# Distributed Adaptive Scheduling for Finite Horizon in Wireless Ad hoc Networks

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***Abstract*— A cooperative ratio-based scheduling scheme with minimal signaling that enhances network throughput and fairness in a wireless *ad hoc* network is presented in this paper. Throughput maximization problem under fairness constraint in a finite horizon is formulated as a novel multi-window optimization problem. Through analysis users' thresholds are shown to be time variant for throughput maximization with fairness in each time window. Simulation results clearly show that compared with non decision-based strategy, simple ratio-based scheme (SR) achieves within 1.6% of the global optimal value in terms of throughput and is scalable in terms of the number of nodes. Fairness index performance is marginally better than non decision-based strategy. Next, we show throughput degradation of SR scheme for asymmetric channels, and introduce general ratio-based scheme (GR) that adapts to provide higher throughput than fairness in a fully distributed manner for asymmetric channel conditions.**

***Index Terms*—*ad hoc* network, finite horizon, ratio-based scheduling, optimal linear scheduling.**

## I. Introduction

Extensive research has been done in the area of wireless opportunistic scheduling, where multiuser time varying channel environment is exploited to schedule users to satisfy their QoS requirements [1], [2]. However, one fundamental requirement is timely feedback from users so that multiuser diversity can be effectively used to enhance users' QoS requirements. In centralized wireless networks, central controller (base station) has relevant information (channel statistics and QoS requirement) of all the users to make optimal scheduling decisions. However, in wireless *ad hoc* network environment, users autonomously contend for the channel resource(s) based on sensing their local environment or limited exchange of signaling to gather local information. Thus, distributed network environment creates unique challenges; such as, time varying channel conditions, random channel contention among users, interference between distant users, limited resources, imprecise network information, dynamic topology, etc., for users to effectively schedule transmissions to achieve optimal throughput and latency. Specifically, multimedia streaming users with short term throughput and latency requirements face greater challenges to meet such stringent QoS requirements [3]. The QoS assurance problem becomes even more formidable in a distributed *ad hoc* network where users have multiple QoS requirements. Clearly, lack of central controller leads to reduced QoS performance and this obviously necessitates some form of control in *ad hoc* networks [4].

Furthermore, end-to-end multi-hop flow in an *ad hoc* network is fundamentally limited by the single hop constraints. [5] shows that multi-hop congestion and throughput performance are closely coupled to MAC contentions. Hence, it is apparent from the above discussion that we need some form of MAC level control and coordination in short term opportunistic scheduling for enhanced performance.

This provides a major motivation for our work to devise a partially controlled opportunistic scheduling method for distributed networks to optimize network throughput in a finite horizon. A scheduling method to maximize short term throughput in a centralized network for a single channel resource was proposed in [6]. Each user is scheduled opportunistically in a frame such that starvation time does not exceed two consecutive frames. In distributed environment it is difficult to fully control slot assignment opportunistically for all the users due to heavy signaling and user coordination requirements. However, if users cooperate and coordinate transmissions, then we can achieve partial control over the network performance [7]. One main issue that arises out of this coordination between users in a single channel distributed environment is that signaling to exchange information can create extra load on the network traffic and thus, potentially reduce throughput. As such, in this paper we address two questions:

1) How to establish partial control in a distributed network with minimal signaling between users?
2) What is the short term (finite horizon) stopping strategy for scheduling to maximize throughput, improve scalability and fairness of the network in a time varying channel environment?

We consider a slotted environment in which users contend for slots in a probabilistic manner as in IEEE 802.11 *ad hoc* networks. The main idea of this research is to divide the finite horizon duration into a number of shorter time windows in which probabilistic control actions are

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taken to optimize throughput. Therefore, due to multi-window optimization structure, the problem then naturally breaks down into a sequence of stopping problems. Note that stopping in this paper implies the target rate limit per window. Thus, a user cannot transmit more than allowed target rate limit in a window.

The rest of the paper is organized as follows. In Section II, related work is covered; Section III presents system preliminaries; Section IV presents two-user optimal policy; Section V presents our simple ratio (SR) based algorithm; Section VI presents simulation results; Section VII introduces general ratio based scheme (GR); and finally, Section VIII concludes the paper.

## II. Related Work

Over the last decade, significant work has been done in opportunistic scheduling for wireless networks. Contributions and ideas in centralized scheduling (downlink) have been extensively adopted for scheduling in distributed networks. Therefore, we categorize our overview of related work as centralized and distributed scheduling techniques. An in-depth survey of earlier centralized wireless scheduling schemes, such as channel-state dependent packet scheduling (CSDPS), class-based scheduling (CBS), weighted fair queuing (WFQ), channel independent fairness (CIF), and many variants of the algorithms are discussed in [8]. Many new scheduling techniques are derived from the combination of the above algorithms for realistic wireless channels. Many of these algorithms use channel states to make long term or short term performance guarantees. The proposed wireless scheduling schemes provide various degrees of performance guarantees, including short-term and long-term fairness bounds. However, they mainly focus on scheduling in centralized networks.

A scheduling scheme based on picking user with maximum signal-to-noise ratio (SNR) in a time slot was proposed in [9]. [10] proposed a scheduling scheme based on picking user with maximum normalized SNR. This method gives higher priority for users with higher instantaneous and lower average SNR. A proportional fairness scheduling (PFS) algorithm for HDR/CDMA (High Data Rate/Code Division Multiple Access) system, where the product of throughput delivered to all the users is maximized was proposed in [11]. The PFS provides long term throughput maximization with poor delay performance for data services which is analyzed in detail in [12]. A Modified largest weighted delay first (M-LWDF) method for real time applications which is throughput optimal and is stable in terms of queue backlog was proposed in [13], [14]. User with largest product of weighted channel rate and packet wait time is scheduled first at the expense of increased queuing delays for other users. Delay related issues with opportunistic scheduling were introduced in [15].

