $R_{n,t(n),j}$ remains constant for a duration of $(L-1)\tau + T$, where T is the data transmission duration and $(L-1)\tau + T$ is no greater than the channel coherence time. Without loss of generality, we impose the following assumption on the transmission rates:

A1) $\{R_{n,t(n),j}\}$ are i.i.d., and $E[R^2_{n,t(n),j}] < \infty, \forall\, n, j$.

A key observation is that the probing costs (in terms of the probing time) for acquiring $R_{n,t(n),0}$ and $R_{n,t(n),j}, j = 1, 2, \ldots, L-1$ are different: It takes a random duration of contention period of $K\tau$ to obtain $R_{n,t(n),0}$, whereas it takes only a constant time τ to obtain $R_{n,t(n),j}, j = 1, 2, \ldots, L-1$. For convenience, we have assumed that a complete handshake (e.g., RTS/CTS) is used to obtain $R_{n,t(n),j}, j = 1, 2, \ldots, L-1$. (This can be improved further, e.g., by combining multiple RTS packets into a single multicast RTS packet, and letting the receivers send back CTS packets sequentially.)

A. Channel Aware Distributed Scheduling for Unicast Traffic

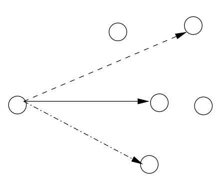

Fig. 3. A sketch of unicast transmissions.

The main focus of this study is on channel aware distributed scheduling for unicast traffic (see Fig. 3). That is, the transmitter transmits to only one receiver each time. Clearly, different probing mechanisms lead to different transmission rates and probing costs. In the following, we characterize their optimal scheduling for four probing mechanisms.

1) Mechanism I: Random Selection (RS): In the random selection (RS) mechanism, the successful transmitter randomly picks one of the receivers to probe, and only the probed receiver sends back the channel condition to the transmitter after the successful channel contention. Accordingly, the optimal scheduling policy is the same as that for the single-receiver case, indicating that the optimal stopping rule, N^* in (3) is applicable here and that the optimal throughput x^*_{RS} can be found by solving (4).

Since the RS mechanism does not utilize the multi-receiver diversity, it has no advantage over the single-receiver case. The RS mechanism is used as a benchmark for performance comparison with other probing strategies.

2) Mechanism II: Exhaustive Sequential Probing With Recall (ESPWR): For probing using exhaustive sequential probing with recall (ESPWR), after a successful channel contention, the corresponding transmitter probes all its receivers sequentially, and the receivers feed back their channel information accordingly. The transmitter then picks the receiver with the best channel condition for possible data transmission (see Fig. 4 for a pictorial illustration).

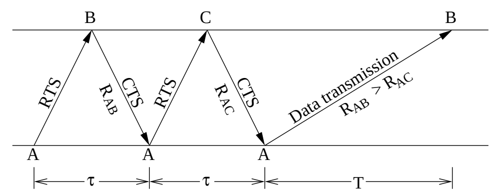

Fig. 4. ESPWR channel probing using RTS/CTS handshakes.

It follows that the transmission rate and the overall duration for probing plus data transmission are given by

$$R_{n,L} \triangleq \max_{j\in\{0,1,\ldots,L-1\}} R_{n,t(n),j}, \tag{5}$$

$$T_n = \sum_{i=1}^{n}[K_i\tau + (L-1)\tau] + T. \tag{6}$$

Proposition 3.1: a) Suppose that exhaustive sequential probing with recall (ESPWR) is used for channel probing. Then the optimal stopping rule for distributed scheduling is given by

$$N^*_{ESPWR} = \min\{n \geq 1 : R_{n,L} \geq x^*_{ESPWR}\}; \tag{7}$$

b) The maximum network throughput x^*_{ESPWR} is an optimal threshold and is the unique solution to

$$E(R_{n,L} - x)^+ = \frac{x[1 + p_s(L-1)]\delta}{p_s}. \tag{8}$$

Remarks. We caution that the optimal throughput of the ESPWR mechanism may not always be larger than that of the RS mechanism because the multi-receiver diversity gain would be offset by the probing cost as L increases. In the extreme case, $x^*_{ESPWR} \to 0$ as $L \to \infty$, whereas x^*_{RS} is positive. As a result, there exists an optimal L^*, such that the throughput gain of ESPWR over RS is maximum.