However, this proposed scheme is designed for HDR/CDMA fixed wireless network where each slot is accessible without any possibility of contention. A throughput optimal exponential scheduling scheme that modifies M-LWDF by giving more weight to queue when delay differences between users is large and shifts to PFS when delay differences are small was proposed in [16]. In [17] PFS bias is discussed with respect to asymmetric fading and a new score based scheduler is proposed for fixed wireless network.

A frame work for opportunistic scheduling to maximize wireless system performance to satisfy QoS requirements was proposed in [18]. The paper investigates scheduling problems with respect to temporal and utilitarian fairness requirements and derives optimal solution to be index-based policies. A weighted throughput based scheduling for HDR throughput optimization that basically schedules user with maximum rate-reward product was proposed in [19]. The scheme is roughly a combination of PFS and M-LWDF techniques using on-line iterative weight adjustment algorithm to compensate for observed deviations from the target throughput. Our work parallels this paper in terms of dynamic weight adaptation. However in our work, we calculate myopic weights based on relative backlog ratios in each window to minimize backlog differences and maximize throughput. Furthermore, our work significantly differs in terms of defining finite horizon multiple stopping framework for backlog minimization in wireless *ad hoc* networks. In [20], opportunistic scheduling policy for short-term fairness constraint is proposed for HDR/CDMA system. Besides, a large volume of scheduling schemes can be found in [21]–[27] and the references therein.

Significant contributions made in distributed networks are discussed hereafter. A dynamic control strategy to achieve optimal fairness for heterogeneous multi-hop network was proposed in [28]. The strategy decouples into separate algorithms for flow control, routing and scheduling, and resource allocation. However, the paper only discusses longterm optimal data rate performance in multi-hop *ad hoc* wireless networks. A cooperative rate adaptation (CRA) and QoS aware opportunistic scheduling schemes to reduce overall energy consumption in a multiuser *ad hoc* network was proposed in [7]. This paper loosely relates to our work in terms of cooperative strategy. An opportunistic scheduling for single hop *ad hoc* network using optimal stopping framework was proposed in [2]. It mainly considers scheduling from network centric aspect and shows that optimal strategy is pure threshold-based policy. However, this paper deals with throughput maximization for infinite horizon only. In contrast, we consider throughput maximization in finite horizon using multi-window framework. Plethora of work in transmission policies using Markov decision process (MDP) for infinite horizon can be found in [29], [30] and the references therein.

## III. System Assumptions and Preliminaries

Consider wireless *ad hoc* network environment where users in a small cluster share and randomly contend for a

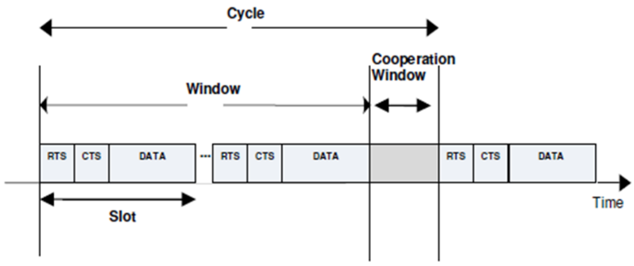


Figure 1. Timing Sequence Illustration.

single channel. We assume that all the users are homogeneous. In this context, it means that all the users have the same priority. Further, for all users' finite horizons end at the same time $T$ due to synchronization.

### A. Network Model

Consider time-slotted system, where time slot synchronization is assumed to be provided by the virtual cluster head ( [31], Section I in [32]). We envision a hierarchical network model, where all the nodes contend for a single channel resource in order to transmit to a single virtual cluster head receiver. Alternatively, we can visualize this problem as multiple flows coming in to the router (virtual cluster head) that later on forwards the data on its pre-established outgoing flows to other virtual cluster heads. We further assume for simplicity that slot size is large enough to accommodate request-to-send (RTS), clear-to-send (CTS) and data packets. Hence, if a user successfully transmits in a slot it implies that the user has successfully exchanged RTS and CTS signals, and has transmitted the data as well. The RTS and CTS signals in the context of this paper represent exchange of control information between the sender and receiver nodes; provides information to other neighboring nodes (backlog and channel), and further help avoid any hidden node problems. Users use CPW (cooperation window) phase to retrieve information and attain slot synchronization. It is also assumed that average channel condition does not change during the data transmission window.

In our system model, finite horizon $T$ refers to a deadline for $i_{th}$ user to transmit $\eta_t^{(i)}$ amount of data remaining at $t_{th}$ window, where $t$ is defined to be in the range $[1, T]$. Thus, a finite horizon consists of $T$ number of windows, where each window comprises $w$ slots. Further, each window is separated by a "Cooperation Window" (CPW), which marks the end of the current window and the start of the new window (Fig. 1). The CPW duration can be extremely short compared to the window size $w$ since it broadcasts total traffic information for the users. We define the duration of window and the CPW as one cycle. In this network model, the virtual cluster head has the responsibility of providing periodic slot timing during the CPW phase and it further defines start of a new window. The cluster head also uses this CPW to provide total traffic information $\eta_{t_{tot}}$ at the $t_{th}$ window to the users so that users can contend for slots in this new window with updated strategies for network throughput maximization. This also requires that new users in a cluster can initiate communication only at the beginning of the new window, once they have informed the cluster head of their backlogs.