3) Mechanism III: Sequential Probing Without Recall (SPWOR): In the mechanism using sequential probing without recall (SPWOR), after a successful contention, the transmitter probes its receivers sequentially, and stops the probing process once it probes a "good" channel, followed by data transmission. As in [19], we assume that in this probing mechanism the transmitter cannot recall the previous probed receivers in the sense that the transmitter can schedule data transmission to the most recently probed receiver only.

[1]It is known that most multi-receiver gain occurs for $L = 2$ and $L = 3$.

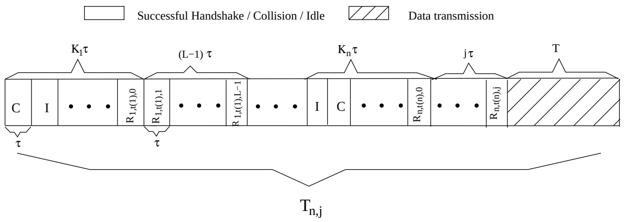

Fig. 5. A sample realization of the SPWOR mechanism.

As illustrated in Fig. 5, suppose that receiver j is selected for data transmission after n rounds of contention. The transmission rate is denoted as $R_{n,t(n),j}$, and the total elapsed time $T_{n,j}$ is given by

$$T_{n,j} = \sum_{i=1}^{n-1} [K_i\tau + (L-1)\tau] + K_n\tau + j\tau + T. \tag{9}$$

Clearly, the total number of probed receivers, denoted as $\mathcal{K}$, is

$$\mathcal{K} = (n-1)L + (j+1). \tag{10}$$

On the other hand, if the total number of probed receivers $\mathcal{K}$ is known, then n and j would be

$$n = \lceil \frac{\mathcal{K}}{L} \rceil, \qquad j = \mathrm{mod}(\mathcal{K}-1, L). \tag{11}$$

Let $\mathcal{K}(N)$ denote the total number of probed receivers at a stopping time N. Then, the average throughput, x, is given by

$$x = \frac{E\left[R_{\lceil \frac{\mathcal{K}(N)}{L} \rceil, t(\lceil \frac{\mathcal{K}(N)}{L} \rceil), \mathrm{mod}(\mathcal{K}(N)-1, L)} \times T\right]}{E\left[T_{\lceil \frac{\mathcal{K}(N)}{L} \rceil, \mathrm{mod}(\mathcal{K}(N)-1, L)}\right]}. \tag{12}$$

Therefore, the next key step is to characterize the optimal stopping rule N^*, such that x in (12) is maximized. i.e.,

$$N^* \triangleq \arg\max_{N \in Q} \frac{E\left[R_{\lceil \frac{\mathcal{K}(N)}{L} \rceil, t(\lceil \frac{\mathcal{K}(N)}{L} \rceil), \mathrm{mod}(\mathcal{K}(N)-1, L)} \times T\right]}{E\left[T_{\lceil \frac{\mathcal{K}(N)}{L} \rceil, \mathrm{mod}(\mathcal{K}(N)-1, L)}\right]}, \tag{13}$$

where

$$Q \triangleq \{N : \mathcal{K}(N) \geq 1, E\left[T_{\lceil \frac{\mathcal{K}(N)}{L} \rceil, \mathrm{mod}(\mathcal{K}(N)-1, L)}\right] < \infty\}. \tag{14}$$

For convenience, with a slight abuse of notation, we use $\mathcal{K}$ instead of $\mathcal{K}(N)$ in the following.

In general, the optimal stopping rule N^* for the SPWOR mechanism depends on the round of channel contention n and the receiver j, and the corresponding optimal structure is more involved than the single receiver case. However, we shall see that the optimal structure is time invariant in n, and takes a simple threshold form. We have the following result.