The question that is still remaining to be answered is how does cluster head know about the total traffic information. Actually, we assume here that when a user joins the cluster it informs the cluster head with a single registration packet (may include backlog data amount to be transmitted within $T$ windows) which should not be larger in size than the RTS type packet. Similarly, when a user leaves it sends a deregistration packet. However, we do not attempt to focus on this problem in this paper. Thus, in an ideal case, the cluster head is aware of users entering and leaving, and the total pending traffic of the users. This helps provide partial control of wireless *ad hoc* distributed network. The partial control also creates room for coordination between the users.

### B. Queue and Channel Behavior

Assume that network has been operational for some time. Consider that each user fills up the lower level queue with data packets that have to be transmitted within the finite horizon $T$. The queue is not filled by higher level queue until the lower level queue is emptied. This way we are only concerned with the amount of data remaining in the lower level queue rather than the arrivals in the upper level queue within the finite horizon. We can think of the higher level queue as the network layer queue and the lower level queue as the data link layer queue. The lower queue state then represents the amount of data that needs to be transmitted within the finite horizon $T$. For the $i_{th}$ user in the $t_{th}$ window ($t$ is a discrete time at the start of the window), the queue state is denoted by $\eta_t^{(i)} = [0, \ldots, U]$. The queue state evolves as $\eta_t^{(i)} = \eta_{t-1}^{(i)} - \lambda_{t-1}^{(i)}$, where $\lambda_{t-1}^{(i)}$ is the random number of slots out of $w$ slots on which user $i$ transmitted in the $t-1$ window. We will also refer to $\lambda$ as the rate in subsequent sections.

The probability of $\lambda_t^{(i)}$ successfully transmitted slots out of $w$ slots for user $i$ in $t_{th}$ window is given by,

$$P(\lambda_t^{(i)}) = \binom{w}{\lambda_t^{(i)}} (P_{s_t}^{(i)})^{\lambda_t^{(i)}} (1 - P_{s_t}^{(i)})^{w - \lambda_t^{(i)}}. \quad (1)$$

Next we need to define probability of success $P_{s_t}^{(i)}$ for user $i$ in the $t_{th}$ window. A user successfully transmits in a slot when no other neighboring user transmits in that same slot and the channel is in a good state; or when other neighboring nodes transmit but relatively their channels are in bad states (diversity gain). For simplicity, we assume that the channel is stationary over the window and it follows a 2-state channel model [33]. It is further assumed that users' statistics are independent and identically distributed (i.i.d.), and the process is ergodic so that *pathwise* statistics is sufficient for optimization. The probability that the channel is good in a slot depends on receiver signal-to-interference (SIR) threshold of the user [33]. The channel fading is invariant over the slot duration, but it varies from slot to slot in a given window. So, the probability that a user $i$ is successful in a given slot in the $t_{th}$ window is given by,

$$P_{s_t}^{(i)} = \tau_t^{(i)} \cdot P_{g_t}^{(i)} \cdot \{ \prod_{j=1;j\neq i}^{n} (1 - \tau_t^{(j)} P_{g_t}^{(j)})\}, \quad (2)$$

in which $P_{g_t}^{(i)}$ is the $i_{th}$ user's probability that its channel is in a good state in the $t_{th}$ window of a slot, $\tau_t^{(i)}$ is the probability that the $i_{th}$ user transmits in a randomly chosen slot. The probability of the $i_{th}$ user's channel being in a good state in the $t_{th}$ window is given by $P_{g_t}^{(i)} = \int_{\gamma_t^{(i)}}^{\infty} f_t^{(i)}(r)dr$, in which $\gamma_t^{(i)}$ is the SIR threshold for the $i_{th}$ user in the $t_{th}$ window and $f_t^{(i)}(r)$ is the density function for the SIR. Distribution for $f_t^{(i)}(r)$ is a bit complicated and is based on the ratio of users' Rayleigh distributed signal fading. Plugging (2) into (1) gives us the probability of $\gamma_t^{(i)}$ successfully transmitted slots which further defines the state transition probability. It is apparent that for any $i_{th}$ user, if we need we can vary the probability of transmission $\tau_t^{(i)}$ in the slot to control the probability of success $P_{s_t}^{(i)}$ in the network for enhanced throughput, scalability and fairness performance. Note that $n$ in (2) is the number of contending users and is given by $n = \pi A^2 \rho$, where $A$ is the coverage area of the node and $\rho$ is the node density. As such, controlling the probability of success $P_s$ to maximize throughput in every window forms the central idea of our proposed approach.

### C. Window Requirement

As mentioned already we divide finite horizon into $T$ windows, where each window consists of $w$ slots. The cluster head provides for the timing synchronization as explained above. The main reason for having windows is to control and coordinate transmissions in a cooperative manner over window-based time scales so that network throughput is maximized in each window until the horizon is reached. We consider worst case situation, where random maximal scheduling for a specific single-hop interference model touches lower bound and achieves only 50% throughput [34]. So if we wish to allocate each of the $n$ users at least $\bar{\eta}$ number of slots on the average in the window, then the window size $w$ should satisfy, $w \geq 2n\bar{\eta}$. Thus, from implementation point of view, this provides lower bound for the window size based on the number of users and the average backlog per user in a window.

## IV. TWO-USER OPTIMAL POLICY

Given the information about the states of the users in the system, backward induction is used recursively to evaluate the optimal sequence of actions for finite horizon problems. However, backward induction technique renders itself impractical due to unpredictability of channel and high computational complexity [35]. The structure of our problem is in the form of control limit policy form [36], whereby each user starts and continues random transmissions when it is below its rate limit and stops when it reaches the required rate limit in a window.

Users contend for slots in a window based on their backlogs and channel states. Thus, multiuser diversity is created due to diverse channel and backlogs between the users. In order to exploit the diversity and maximize network throughput (minimize network backlog) opportunistically in a finite horizon $T$, users dynamically adapt and coordinate the access probability in a slot based on their own backlogs and the total backlog at the start of every window. This means that a user opportunistically transmits in a certain number of slots based on the rate threshold setting in each window.

Consider two users in $t_{th}$ window with large backlogs $\eta_t^{(1)} > w$ and $\eta_t^{(2)} > w$. Assume network has been operational for some time and all users are synchronized. As already mentioned our objective is to minimize backlogs in the $t+1$ window, or maximize throughput for both the users in the window as follows,

$$\min\{E[\eta_t^{(1)} - \lambda_t^{(1)}]^+ + E[\eta_t^{(2)} - \lambda_t^{(2)}]^+\}, \quad (3)$$

note that $[x-y]^+ = \max\{x-y, 0\}$.

For large backlogs, $\eta_t^{(1)} - \lambda_t^{(1)}$ and $\eta_t^{(2)} - \lambda_t^{(2)}$ are always positive, and therefore, $\min\{E[\eta_t^{(1)} - \lambda_t^{(1)}]^+ + E[\eta_t^{(2)} - \lambda_t^{(2)}]^+\} \approx \min\{E[\eta_t^{(1)} - \lambda_t^{(1)}] + E[\eta_t^{(2)} - \lambda_t^{(2)}]$. Taking expectation, we reduce our objective function to $\min\{\sum_0^w \eta_t^{(1)} P(\lambda_t^{(1)}) + \sum_0^w \eta_t^{(2)} P(\lambda_t^{(2)}) - \sum_0^w \lambda_t^{(1)} P(\lambda_t^{(1)}) - \sum_0^w \lambda_t^{(2)} P(\lambda_t^{(2)})\}$. Since $\eta_t^{(1)}$ and $\eta_t^{(2)}$ are known at the start of the $t_{th}$ window, and both $P(\lambda_t^{(1)})$ and $P(\lambda_t^{(2)})$ are binomial distributions (1), the objective function then simplifies to $\min\{\eta_t^{(1)} + \eta_t^{(2)} - wP_{s_t}^{(1)} - wP_{s_t}^{(2)}\}$. Hence, our final objective function that needs to be minimized with the fairness constraint takes the form,

$$\min\{\eta_t^{(1)} + \eta_t^{(2)} - wP_{s_t}^{(1)} - wP_{s_t}^{(2)}\},$$
$$\text{subject to } (\eta_t^{(1)} - \eta_t^{(2)} - wP_{s_t}^{(1)} + wP_{s_t}^{(2)})^2 \leq \Delta^2, \quad (4)$$

where $\Delta \ll w$ is the backlog difference bias. The Lagrangian using Kuhn-Tucker theorem is then given by (5), in which $u \geq 0$.

Taking derivatives of $L$ with respect to $\tau_t^{(1)}$ and $\tau_t^{(2)}$, we get (6) and (7).

For $u \geq 0$, the point at which objective function is minimum satisfies $P_{g_t}^{(1)}\tau_t^{(1)} + P_{g_t}^{(2)}\tau_t^{(2)} = 1$. For the case when the constraint is inactive, *i.e.*, $u = 0$, the optimal probabilities are given by, $\tau_t^{(1)*} = \frac{1}{2P_{g_t}^{(1)}}$ and $\tau_t^{(2)*} = \frac{1}{2P_{g_t}^{(2)}}$. It is noteworthy that when the solution lies inside the constraint region, the transmission probabilities are independent of the backlogs ($\eta_t^{(1)}$ and $\eta_t^{(2)}$). This provides direct comparison between two users based on their respective channel conditions. However, an interesting case arises when the constraint is active, *i.e.*, $u > 0$ and the minimum that is achievable is at the constraint boundary. To determine optimal transmission probabilities in this case we substitute $P_{g_t}^{(2)}\tau_t^{(2)} = 1 - P_{g_t}^{(1)}\tau_t^{(1)}$ into the complementarity condition given by $u\{\Delta^2 - [\eta_t^{(1)} - \eta_t^{(2)} -$

$$L(\tau_t^{(1)},\tau_t^{(2)},u) = \eta_t^{(1)}+\eta_t^{(2)} - wP_{g_t}^{(1)}\tau_t^{(1)}(1-P_{g_t}^{(2)}\tau_t^{(2)}) - wP_{g_t}^{(2)}\tau_t^{(2)}(1-P_{g_t}^{(1)}\tau_t^{(1)}) - u\{\Delta^2 - [\eta_t^{(1)} - \eta_t^{(2)} - wP_{g_t}^{(1)}\tau_t^{(1)}(1-P_{g_t}^{(2)}\tau_t^{(2)}) + wP_{g_t}^{(2)}\tau_t^{(2)}(1-P_{g_t}^{(1)}\tau_t^{(1)})]^2\}, \tag{5}$$

$$\frac{\partial L}{\partial \tau_t^{(1)}} = 0 \rightarrow 2u\cdot[\eta_t^{(1)}-\eta_t^{(2)}-wP_{g_t}^{(1)}\tau_t^{(1)}(1-P_{g_t}^{(2)}\tau_t^{(2)})+wP_{g_t}^{(2)}\tau_t^{(2)}(1-P_{g_t}^{(1)}\tau_t^{(1)})] = \frac{wP_{g_t}^{(2)}\tau_t^{(2)}P_{g_t}^{(1)} - wP_{g_t}^{(1)}(1-\tau_t^{(2)}P_{g_t}^{(2)})}{wP_{g_t}^{(1)}}, \tag{6}$$

$$\frac{\partial L}{\partial \tau_t^{(2)}} = 0 \rightarrow 2u\cdot[\eta_t^{(1)}-\eta_t^{(2)}-wP_{g_t}^{(1)}\tau_t^{(1)}(1-P_{g_t}^{(2)}\tau_t^{(2)})+wP_{g_t}^{(2)}\tau_t^{(2)}(1-P_{g_t}^{(1)}\tau_t^{(1)})] = \frac{wP_{g_t}^{(2)}(1-\tau_t^{(1)}P_{g_t}^{(1)}) - wP_{g_t}^{(2)}\tau_t^{(1)}P_{g_t}^{(1)}}{wP_{g_t}^{(2)}}. \tag{7}$$