Proposition 3.2: a) Suppose that sequential probing without recall (SPWOR) is used for channel probing. Then the optimal stopping rule for distributed scheduling is given as follows:

$$N^*_{SPWOR} = \min\{\kappa \geq 1 : R_{n,t(n),j} \geq \theta^*_j, \text{ where } n = \lceil \frac{\kappa}{L} \rceil, j = \mathrm{mod}(\kappa-1, L)\}, \tag{15}$$

and the thresholds $\{\theta^*_j\}$ are determined by

$$\theta^*_j = x^*_{SPWOR} + v^*_{j+1}, \forall\, j = 0, 1, \ldots, L-1, \tag{16}$$

b) The maximum network throughput x^*_{SPWOR} is the unique solution to the following fixed point equation:

$$E[\max(R - x, v^*_1(x))] - \frac{x\delta}{p_s} = 0, \tag{17}$$

where R is a random variable with distribution $F_R(r)$, and $\{v^*_j(x)\}$ are defined (in a backward order) as follows:

$$v^*_L(x) \triangleq 0, \tag{18}$$

$$v^*_j(x) \triangleq E[\max(R - x, v^*_{j+1}(x))] - x\delta, \quad \forall\, j = L-1, L-2, \ldots, 1. \tag{19}$$

c) $v^*_j \triangleq v^*_j(x^*_{SPWOR}), \forall\, j = 1, 2, \ldots, L$.

Remarks. Proposition 3.2 reveals that the optimal scheduling policy corresponding to SPWOR probing exhibits a multi-stage threshold structure. Furthermore, observe that the optimal thresholds given by (16) only depends on the number of receivers that the transmitter has probed, indicating that the optimal stopping rule in (15) is amenable to easy distributed implementation.

As expected, the optimal thresholds at earlier-probed receivers are larger than that at later-probed receivers, i.e., $\theta^*_i \geq \theta^*_j, \forall\, i \leq j$. Intuitively speaking, at receiver i, more receivers (i.e., $L-i-1$ remaining receivers) are available for further probing (and can be possibly utilized), compared to at receiver j. The following corollary formalizes this idea.

Corollary 3.1: The optimal thresholds $\{\theta^*_j, \forall\; j = 0, 1, \ldots, L-1\}$ defined in (16) monotonically decrease, i.e.,

$$\theta^*_0 \geq \theta^*_1 \geq \cdots \geq \theta^*_{L-1}. \tag{20}$$

4) Mechanism IV: Sequential Probing With Recall (SPWR): As noted above, the SPWOR mechanism assumes that transmitters cannot recall the previous probed receivers that might have better channel condition than the most recent one. In contrast, in SPWR probing, we assume that each transmitter can schedule data transmission to any of its probed receivers and therefore it would pick from the probed receivers the one with the highest rate. That is, if the current transmitter is $t(n)$, and the current probed receiver is j, then transmitter $t(n)$ can transmit to one of the receivers in $\{0, 1, \ldots j\}$ that has the best condition. We call this mechanism sequential probing with recall (SPWR).

Define $R_{n,j} \triangleq \max(R_{n,t(n),1}, R_{n,t(n),2}, \ldots, R_{n,t(n),j})$. Similar to the case using SPWOR probing, the objective here is to find the optimal stopping rule N^* with

$$N^* \triangleq \arg\max_{N \in Q} \frac{E\left[R_{\lceil \frac{\kappa}{L} \rceil, \mathrm{mod}(\kappa-1, L)} \times T\right]}{E\left[T_{\lceil \frac{\kappa}{L} \rceil, \mathrm{mod}(\kappa-1, L)}\right]}. \tag{21}$$

Proposition 3.3: a) Suppose that sequential probing with recall mechanism (SPWR) is used for channel probing. Then the optimal stopping rule for distributed scheduling is given as follows:

$$N^*_{SPWR} = \min\{\kappa \geq 1 : R_{n,j} \geq \theta^*_j, \text{ where } n = \lceil \frac{\kappa}{L} \rceil, j = \mathrm{mod}(\kappa-1, L)\}, \tag{22}$$

and the thresholds $\{\theta^*_j\}$ are determined by

$$\theta^*_{L-1} = x^*_{SPWR}, \tag{23}$$

$$\theta^*_j = \min\{z : \psi^*_j(z) \leq 0\}, \forall\, j = L-2, L-3, \ldots, 0. \tag{24}$$

and $\{\psi_j^*(z), \forall\ j = L-2, L-3, \ldots, 0\}$ are defined as

$$\psi_{L-2}^*(z) \triangleq E\left[\left(\max\left\{R-z, x_{SPWR}^* - z\right\}\right)^+\right] - x_{SPWR}^*\delta, \quad (25)$$

$$\psi_j^*(z) \triangleq E\left[\left(\psi_{j+1}^*\left(\max\{z, R\}\right)\right)^+ + (R-z)^+\right] - x_{SPWR}^*\delta, \quad \forall\ j = L-3, L-4, \ldots, 0, \quad (26)$$

where R is a random variable with distribution $F_R(r)$.