$wP_{g_t}^{(1)}\tau_t^{(1)}(1-P_{g_t}^{(2)}\tau_t^{(2)})+wP_{g_t}^{(2)}\tau_t^{(2)}(1-P_{g_t}^{(1)}\tau_t^{(1)})]^2\} = 0$. A minor simplification gives us the optimal values of $\tau_t^{(1)*}$ and $\tau_t^{(2)*}$. Therefore, user 1 and user 2 set their *linear optimal transmission probabilities* in each slot as,

$$\tau_t^{(1)*} = \frac{1}{2P_{g_t}^{(1)}} + \frac{\eta_t^{(1)} - \eta_t^{(2)} - \Delta}{2wP_{g_t}^{(1)}} \tag{8}$$

and

$$\tau_t^{(2)*} = \frac{1}{2P_{g_t}^{(2)}} + \frac{\eta_t^{(1)} - \eta_t^{(2)} - \Delta}{2wP_{g_t}^{(2)}}. \tag{9}$$

Note that an offset adds to the optimal transmission probabilities compared to the case when the constraint is inactive. This allows us to pick a user who is relatively unfortunate, or resource starved. It is important to understand that for short term throughput maximization with fairness, the access probability is increased when a user is behind its share of resource (see refs. in [17]). Further, note that the optimal values of $\tau_t^{(1)*} \geq 0$ and $\tau_t^{(2)*} \geq 0$ should satisfy $P_{g_t}^{(1)}\tau_t^{(1)*} + P_{g_t}^{(2)}\tau_t^{(2)*} = 1$. Ideally, we would prefer to set the bias ($\Delta$) to a negligible value or zero. Thus, optimal probabilities of success are given by, $P_{s_t}^{(1)*} = (\frac{1}{2} + \frac{\eta_t^{(1)}-\eta_t^{(2)}-\Delta}{2w})^2$ and $P_{s_t}^{(2)*} = (\frac{1}{2} + \frac{\eta_t^{(1)}-\eta_t^{(2)}-\Delta}{2w})^2$. The optimal stopping rates for user 1 and user 2 are $\lambda_t^{*(1)} = w\tau_t^{(1)*}$ and $\lambda_t^{*(2)} = w\tau_t^{(2)*}$, respectively. It is obvious from optimal transmission probability equations that when user 2 backlog is greater than user 1 then $P_{g_t}^{(2)*} > P_{g_t}^{(1)*}$. When user 1 and user 2 have equal backlogs, then $P_{g_t}^{(2)*} = P_{g_t}^{(1)*}$.

In realistic *ad hoc* networks with more than two users, it becomes very complex to find backlog differences based optimal values and therefore such approach is infeasible. Hence, in Section V we propose a simple ratio-based (SR) scheduling algorithm where users only need to know the total backlog in the network which can be easily obtained during the CPW phase. The transmission probabilities in our SR scheduling scheme depends on the relative backlogs' ratios only as opposed to backlog differences in a linear scheme.

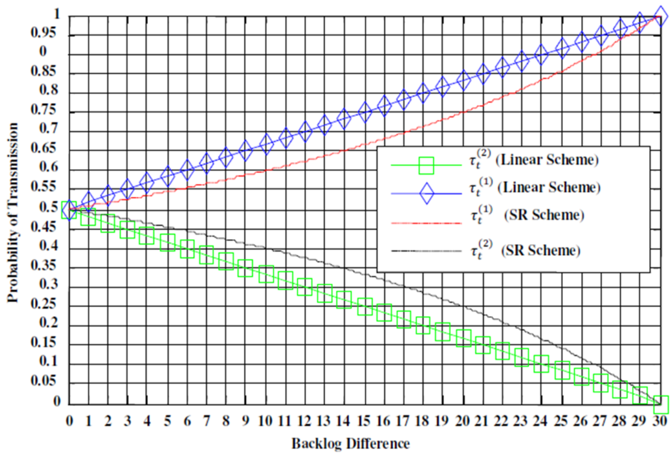


Figure 2. Two-user probability of transmission comparison between linear and SR schemes with $w = 30$, $P_{g_t}^{(1)} = P_{g_t}^{(2)} = 1$ and $\Delta = 0$.

## A. *SR Versus Linear Optimal Strategy*

For SR scheme, the transmission probability for the $i_{th}$ user in the $t_{th}$ window is given by $\tau_t^{(i)*} = \frac{\eta_t^{(i)}}{\sum_{k=1}^{n}\eta_t^k}$ and the probability of success for the $i_{th}$ user comes out to be as,

$$P_{s_t}^{(i)*} = \frac{P_{g_t}^{(i)}\eta_t^{(i)}\{\prod_{j=1;j\neq i}^{n}(\sum_{k=1}^{n}\eta_t^{(k)} - \eta_t^{(j)}P_{g_t}^{(j)})\}}{(\sum_{k=1}^{n}\eta_t^{(k)})^n}, \tag{10}$$

for $n \geq 2$ (proof is not shown due to space). In Fig. 2, we compare the SR scheme and linear scheme for the identical condition when users' backlog difference increases from 0 to 30. Fig. 2 shows that when the backlog difference is 15 (50% of the window size), user 1 gets 75% of the slots in the window relative to user 2 for the linear scheme, while for the ratiobased scheme user 1 gets about 65% of the slots. We observe that SR reduces the backlog difference more conservatively compared to the linear scheme. However, SR is far simpler to implement than linear optimal strategy. We assume that links are symmetric. Any random channel variations (fast fading) or temporary bad channel (asymmetric) conditions that affect user's success rate in a window shows up as an increase in users backlog in the following window. Consequently, threshold values are adapted accordingly and coordinated between the users to compensate for any change in relative backlogs. The threshold requirement for maximizing network throughput (minimizing backlog) in a fair manner is proposed.

*Proposition:* The myopic optimal stopping rule is a time variant threshold which maximizes network throughput with fairness.

*Proof:* Consider the probability of success under the same channel conditions ($P_{g_t}^{(1)} \approx P_{g_t}^{(2)}$) for two users. Suppose each user has a backlog $\eta_t^{(1)}$ and $\eta_t^{(2)}$ at the start of window $t$. Further assume that $\frac{\eta_t^{(1)}}{\eta_t^{(2)}} = \alpha$, such that $\alpha \geq 1$[1]. After minor simplification, users are set to achieve the probability of success as $P_{s_t}^{(1)*} \approx \{\frac{\alpha}{1-P_{g_t}^{(1)}}\} P_{s_t}^{(2)*}$. This implies that we expect $\lambda_t^{(1)} > \lambda_t^{(2)}$. However, due to slot contentions and channel fading assume that user 1 achieves the same random rate as user 2, *i.e.*, $\lambda_t^{(1)} = \lambda_t^{(2)} = \lambda$ and assume that $\lambda < \eta$.

Then the new backlogs for user 1 and 2 become

$$\frac{\eta_{t+1}^{(1)}}{\eta_{t+1}^{(2)}} = \frac{\eta_t^{(1)} - \lambda_t^{(1)}}{\eta_t^{(2)} - \lambda_t^{(2)}} \approx \frac{\alpha - (\lambda/\eta_t^{(2)})}{1 - (\lambda/\eta_t^{(2)})} \approx \frac{\alpha}{1 - (\lambda/\eta_t^{(2)})}. \tag{11}$$

Since $1 - (\frac{\lambda}{\eta_t^{(2)}}) < 1$, this implies that $\frac{\eta_{t+1}^{(1)}}{\eta_{t+1}^{(2)}} > \alpha$. So as the backlog gap widens between user 1 and 2, so does the threshold gap increase to $\frac{P_{s_{t+1}}^{(1)*}}{P_{s_{t+1}}^{(2)*}} > \frac{P_{s_t}^{(1)*}}{P_{s_t}^{(2)*}}$. This proves that the optimal thresholds will change in the next window if users' backlog ratio changes in the next window. Hence, it is very intuitive that as the backlog of one user increases due to severe fading on its link compared to other users, the optimal threshold setting would be to give more weight to that user with bad link in the next window. This will maximize network throughput with fairness in a finite horizon.

## V. SR SCHEDULING STRATEGY

Consider a single cluster-based homogeneous environment. Homogeneous environment in the context of this scheme means that all users have same priority. The ratio-based scheduling strategy for a user $i$ in the $t_{th}$ window entails the following steps:

Step 1: Calculate the weight for the $t_{th}$ window given by $\tau_t^{(i)*} = \frac{\eta_t^{(i)}}{\sum_{k=1}^{n} \eta_t^{(k)}}$.

Step 2: Set the target rate in the $t_{th}$ window to $\lambda_t^{(i)*}(\tau_t^{(i)*}) = w\tau_t^{(i)*}$.

Step 3: Transmit packets in slots until the threshold rate $\lfloor \lambda_t^{(i)}(\tau_t^{(i)*}) \rceil$ (round to nearest integer) is achieved or the slots in the current window finish.

Step 4: Repeat Steps 1-3 in every window.

[1]If users' backlogs gap increases then the respective thresholds will be adapted accordingly to reduce the backlog. Thus, user 1 having larger backlog than user 2 shows that due to initial backlog or due to bad channel condition, if user 1 has larger backlog and channel is consistently bad then the backlog gap between the two users will widen and thresholds will have to adapted accordingly to reduce backlog gap.

## VI. SIMULATION RESULTS AND DISCUSSION

A single hop time-slotted distributed wireless environment in a finite horizon $T$ is simulated to validate the performance of SR scheduling scheme. CPW duration is assumed to be 2 slots (which is subdivided into mini slots for synchronization and traffic information dissemination) compared to the data transmission window. Our SR scheme, henceforth termed as decision-based scheme, is compared with the non decision-based scheduling as the bench mark. In non decision-based scheme, all users transmit at a fixed rate without adapting rates in each window up to the finite horizon. Aggregate throughput comparison is made under no fading and independent Rayleigh fading channel conditions. Further, scalability, average throughput variance per window and Jain's fairness index [37] comparisons between the two schemes are made under independent Rayleigh fading channel conditions. It is noteworthy that in no fading condition, only slot contentions determine successful transmission and under Rayleigh fading channel condition contentions and relative SIR determine successful transmission. We assume that the fast fading does not change during the slot duration and furthermore average received signal remains constant during the finite horizon duration. Details of the simulation parameters are listed in Table 1.