b) The maximum throughput x_{SPWR}^* is the unique solution to the following fixed point equation:

$$E\left[\max\left\{R-x, U_1^*(R)\right\}\right] - \frac{x\delta}{p_s} = 0 \quad (27)$$

where $U_1^*(z)$ is iteratively defined as follows:

$$U_{L-1}^*(z) \triangleq E\left[\max\left\{z, R_{L-1}, x\right\}\right] - x\delta - x, \quad (28)$$

$$U_j^*(z) \triangleq E\left[\max\left\{z, R_j, U_{j+1}^*(\max\{z, R_j\}) + x\right\}\right] - x\delta - x, \quad \forall\ j = L-2, L-1, \ldots, 1, \quad (29)$$

where $\{R_j, j = 1, 2, \ldots, L-1\}$ are i.i.d. random variables with distribution $F_R(r)$.

Remarks. Again, we observe that the optimal thresholds determined by (23) and (24) are functions of the number of probed receivers only. As a result, the transmitter with reserved channel can decide to transmit or not simply based on the current link condition and the threshold corresponding to the number of probed receivers.

We have the following result regarding the relationship of the optimal thresholds.

Corollary 3.2: The optimal thresholds $\{\theta_j^*, \forall\ j = 0, 1, \ldots, L-1\}$ determined by (23) and (24) satisfy the following relationship:

$$\theta_{L-1}^* \leq \theta_0^* \leq \theta_1^* \leq \cdots \leq \theta_{L-2}^*. \quad (30)$$

Remarks. Corollary 3.2 reveals that the optimal thresholds monotonically increase from receiver 0 to receiver $L-2$, and then decrease; and the optimal threshold for last receiver $L-1$ is the lowest among all the thresholds. This is in sharp contrast to the fact that the optimal thresholds in SPWOR probing monotonically decrease. Our intuition is as follows: 1) The monotonic increasing of the initial $L-1$ thresholds in SPWR is due to the fact that SPWR can recall the previous probed receivers. Therefore, the transmission rate $R_{n,j}$ is a non-decreasing function of j as probing continues, and consequently, the corresponding thresholds increases. 2) Note that θ_{L-1}^* is the threshold at which the transmitters decide to re-contend or not. Since channel contention (the channel probing in Phase I) costs more time resources than the channel probing in Phase II, thus the threshold for further channel probing in Phase I (i.e., θ_{L-1}^*) should be the smaller than the thresholds in Phase II (i.e., $\{\theta_j^*, j = 0, 1, \ldots, L-2\}$).

B. Generalization to Heterogeneous Cases

In the following, we generalize the above study to the model where different transmitters may have different numbers of receivers. Let L_m denote the number of receivers for transmitter m. Without loss of generality, we assume that $L_1 \leq L_2 \leq \cdots \leq L_M$.

We have the following proposition regarding the optimal stopping rules in heterogenous networks using SPWR probing. We note that similar study can be carried over to SPWOR probing.

Proposition 3.4: Suppose that sequential probing with recall strategy (SPWR) is used for channel probing. Then the optimal scheduling rule for distributed scheduling exhibits a multi-stage threshold structure with thresholds $\{\theta_0^*, \theta_1^*, \ldots, \theta_{L_M-1}^*\}$. Specifically, for each successful transmitter $t(n)$, the optimal thresholds are $\{\theta_0^*, \theta_1^*, \ldots, \theta_{L_{t(n)}-1}^*\}$, i.e., it continues probing until at some receiver j ($0 \leq j \leq L_{t(n)} - 1$), $R_{n,j} \geq \theta_j^*$, followed by data transmission.

Sketch of the proof. The proof is built upon Proposition 3.3, and mainly uses the fact that the system restarts each time when a new channel contention begins. So we can still use backward induction to derive the optimal stopping rule. Note that another key point is that the channel probing cost $x^*\tau$ is the same for all the transmitters. Therefore, for any transmitters $i, j \in \{1, 2, \ldots, M\}$, they share the same thresholds from receiver 0 to $\min(L_i - 1, L_j - 1)$.