TABLE I.
SIMULATION PARAMETERS.

| Parameter | Value |
|---|---|
| Finite horizon duration (T) | 3000 slots |
| Slot duration | 1 ms |
| Transmitting nodes | 4 |
| Channel access | Random |
| Frequency | 2.4 GHz |
| Doppler shift | 80 Hz |
| Window duration | 100 slots |
| Node data rate per horizon | 100-1300 packets |
| SIR thresh | 10 dB |

TABLE II.
JAIN'S FAIRNESS INDEX COMPARISON.

| Data Rate (packets per horizon) | Decision-Based (SR) (%) | Non Decision (%) |
|---|---|---|
| 1200 | 99.9 | 99.8 |
| 2000 | 99.9 | 99.8 |
| 2800 | 99.7 | 99.6 |

Simulation experiment is run more than 1000 times so that data is averaged over 3,000,000 slots. Fig. 3 shows the aggregate throughput comparison results of our decision-based and non decision-based scheduling schemes. In non decision-based scheme all nodes set their rates at the start of the finite horizon duration and no transmission probability adaptation is performed. Since the rates are set for the finite horizon duration the non decision-based scheme with fading achieves a global maximum aggregate

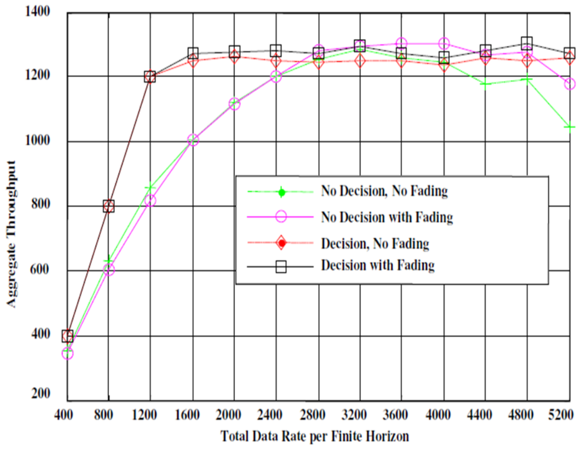


Figure 3. Aggregate Throughput per Finite Horizon.

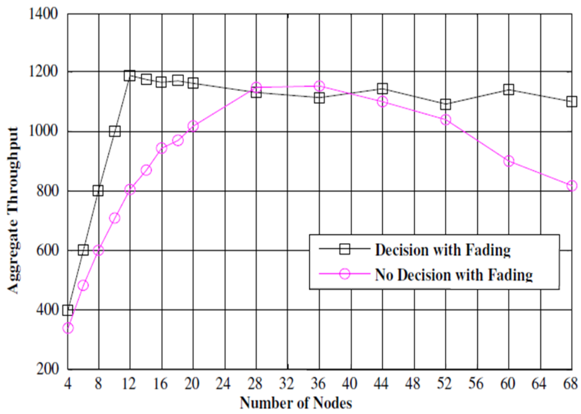


Figure 4. Aggregate Throughput Scalability (Each node transmits 100 packets).

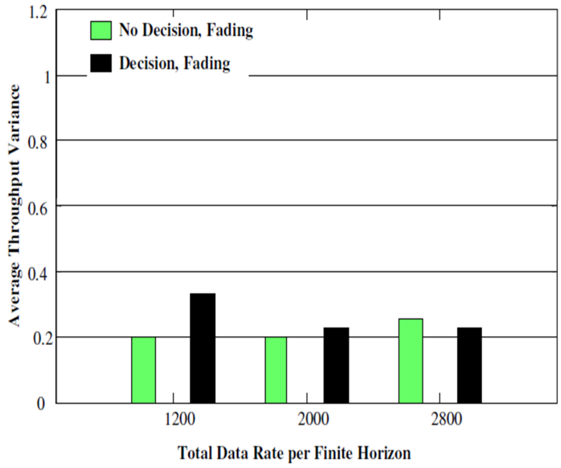


Figure 5. Average Throughput Variance per Window.

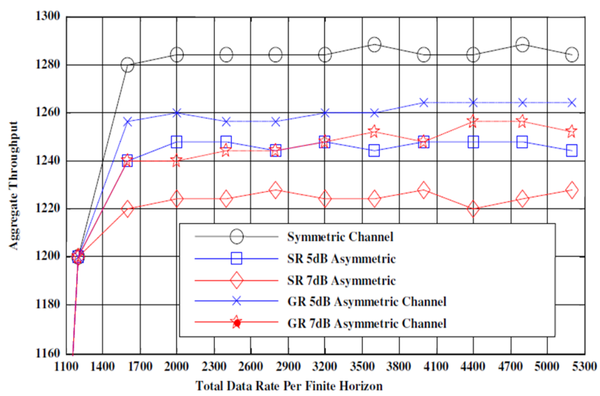


Figure 6. Aggregate Throughput Performance for SR and GR at 5 dB and 7 dB of Channel Asymmetry.

throughput of 1300 packets at the total data rate of 3600 packets per horizon. This corresponds to about 43% utilization within the finite horizon duration of 3000 slots. Fig. 3 shows that non decision-based scheme fails to meet the total data rate requirement even when the total data rate required is 50% (*i.e.*, 1600 packets) of the finite horizon duration. This is due to the fact that it sets its rate based on the finite horizon duration.

Hence, it does not achieve maximum aggregate throughput in each window. On the other hand, decision-based scheme myopically adapts in each window to maximize aggregate throughput with fairness. For total data rate from 2800 to 4400 packets per horizon, decision-based scheme performs as well as non decision-based scheme. When the total data rate is below 2800 or above 4400 packets, the performance of decision-based scheme is better than the non decision-based scheme.

As expected, decision-based scheme does not achieve global maximum aggregate throughput of 1300 packets, but on average remains within 1.6% of the maximum aggregate throughput for fading case. Fig. 4 compares the scalability performance of the two schemes for fading case only. The decision-based scheme's aggregate throughput clearly scales well with the number of nodes. The reason is that we adapt transmission probabilities of all users in proportion to their relative backlogs and fading effects to maximize utilization in a current window. Average throughput variance per window for the two schemes is compared in Fig. 5 for the feasible data rates of 1200, 2000 and 2800 packets. It is apparent that our decision-based scheme in addition to enhancing aggregate throughput within the finite horizon, also keeps the average throughput variance within 1 slot in the case of fading. To measure fairness, we use Jain's fairness index [37]. For $n$ nodes, the fairness index ($f$) is given by, $f = \frac{(\sum_{i=1}^{n} x_i)^2}{n\sum_{i=1}^{n} x_i^2}$. Fairness index value of 1 indicates ideal fairness and $\frac{1}{n}$ indicates no fairness. In Table 2, Jain's fairness index calculated over the finite horizon clearly indicates that the proposed scheme fairness is relatively better than the non decision-based scheme. This is due to the reason that decision-based scheme minimizes the backlog gap between users in each window in addition to maximizing the utilization in each window.

## VII. GENERAL RATION BASED SCHEME

The SR algorithm performs well compared to non decision-based scheme in terms of network throughput, scalability and fairness for symmetric channel conditions.

However, if a couple of users on average encounter bad channel conditions in every window, relative to other users, then the access probabilities for these users would continue to increase monotonically until the finite horizon is reached. This would lead to a significant network throughput degradation of SR scheme. As such, user will consume a large amount of resource in every window and consequently may starve other users with better channel conditions. This necessitates users' channel states to be taken in to consideration along with the users' backlogs for setting the threshold rates.

In this section, we generalize the simple-ratio based (SR) scheduling to general ratio-based (GR) scheme by considering the channel states in each window. The general transmission probability of $i_{th}$ user is mathematically represented as, $\tau_t^{(i)*} = \frac{C_i \eta_t^{(i)}}{\sum_{k=1}^{n} C_k \eta_t^{(k)}}$. Where, $C_i$ represents general weight of the user. In this work, it represents a product of $i_{th}$ user priority and channel condition. Since we consider homogeneous network where all users have the same priority, the transmission probability of the $i_{th}$ user simplifies to

$$\begin{aligned} \tau_t^{(i)*} &= \frac{\eta_t^{(i)} \int_{\gamma_t}^{\infty} f_t^{(i)}(r)dr}{\sum_{k=1}^{n} [\eta_t^{(k)} \int_{\gamma_t}^{\infty} f_t^{(k)}(r)dr]}; \\ C_{(i)} &= \int_{\gamma_t}^{\infty} f_t^{(i)}(r)dr. \end{aligned} \tag{12}$$

Let $P_g^{(i)} \equiv \int_{\gamma_t}^{\infty} f_t^{(i)}(r)dr$, where $P_g^{(i)}$ is the probability of a channel being in a good state and $\gamma_t$ is the SIR threshold that is considered same for all the users. The $P_g^{(i)}$ can be updated by each user $i$ for every window using well-known exponential averaging technique based on the past history of the user (see section 6.4.3.1 of [38]).

Each user in the GR scheme cooperatively sets the access probability by taking the ratio of the product of its backlog and the probability of its channel being in good state in a given window to the sum of products (of backlogs and channel states) of all the users in the network (8). The sum of the products of all the users is broadcast to the users by the cluster head that monitors the network. Note that users can easily provide their backlogs and channel states products information through RTS and CTS portion of the slot. The GR scheduling algorithm for a user $i$ in the $t_{th}$ window entails the same steps as the SR scheme with $\tau_t^*$ as in (12).

Simulations under same settings are performed to demonstrate throughput degradation of the SR scheme. For simulation purpose we assume that the precise value of $P_g^{(i)}$ is known to the $i_{th}$ user. Specifically, two cases are simulated: in the first case, two users have an equal average SIR that is 5 dB below the other two users in the network during the entire finite horizon duration. In the second case, the average SIR of the two users is set 7 dB below the other two users in the network. From Fig. 6, it is clear that for 5 dB channel asymmetry the SR scheme's aggregate throughput degrades by 2% on the average, and for the 7 dB channel asymmetry it degrades by 4%. The reason for throughput degradation is due to the fact that the two users with consistent bad channels (*i.e.*, with lower average SIR) cannot get rid of their backlogs and consequently lead to starvation of the other users with better channel conditions. The proposed GR scheme considers relative channel states of the users along with the backlogs to give higher precedence to users with relatively larger backlogs and better channel states products. Note that when users' channels are symmetric then GR scheme transforms to SR scheme. The dotted lines in Fig. 6 clearly show aggregate throughput improvement when GR scheme is employed in case of asymmetric channels. For 5 dB channel asymmetry, GR improves aggregate throughput by 1% and for 7 dB channel asymmetry the aggregate throughput improves by about 2%. Furthermore it is noteworthy to point out that for SR and GR scheduling schemes, each user always gets some share of slots in a window and is not starved, unless the product of their backlog and the channel state is zero.

## VIII. Conclusion

A novel approach of multi-window adaptation for throughput maximization with fairness in a finite horizon has been presented. Besides an SR (termed decision-based) scheme is proposed in which thresholds are myopically adapted for optimization in each window. Simulation results clearly show that compared to non decision-based strategy, throughput performance of our decision-based scheme comes very close to the optimal throughput of the non-decision based scheme, achieves comparable fairness, and is highly scalable (stable). The proposed GR scheme is shown to outperform the SR scheme in case of asymmetric channels by considering users backlogs and channel states in a window.

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