C. Channel Aware Distributed Scheduling for Multicast Traffic

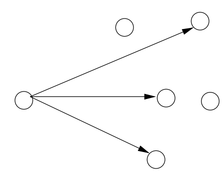

Fig. 6. An example of multicast transmission.

In this section, we consider channel aware distributed scheduling for multicast traffic (see Fig. 6), where all receivers corresponding to one transmitter require the same data from that transmitter. In this case, the channel probing process follows the same line of that in the ESPWR mechanism for the unicast traffic (see Section III-A2): The transmitter probes all the receivers to observe $\{R_{n,t(n),j}, j = 0, 1, \ldots, L-1\}$. Hence for each data transmission, the reward is a function of $\{R_{n,t(n),j}, j = 0, 1, \ldots, L-1\}$. Depending on the reward of interest, we consider the following two multicast scenarios:

1) Case I: the reward is defined to be the number of ready receivers [10], where by "readiness" we mean the rate $R_{n,t(n),j}$ is larger than some threshold R_{th}. Therefore, the reward for each transmission is given by

$$R_1 = \sum_{j=0}^{L-1} \mathbf{I}\left[R_{n,t(n),j} \geq R_{th}\right]. \quad (31)$$

Clearly, R_1 is a binomial random variable with parameters (L, p), where $p = P(R_{n,t(n),j} \geq R_{th})$.

2) Case II: suppose the transmitter send the information at a constant rate R_c, and the reward is defined to be the sum rate, i.e.,

$$R_2 = R_c \sum_{j=0}^{L-1} \mathbf{I}\left[R_{n,t(n),j} \geq R_c\right]. \quad (32)$$

It is clear that R_2 is a product of a constant R_c and a binomial random variable with parameters (L, p), where $p = P(R_{n,t(n),j} \geq R_c)$.

For both scenarios, the optimal scheduling policy and the optimal throughput can be obtained as follows.

Proposition 3.5: a) The optimal stopping rules for distributed scheduling in both multicast cases take the following form:

$$N^* = \min\{n \geq 1 : R \geq x^*\}, \tag{33}$$

b) the maximum multicast network throughput x^* is a optimal threshold, and is the unique solution to

$$E(R-x)^+ = \frac{x[1+p_s(L-1)]\delta}{p_s}, \tag{34}$$

where R is a random variable with the same distribution as R_1 (or R_2).

IV. Iterative Algorithm for Computing the Optimal Thresholds

A. Iterative Algorithm Using Fractional Maximization

In the following, we develop iterative algorithms for computing the thresholds.

First, observe that for both SPWOR and SPWR, the optimal stopping rules for distributed scheduling are multi-threshold policies. Denote the thresholds by $\vec{\theta} = [\theta_0, \theta_2, \ldots, \theta_{L-1}]^T$, and the average throughput by $\Phi(\vec{\theta})$. Based on (1), $\Phi(\vec{\theta})$ usually takes the form of $U(\vec{\theta})/V(\vec{\theta})$, and the optimal threshold $\vec{\theta}^*$ is then the one that maximizes $U(\vec{\theta})/V(\vec{\theta})$. However, since direct maximization of $U(\vec{\theta})/V(\vec{\theta})$ is often prohibitive, we resort to the technique of fractional maximization [5].

To this end, define the function $W(\vec{\theta}, x) \triangleq U(\vec{\theta}) - xV(\vec{\theta})$, where x is a real positive value. For a given x, the corresponding $\vec{\theta}(x)$ that maximizes $W(\vec{\theta}, x)$ is denoted as $\vec{\theta}(x) = \arg\max_{\vec{\theta}} W(\vec{\theta}, x)$.

Let $W(x) \triangleq W(\vec{\theta}(x), x)$, and x^* denote the solution to $W(x) = 0$. It can then be shown that x^* is the optimal throughput, and that $\vec{\theta}(x^*)$ is the optimal threshold. To construct iterative algorithms for computing x^* and $\vec{\theta}(x^*)$, we need the following lemma [12].

Lemma 4.1: $W(x)$ is decreasing and convex in x.

It can also be shown that for any given x', $z = W(x') - V(\vec{\theta}(x'))(x - x')$ is a supporting hyperplane for $W(x)$ at x'. Then, Newton's method yields that

$$x_{n+1} = x_n - \frac{W(x_n)}{W'(x_n)} = \Phi(\vec{\theta}(x_n)). \tag{35}$$

It can be shown that the above iterative algorithm converges quadratically to x^* [5]. Summarizing, we have the following proposition.

Proposition 4.1: Given any positive initial value x_0, the following iterative algorithm

$$\begin{cases} \vec{\theta}_n = \arg\max_{\vec{\theta}} W(\vec{\theta}, x_n), \\ x_{n+1} = \Phi(\vec{\theta}_n), \end{cases}$$

converges, i.e., $x_n \to x^*$ and $\vec{\theta}_n \to \vec{\theta}^*$, and the convergence rate is quadratic.

Building on Proposition 4.1, in what follows, we derive iterative algorithms for computing the optimal thresholds for the four probing mechanisms. For ease of exposition, we consider the continuous rate case only, i.e., we assume that $f_R(r) > 0$ for all $r > 0$. Similar studies can be carried out for the discrete rate case.

B. Iterative algorithm for RS and ESPWR Probing

Recall that the optimal scheduling algorithm for the RS mechanism is the same as that in the single-receiver case, i.e., a single-threshold policy. For a given threshold θ, the throughput of the RS mechanism can be shown to be

$$\Phi(\theta) = \frac{\int_\theta^\infty r dF_R(r)}{\delta/p_s + \int_\theta^\infty dF_R(r)}. \tag{36}$$

Accordingly, $U(\theta) = \int_\theta^\infty r dF_R(r)$ and $V(\theta) = \delta/p_s + \int_\theta^\infty dF_R(r)$. It can also be shown that (cf. Lemma 3.1 in [24]), for any given x_n, $\theta_n = \arg\max_\theta W(\theta, x_n) = x_n$.

Thus, appealing to Proposition 4.1, for any positive initial value x_0, the iterates generated by the following algorithm:

$$x_{n+1} = \Phi(x_n), \tag{37}$$

converge to the optimal threshold and the maximum network throughput x^* quadratically.

We note that the same algorithm in (37) can be applied to the ESPWR mechanism as well.

C. Iterative algorithm for SPWOR Probing

Given a threshold $\vec{\theta}$, it can be shown that the average throughput of the SPWOR mechanism is given by

$$\Phi(\vec{\theta}) = \frac{p_s\left[\sum_{j=0}^{L-1} p_j \frac{\int_{\theta_j}^\infty r dF_R(r)}{1-F_R(\theta_j)} T\right]}{(1-p_s)\tau + p_s\left[\left(1 - \sum_{j=0}^{L-1} p_j\right) L\tau + \sum_{j=0}^{L-1} p_j((j+1)\tau + T)\right]}, \tag{38}$$

where $p_j = \prod_{i=0}^{j-1} F_R(\theta_i)(1 - F_R(\theta_j))$ is the probability that the transmitter transmits to the j-th receiver.

It is not difficult to show using the first order derivative condition that

$$\theta_{L-1} = x, \tag{39}$$

and for $j = L-2, L-3, \ldots, 0$,

$$\begin{aligned} \theta_j \quad = \quad & \sum_{k=j+1}^{L-1} \prod_{i=j+1}^{k-1} F_R(\theta_i) \int_{\theta_k}^\infty r dF_R(r) \\ & -x \left\{ \sum_{k=j+1}^{L-1} \prod_{i=j+1}^{k-1} F_R(\theta_i)(1 - F_R(\theta_k)) \right. \\ & \left. \times \left[1 - (L-1-k)\frac{\tau}{T}\right] + (L-1-j)\frac{\tau}{T} - 1 \right\}, \end{aligned} \tag{40}$$

are the optimal thresholds that maximize $W(\vec{\theta}, x)$.

We note that the updating procedure of these thresholds follows a reverse order from $L-1$ to 0, since the updating of θ_j (using (40)) requires the knowledge of the updated values of θ_{j+1} to θ_{L-1}.

Summarizing, for every x_n, the corresponding $\vec{\theta}(x_n)$ can be obtained using (39) and (40), and then x_{n+1} can be found using $x_{n+1} = \Phi(\vec{\theta}(x_n))$ in (35).

$$\Phi(\vec{\theta}) = \frac{p_s \left\{ \sum_{j=0}^{L-2} p_j \frac{\int_{\theta_j}^{\infty} r dF_R(r)}{1-F_R(\theta_j)} + p_{L-1} \left[\frac{\frac{\int_{\theta_{L-1}}^{\theta_0} r dF_R^L(r)}{\prod_{j=1}^{L-2} F_R(\theta_j)} + \sum_{j=0}^{L-3} \frac{\int_{\theta_j}^{\theta_{j+1}} r dF_R^{L-j-1}(r)}{\prod_{i=j+1}^{L-2} F_R(\theta_i)} + \int_{\theta_{L-2}}^{\infty} r dF_R r}{1 - \frac{F_R^L(\theta_{L-1})}{\prod_{j=0}^{L-2} F_R(\theta_j)}} \right] \right\} T}{(1-p_s)\tau + p_s \left[\left(1 - \sum_{j=0}^{L-1} p_j\right) L\tau + \sum_{j=0}^{L-1} p_j((j+1)\tau + T) \right]}. \quad (41)$$

D. Iterative algorithm for SPWR Probing

According to Proposition 3.2, without loss of optimality, we can assume that $\theta_{L-1} \leq \theta_0 \leq \theta_1 \leq \cdots \leq \theta_{L-2}$. It can then be shown that the average network throughput of the SPWR mechanism is given by (41).

Note that p_j, the probability that the transmitter transmits to the j-th receiver, is now given by

$$p_j = \prod_{i=0}^{j-1} F(\theta_i)(1 - F_R(\theta_j)),\ \forall\ j = 0, 1, \ldots, L-2, \quad (42)$$

$$p_{L-1} = \prod_{i=0}^{L-2} F(\theta_i) \left[1 - \frac{F_R^L(\theta_{L-1})}{\prod_{j=1}^{L-2} F_R(\theta_j)} \right]. \quad (43)$$

In practice, the number of receivers per transmitter is usually not large. We also note that most multi-receiver gain occurs when $L = 2$ and $L = 3$. In what follows, we study the case when $L = 2$. It can be shown that the following two time-scale algorithm converges to the optimal thresholds of the SPWR mechanism:

$$\theta_1(n) = x_n, \quad (44)$$

$$\theta_0(n) = y_\infty, \quad (45)$$

$$x_{n+1} = \Phi(\vec{\theta}_n), \quad (46)$$

where y_∞ is the limit of the following iterative algorithm:

$$y_{m+1} = \frac{\int_{y_m}^{\infty} r dF_R(r) - x_n \delta}{1 - F_R(y_m)}. \quad (47)$$

V. Numerical Results

In this section, we provide numerical results for the continuous rate case, assuming that the transmission rate is given by the Shannon channel capacity:

$$R(h) = \log(1 + \rho h) \text{ nats/s/Hz},$$

where ρ is the normalized average SNR, and h is the random channel gain corresponding to Rayleigh fading. Therefore, the transmission rate R has the following distribution

$$F_R(r) = 1 - \exp(-\frac{\exp(r) - 1}{\rho}). \quad (48)$$

Unless otherwise specified, we will fix $p_s = \exp(-1)$.

We first examine the convergence speed of the iterative algorithm proposed in Section IV, and specifically, the iterative algorithm (39), (40) and (35) for the SPWOR mechanism. The results are presented in Table I and Table II. Specifically, Table I presents the convergence of x_n for different ρ and δ. It can be observed that the iterative algorithm converges fast (within 3 or 4 iterations). Table II presents the convergence behavior of the thresholds for given ρ and δ.

TABLE I
Convergence of the iterative algorithm ($L = 3$).

(ρ, δ)	x_0	x_1	x_2	x_3	x_4
(0.1, 0.1)	2	0	0.1048	0.1240	0.1245
(0.5, 0.5)	2	0.1533	0.1966	0.1969	0.1969
(1, 1)	0.5	0.1740	0.1921	0.1922	0.1922

TABLE II
Convergence of the thresholds ($L = 3, \rho = 1, \delta = 1$).

$Iterations$	0	1	2	3
θ_0	0.1201	0.5164	0.4921	0.4920
θ_1	0.2185	0.4374	0.4226	0.4225
θ_2	0.5000	0.1740	0.1921	0.1922

Next, we compare the performance of ESPWR probing with SPWOR probing. Fig.7 depicts the throughput of these two strategies as the number of receivers increases. It can be seen that for the same setting, the throughput of the SPWOR mechanism is always larger than that of the ESPWR mechanism. Note that although the throughput corresponding to SPWOR increases as the number of receivers increases, the performance gain decreases. In contrast, the throughput corresponding to ESPWR deteriorates as L increases after the probing cost dominates.

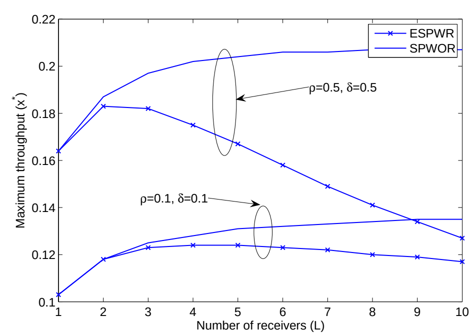

Fig. 7. Throughput as a function of number of receivers.

We also compare the performance between SPWOR and SPWR when $L = 2$. The results are presented in Table III. Clearly, the throughput of the SPWR mechanism is always higher than that of the SPWOR mechanism, but their performance is quite comparable. Given the complexity of the SPWR mechanism, we argue that SPWOR might be preferable in practice.

Last, we study the impact of the parameters ρ and δ on the

TABLE III
PERFORMANCE COMPARISON BETWEEN SPWR AND SPWOR ($L = 2$).

(ρ, δ)	$(0.1, 0.1)$	$(0.5, 0.5)$	$(0.5, 1)$	$(1, 1)$
x^*_{SPWR}	0.119	0.190	0.116	0.187
x^*_{SPWOR}	0.118	0.187	0.114	0.185

performance of the optimal scheduling. Using SPWOR as an example, Table IV outlines the performance gain of SPWOR as a function of L, comparing to RS probing. As expected, the performance gain decreases as ρ increases. Table IV reveals that the performance gain is neither decreasing nor increasing in δ. Indeed, it can be observed from the first three rows (or the last three rows) that the performance gain first increases from 13.97% to 14.32%, as δ decreases from 1 to 0.5, but decreases to 12.28% as $\delta = 0.1$. Our intuition is as follows: as δ becomes sufficiently small, the difference between the random contention probing cost $x^*\delta/p_s$ and the constant probing cost $x^*\delta$ becomes negligible. Hence, the performance gain from multi-receiver diversity becomes negligible, and the multiuser diversity gain dominates.

TABLE IV
PERFORMANCE GAIN AS A FUNCTION OF L.

L	2	3	4	5
$\rho = 0.5, \delta = 1$	13.97%	19.35%	21.82%	23.04%
$\rho = 0.5, \delta = 0.5$	14.32%	20.14%	23.00%	24.54%
$\rho = 0.5, \delta = 0.1$	12.28%	17.64%	20.61%	22.45%
$\rho = 1, \delta = 1$	12.62%	17.22%	19.21%	20.14%
$\rho = 1, \delta = 0.5$	12.98%	18.02%	20.40%	21.61%
$\rho = 1, \delta = 0.1$	11.08%	15.81%	18.38%	19.95%

VI. CONCLUSION

We studied channel aware distributed scheduling for ad hoc communications where each transmitter node has multiple intended receivers. A key observation is that channel probing must be done efficiently to balance the tradeoff between the throughput gain from better channel conditions and the probing cost. We characterized the optimal tradeoff in a stochastic decision-making framework, and developed the corresponding distributed scheduling to leverage the multi-receiver diversity and multiuser diversity in a joint manner. Specifically, we studied the scheduling problem using optimal stopping theory, and considered four probing mechanisms in phase II, namely, 1) random selection, 2) exhaustive sequential probing with recall, 3) sequential probing without recall, and 4) sequential probing with recall. We derived the corresponding optimal scheduling policies. We showed that these optimal scheduling policies have threshold structures, and the optimal thresholds and the maximal throughput can be obtained by solving fixed point equations. We further devised iterative algorithms to obtain the optimal thresholds. We established the convergence of the iterative algorithm, and showed that the convergence speed is quadratic. Numerical examples were provided to corroborate the theoretic findings, and we found that SPWOR has the best performance in terms of throughput and complexity.

Due to space limitation, we omitted most details of the proofs, which can be found in our online report [23].

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